Climate-related natural disasters, economic growth, and armed civil conflict

Drago Bergholt
BI Norwegian Business School

Päivi Lujala
Norwegian University of Science and Technology (NTNU)

This is the authors' final, accepted and refereed manuscript to the article published in

Journal of Peace Research, **49(2012)1: 147-162**

DOI: http://dx.doi.org/10.1177/0022343311426167

CLIMATE-RELATED NATURAL DISASTERS, ECONOMIC GROWTH, AND ARMED CIVIL CONFLICT

Drago Bergholt

Department of Economics
Norwegian Business School (BI)
&
Centre for the Study of Civil War (CSCW), Peace Research Institute Oslo (PRIO)

Päivi Lujala

Department of Economics and Department of Geography
Norwegian University of Science and Technology (NTNU)
&
Centre for the Study of Civil War (CSCW), Peace Research Institute Oslo (PRIO)

Abstract

Global warming is expected to make the climate warmer, wetter, and wilder. It is predicted that such climate change will increase the severity and frequency of climate-related disasters like flash floods, surges, cyclones and severe storms. This article uses econometric methods to study the consequences of climate-induced natural disasters on economic growth, and how these disasters are linked to the onset of armed civil conflict either directly or via their impact on economic growth. The results show that climate-related natural disasters have a negative effect on growth and that the impact is considerable. The analysis of conflict onset shows that climate-related natural disasters do not increase the risk of armed conflict. This is also true when we instrument the change in GDP growth by climatic disasters. The result is robust to inclusion of country and time fixed effects, different estimation techniques, various operationalization of the disasters measure as well as for conflict incidence and war onset. These findings have two major implications: if climate change increases the frequency or make weather-related natural disasters more severe, it is an economic concern for countries susceptible to these types of hazards. However, our results suggest—based on historical data—that more frequent and severe climate-related disasters will not lead to more armed conflicts through their effects on GDP growth.

Key Words: Climate-related natural disasters, climate change, economic growth, armed civil conflict

INTRODUCTION

Catastrophes such as typhoons and floods have caused significant economic and human losses throughout the history. The heavy monsoon that hit Pakistan in July 2010 caused floods that ravaged the country, bringing enormous damage to homes, schools, fields, and infrastructure. The reported death toll for the event is about 2,000, while an estimated 20.3 million people, or more than 10% of the Pakistani population, were affected (OFDA, 2010).

We might be able to grasp the gravity of disaster damages through testimonies from victims, relief workers, and journalists, but the short- and long-term effects on economic growth and peace remain largely unknown. What happens to production and national income in the short run? Furthermore, with regard to ongoing transnational efforts to prevent armed civil conflicts, what are the effects of climate-related events?

The potential impact of climate change in the form of natural disasters is relevant not only for Pakistan: on average more than 270 devastating floods and storms are reported every year throughout the world (CRED, 2011).[1] Although it is the large-scale events that make the headlines, the frequency of smaller events is equally striking: Even in absence of large-scale events in 2009, more than 100 million people were victims of climatic disasters (Vos et al., 2010).

Questions about the impacts of such disasters are clearly of great importance for the livelihoods of a large number of people and countries and hence for international development agencies and policymakers throughout the global community. As global warming is expected to lead to an increase in both the severity and the frequency of climate-related disasters (IPCC, 2007: 43–54), it is important to understand how climate change will affect economies, and whether these will translate into more armed conflicts, directly or via impacts on economic growth. However, only a few studies have attempted to quantify the impact of these events using econometric methods and large N-scale panel datasets. In this article, we examine how climate-related natural disasters, including flash floods, surges, cyclones, blizzards, and severe storms, affect economic growth and peace. We label these events climatic disasters throughout the analysis.

---

[1] In fact, these two disaster classes alone represent more than 70% of all disasters reported in CRED's EM-DAT database the latest decade. See www.emdat.be.

By using ordinary least squares (OLS) and panel data on climate-related disasters and short-run economic growth,[2] we confirm that climate-related disasters have a negative impact on growth. However, our analysis of disaster data and conflict onset shows that climate-related natural disasters do not have any direct effect on conflict onset. We then instrument economic growth using our disaster measure in a two-stage least squares (2SLS) analysis to study whether climate-related disasters have an indirect effect on conflict onset via slowdown in economic growth. By doing this, we also address the simultaneity problem between income and conflict: as well as slow and negative economic growth may cause conflict, an approaching conflict may lead to slow growth, for example, when extractive industries withdraw from unstable countries that are on the brink of sliding into conflict. Instrumenting growth using climatic disasters allows us to impose exogenous growth variation in growth. However, we do not find any evidence that economic shocks caused by climate-related disasters have an effect on conflict onset. This result differs from the negative causal link between economic growth and conflict found in other studies, including Collier & Hoeffler (2004) and Miguel et al. (2004). However, our findings are similar to those in the recent cross-country study by Ciccone (2011).

Our study differs from previous work on natural disasters, economic growth, and conflict onset in several important ways. First, much of the previous work considers the economic effects of large-scale disasters. By contrast, this study includes small disasters in the analysis, and thereby takes into consideration that the large majority of what we define as natural disasters are actually small-scale events. Second, we use fixed effects methods to control for unobserved factors that may affect the results. For example, climate and closeness to coastline may affect both the occurrence of natural disasters and economic growth, or there may be overreporting on disaster magnitude in less developed countries to attract international aid. Finally, while most previous disaster studies ignore the possibility that different disaster types have different effects on the economy (for instance by aggregating geophysical events such as volcano eruptions and earthquakes, biological events such as famines, and slow onset events such as droughts, and then treat them as one), we only look at climatic disasters that come as sudden shocks and last for no longer than one month.

The article proceeds as follows. We begin by discussing the effect of climatic disasters on economic performance, drawing on recent literature, and how previous studies have considered natural phenomena in armed civil conflict research. Then we present our main

[2] We define the short run as the current year and next year.

hypotheses. Before turning to the analysis, we present our data and how our disaster variables have been constructed. We conclude by discussing the main results and their implications.

ECONOMIC EFFECTS OF NATURAL DISASTERS

As the devastating 2010 floods in Pakistan demonstrate, climate-related natural disasters undoubtedly cause very real economic damage when they occur: lives are lost, people are forced to leave their homes, buildings and other infrastructure collapse, and extractable resources become unavailable. All these consequences can be defined as direct impacts in the sense that they arise as immediate outcomes of disasters. Such impacts are obviously negative for most of the affected individuals and their economic activities. There are also a number of indirect impacts that follow in the aftermath of natural disasters and that are linked to economic activity such as income changes; demand and supply shocks; shifting terms of trade; and increased inflation.

The net effect on overall economic performance is the sum of the direct and indirect impacts. Although many authors believe that natural disasters are likely to have a negative impact on economic growth (Noy, 2009), this is not so clear from a theoretical point of view, at least not in the medium and long term, and at the aggregate national level. People and companies repair the damage, governments set up large infrastructure projects to repair damages and to prepare better for future disasters, and there may be substantial inflows of emergency aid. All these actions generate economic activity that may exceed the direct damages caused by the disaster. Consequently, the short-run effects on economic growth that this article considers are really a matter of dynamics and the selected time frame, and hence an empirical question. In the face of global warming, it is imperative to study these effects.

Surprisingly little research has been conducted to identify the relationship between climatic natural disasters and economic growth. Of these studies, Skidmore & Toya (2002) report a positive link between persistent climatic events such as droughts, extreme temperatures, wildfires, and economic growth while Loyza et al. (2009) find a positive effect on economic growth from floods and a negative effect from droughts. Raddatz (2007, 2009) reports that large-scale climatic disasters are negatively linked to economic growth. A negative effect on growth is also reported by Noy (2009) who assumes that geophysical, climatic, and biological disasters all have the same effect on growth and thus aggregates all these disasters together. As the results are partially ambiguous and the impacts of natural disasters may vary depending on their nature, more research is required. In this article we study a set of weather-related disasters which are likely to become more frequent in the future as they are related to climate change.

CLIMATIC DISASTERS, ECONOMIC GROWTH, AND CONFLICT

Research indicates that economic growth is related to the occurrence of armed conflict. If sudden changes in economic growth increase the risk of armed conflict, and weather-related disasters cause negative growth shocks, a logical consequence would be that such disasters can cause armed conflict via their negative impact on growth.

Several empirical studies document that slow economic growth and low income levels are important in predicting which countries will experience a conflict: armed civil conflict is more likely to occur in poor countries than in rich (see, among others, Collier & Hoeffler, 2004; Fearon & Laitin, 2003; Hegre & Sambanis, 2006). This can be the result of frustration and grievances, ease of recruiting rebels when even modest compensations to the rebel and his/her family exceed their present income, and lack of military capabilities and state capacity to prevent and suppress armed conflicts.

Of course, the political and social unrest that frequently precedes the onset of armed conflict often erodes economic institutions, causing economic havoc and making it more difficult to maintain peace. Herein lays a great econometric challenge: the latent start of a conflict may occur long before the unrest qualifies as a conflict onset in traditional conflict datasets such as the UCDP/PRIO armed conflict data. This implies a very real endogeneity problem because the low income growth may be as much a result of an approaching armed conflict as of a conflict itself. Many studies point to the importance of economic factors in explaining conflict onset, but only a few provide convincing solutions to this endogeneity problem. Most studies—such as those just mentioned—understandably rely on lagged regressors, and conclude that because low income level and negative income shocks tend to occur before the commencement of civil conflicts, they appear to be likely causes.

Methods of overcoming the simultaneity problem include the use of instrumental variables, as in Miguel et al. (2004), in which the researchers use rainfall in sub-Saharan Africa as instrument for GDP per capita growth. They find that a one percentage point decrease in rainfall raises the likelihood of a country experiencing conflict incidence by about two percentage points and conflict onset by three percentage points. Given that rainfall causes exogenous economic growth shocks, the 2SLS instrumental variable approach shows not only how growth correlates with conflict, but also justifies the causal assertion.

Bernauer et al. (2012) use deviation in temperature and rainfall (from long run averages) as instruments for economic growth in a global dataset for the period 1980–2004. They find no significant link between climate variability, economic growth, and the risk of conflict onset. This conclusion remains robust for a sub-sample including only African countries, thus contrasting with the results of Miguel et al. (2004). The Miguel et al. study is further challenged by Ciccone (2011) who shows that a misspecification of rainfall measures may explain the observed negative relation between rainfall and conflict.[3]

Some studies focus solely on the reduced-form relation between climate and the risk of conflict. Burke et al. (2009) study panel data on African countries between 1981 and 2002 by means of fixed effects transformed models, and find that a one degree Celsius increase in temperature will increase the risk of armed civil conflict by as much as 4.5 percentage points within the same year. However, Buhaug (2010) compares different data and model specifications, and concludes that climate variability in terms of temperature is a poor predictor of armed civil conflict.

A few studies consider the effects of climate-related disasters[4] on conflict using disaster dummies and frequencies.[5] Studies by Nel & Righarts (2008) and Besley & Persson (2011) find that climate disasters increase the risk of armed conflict. Slettebak (2012), however, finds that if anything, climate related disasters seem to reduce the risk of armed conflict onset.[6] All three studies are vulnerable to unobserved country heterogeneity in the sense that the distribution of natural disasters across countries probably is non-random. Indeed, the use of fixed effects transformations in our study is motivated by this econometric challenge.

[3] The same Ciccone study shows that Miguel et al. results do not hold when the time series are extended from 1999 to 2009. Brückner & Ciccone (2010) shows that the Miguel et al. study is not robust to using year fixed effects.

[4] Variation in temperature and rainfall may reflect climate-related disasters such as droughts and floods, but only indirectly and only when these are large and intense enough to affect the annual figures. These measures may also reflect other variations that are not related to climate shocks and thus fall outside the definition of natural disaster.

[5] By doing so the studies pay equal attention to events affecting 100 people as those affecting 100,000 people, for instance.

[6] In addition to these studies on climate-related disasters, Brancati (2007) and Nel & Righarts (2008) find that earthquakes increase the likelihood of incidence of armed conflict.

Although there is strong evidence that slow growth is linked to conflict onset, the other elements in the potential natural disaster to conflict pathway are less studied and understood. Clarifying the effects of natural disasters, particularly climate-related hazards, on the economy and on peace becomes important as we face global warming. Some previous studies indicate that natural disasters can have a negative impact on growth, but there is little research that examines whether these in turn trigger armed conflict. Given the causal pathway from natural disasters to slow growth and to armed civil conflict, the link between climate-related disasters and economic growth on the one hand, and economic fluctuations triggered by nature and armed civil conflict on the other hand, has not yet been investigated comprehensively. This article analyzes these relationships.

HYPOTHESES

To identify and quantify the short-run causal effects between climatic disasters, income growth, and armed civil conflict, our study proceeds in two stages. Because it is crucial to understand the effect of climate-related natural disasters on economic growth, we have chosen to analyze this relationship separately and in more detail than a mere instrumental variable analysis entails. Therefore, we first study the relationship between climate events and economic growth, and then the effect of growth on armed conflict onset.

Natural disasters are likely to affect growth immediately through their impact on production inputs: when severe climate-related natural disasters come as sudden and unexpected shocks or events, they cause damage to humans and infrastructure. Floods, winds related to heavy precipitation, unusually strong monsoons, storms, and tropical cyclones, destroy crops, kill farm animals, and can postpone the planting or harvesting season, thus having severe effects on people's income and assets. Damage to houses and farm buildings may force people to leave their homes and land, further limiting their income opportunities until they are able to return, rebuild, and plant, and the next harvesting season arrives. Even then, the land or equipment may be damaged to an extent that makes the first harvests unusually small. Disasters may also damage other infrastructure such as roads and factories and cause considerable harm to settlements in villages and cities, as demonstrated by the flooding that occurred in Pakistan in 2010. Even when there is substantial international relief assistance, these shocks alter input stocks that are used to create income and economic growth to the extent that in the short run we expect to see decline in economic growth.

H1: Climate-related disasters have a negative effect on economic growth

The previous literature on conflict onset has shown that slow economic growth is negatively related to increased risk of conflict onset. We take this as our point of departure and expect that negative economic shocks caused by climate events will increase the risk of armed conflict onset.

H2: Negative income growth shocks caused by climate-related disasters increase the likelihood of armed civil conflict onset

Even though much of the identification strategy for our second hypothesis relies heavily on arguments similar to those in Miguel et al. (2004) and Bernauer et al. (2012), our approach differs in some important ways. In contrast to these studies on temperature- and rainfall-induced conflict, we investigate disasters that come as sudden and more unexpected shocks. While most climatic disasters last for only some days, and so appear as impulses in the time dimension, for temperature and rainfall the variation in annual rainfall levels is a rather gradual phenomenon in most countries. Droughts in particular can go on for long periods of time and this time persistence may lead to expectations; for example, during a drought period a best prediction for near future is that the drought continues. In this way rainfall expectations among farmers and potential rebels may affect their willingness to join rebel movements. This in turn, may lead to endogeneity in models where rainfall is used as an instrument for economic growth.[7] By contrast, it is much harder to forecast sudden climatic disasters as they tend to come more as discrete shocks than as continuous events making them less predictable. Therefore, climate-related events as defined in this article serve as exogenous events in our second-stage analysis.

Furthermore, rainfall can have very heterogeneous effects on economic performance across countries. For instance, it is likely that agricultural economies in Sub-Saharan Africa are affected more heavily by rainfall variation than those in countries that use more advanced cultivation methods or have more diversified economies. Floods, cyclones, and storms, on the other hand, should have a negative impact whenever and wherever they occur. In this way, we

[7] Such expectations would have direct effects on conflict risk, independent of current economic conditions.

find it likely that climate-related disasters perform better as an instrument for economic growth in global panel studies than rainfall and temperature variation do.

Obviously, consequences of sudden natural disasters differ across countries. This may be due to culture, infrastructure, political institutions, etc. Some of these aspects we can control for by including control variables in the analysis while others effect on results is reduced by the inclusion of country-fixed effects.

DATA

Our panel dataset covers the period 1980–2007 and includes 171 independent countries and 4,455 country-year observations, although some are lost during analysis because of missing control variables (see summary statistics in Table I). We only include the data since 1980 because older disaster data are less reliable (Bureau for Crisis Prevention and Recovery, 2004).

Dependent variable 1: economic growth

The dependent variable in our growth analysis (Hypothesis 1) is the real GDP per capita growth rate (in terms of purchasing power parity). Data come from Penn World Table Version 6.3 (Heston, Summers & Aten, 2009). As the summary statistics in Table I show, average annual real GDP per capita growth was 1.7% during the period 1980–2007. The data clearly have some extreme values, ranging from -65.1% in Iraq (1991) and -62.4% in Liberia (1990) to 123.3% in Equatorial Guinea (1997). The first two figures are related to conflicts—the first Gulf War in Iraq and civil war in Liberia—and the latter to the discovery of large oil reserves in Equatorial Guinea in the mid-1990s. Despite some extreme values, the variable has approximately a normal distribution and 90% of observations are inside the -8.8% to 10.1% range.

Table I about here

Dependent variable 2: armed civil conflict

We use armed civil conflict onsets from the annually updated UCDP/PRIO Armed Conflict Dataset (Gleditsch et al., 2002; Harbom & Wallensteen, 2010) as our dependent variable in the conflict analysis. The dataset has a relatively low inclusion criterion (25 annual battle-related deaths), which allows us to include low-intensity conflicts. We include all internal and internationalized internal conflicts in our dataset. We use a dummy variable with a value of 1 when a new conflict emerges, when one of the parties in the conflict has changed completely, or when a conflict that has been inactive for more than two calendar years reemerges. In total, our dataset has 155 onsets, which comprise 3.5% of all country-year observations (Table I). As an alternative measure for a robustness check we include a dummy for conflict incidence with a value of 1 for all country-years with conflict. We also construct an onset dummy for conflicts which accumulate more than 1,000 battle-related deaths during the course of the conflict. All data comes from the UCDP/PRIO Armed Conflict Dataset.

As a country with an ongoing armed conflict can experience an outbreak of a new conflict, we include all country-year observations following the conflict onset. This allows us to include all conflict onsets in the dataset. To control for the possibility that a country that is already experiencing conflict, or that recently endured one, may be more likely to experience another conflict, we include a variable that counts the years since the last year of conflict, as suggested by Beck, Katz & Tucker (1998). This also controls for time dependence.

Climate-related disasters

In this study, we use disaster data from the Emergency Events Database (EM-DAT), developed by the Centre for Research on the Epidemiology of Disasters (CRED).[8] EM-DAT is a global dataset that has records on disasters since 1900. To qualify for inclusion in EM-DAT, an event must meet at least one of the following criteria: 10 or more casualties, 100 or more people affected, declaration of a state of emergency, or call for international assistance.

EM-DAT includes both natural and man-made disasters. We focus on climate-related disasters and, because we are especially interested in the exogeneity associated with shock-like natural events, we only include hazards sorting under the disaster classes floods and storms in EM-DAT.[9] They typically have rapid onsets and disappear within one month. As long as these events occur as shocks (that is, they last less than one month), they are included

[8] EM-DAT is available publicly at www.emdat.be.

[9] Previous versions of this article also included *wet mass movements*. These account for only 9% of the 1758 climatic disaster observations in our data. A robustness check revealed that they are not robustly related to climatic disasters and that they do not affect our results when excluded. Consequently, we only investigate floods and storms in this article.

in the analysis. An overview of all thirteen climate-related disasters included in our analysis is provided in Table II.

Table II about here

EM-DAT includes information on the numbers of people killed and people affected by the event, and the total direct damage (in current US dollars). We use the number of people affected as our main variable of interest.

How a disaster affects national income in any given year is likely to depend on the relative magnitude of the disaster as well as the time elapsed since the event took place. We normalize all disasters in a similar fashion to Noy (2009) in order to take these two factors into account. To account for magnitude, we normalize the size of an event by dividing the size of the affected population by total country population, using lagged figures for total population to ensure that the effect of the event does not enter into the denominator. Population numbers are taken from United Nations Statistical Data (UNSD 2011).

With regard to timing, because we measure economic growth on annual basis, we need to correct for event time; an event that happened in January potentially has a larger effect on the current year's income than an event that happened toward the end of year, which is more likely to affect the following year's growth figure. To address this concern, we weight the time elapsed since the event using the devaluation rate ($12–event\ month_{ijt}$)/12 in which j is a natural disaster in country i in year t. In other words, if an event took place in January (event month is 1), the normalized affected population is multiplied by 11/12. If the event happened in July, the multiplier is 5/12. This time appreciation allows disasters occurring in January this year to have a larger impact on current economic growth than disasters occurring in December this year. If a country has experienced several events during one year, the individual values are aggregated.

The annual, normalized, time-adjusted size of *population affected* over the year is thus calculated as:

$$\frac{\qquad}{\qquad}\;\frac{\qquad}{\qquad} \qquad (1)$$

where $population\ affected_{ijt}$ is the number of people affected in country i by disaster j at year t, $total\ population_{it-1}$ is the previous year's population size, and ($12–event\ month_{ijt}$)/12 is the imposed time weight. The left hand side of the equation thus represents the aggregated *population affected* over all climate-related disasters during year *t*.

Table I reports the disaster variable as a percentage—on average less than 0.45% of the population is reported to need immediate assistance because of climate-related natural disasters for a given country-year observation. The variation, though, is considerable. Although 2,960 country-year observations report that no disasters took place, the largest disasters affected up to 62% of the population.[10] For any given event, on average 1.4% of the population is affected (not reported). Table I shows that the time-weighted *population affected* (as defined in Equation 1) is roughly half the size of the non-weighted figure. This confirms that disasters, on a global scale, are distributed equally over the year. The table also shows that floods and storms are very similar in terms of *population affected.*

Control variables: economic growth model

Controls that we include in the economic growth model follow the literature on natural disasters and economic growth, such as Noy (2009) and Raddatz (2009). All control variables are lagged by one year to minimize the occurrence of reversed causality.

Our first control is lagged GDP per capita growth. Inclusion of lagged growth controls indirectly for omitted variables, at least to the extent that it embodies information on what was important in determining the dependent variable in the previous year (Andersen, 2002). In addition, a lagged growth variable allows us to estimate both the direct effect of the exogenous disaster shocks on current growth and their indirect effect on the following year's growth via lagged growth. Indeed, to the extent that current economic growth is determined by growth last year, natural disasters occurring today can affect future economic growth. The other controls include measures for trade openness (absolute value of imports and exports relative to GDP), inflow and outflow of foreign direct investment (FDI) as a share of GDP, investment share of real GDP, the size of government expenditures relative to real GDP, and (logged) inflation using the consumer price index (CPI).[11] Data for trade openness, investment, and governments expenditures come from Penn World Table Version 6.3

[10] Moldova experienced a large-scale storm in November 2000 that affected roughly 2.6 million people (EM-DAT, 2010). The second and third largest disasters (in terms of population affected relative to total population) in our data are the tropical cyclone that hit Solomon Islands in May 1986 and Hurricane Michelle, which hit Cuba in November 2001. They affected 55% and 53% of the population, respectively.

[11] Inclusion of these variables as controls in growth models is discussed in detail in Barro & Sala-i-Martin (2004: 518-540).

(Heston, Summers & Aten, 2009). Data for foreign direct investments and inflation come from The World Bank (2010).

Control variables: armed conflict model

Previous quantitative work on armed conflict has identified several factors that affect the onset of conflict. To keep our regression models as simple and parsimonious as possible in the second stage, we have limited the selection of controls to population size and regime type. Several other factors have been tested as part of the sensitivity assessment, but these do not affect the main results.

Population data come from Penn World Table Version 6.3. These data are both lagged and logged. We use a lagged Polity IV variable (Marshall & Jaggers, 2009) to measure level of democratization. It varies from 0 to 20, in which 0 denotes the most autocratic and 20 the most democratic state. Following Hegre et al. (2001), we include both the linear and squared measure in the model. The summary statistics for these variables are given in Table I.

ANALYSIS

Climatic disasters and economic growth

To test our first hypothesis, we estimate regression models with different transformations of the relevant explanatory variable, *population affected*.[12] In the analysis we estimate the following two-way error component model:

(2)

where

For each country *i* at year *t* we denote the following: y_{it} is the per capita GDP growth rate; α_1 is the disaster coefficient for the sum of the population affected by all disasters *j* in that year

[12] We also constructed similar measures for *people killed* and *economic damage* in which the number of people killed by the disaster are normalized by the size of total population and the amount of economic damage by GDP. Both measures use the same weight structure as *people affected* (Equation 1). Of these variables *population affected* was the best predictor of growth. It also renders the other two measures insignificant when all three variables are included in the base models simultaneously (the results are not shown).

(as defined in Equation 1); α_2 is the coefficient for lagged economic growth $y_{it\text{-}1}$;[13] $\boldsymbol{\kappa}_{it\text{-}1}$ is a vector of control variables (we follow the short-run growth literature by lagging them one year); and u_{it} is the error term composed of country-specific, unobserved factors independent of time, $\boldsymbol{\eta}_i$, year-specific, unobserved factors independent of country-characteristics, $\boldsymbol{\tau}_t$, and an idiosyncratic error term ε_{it}. $\boldsymbol{I}_\eta$ and $\boldsymbol{I}_\tau$ are two column vectors of ones.

A valid critique of previous studies is that they ignore time-independent geographic factors such as climate and closeness to the coastline or the equator, which affects the occurrence of natural disasters and economic growth (Gallup, Sachs & Mellinger, 1999). Furthermore, while developed countries may experience less human and infrastructural damage when disasters strike them, developing countries may have a tendency to exaggerate the impact of disasters to attract more aid from abroad (Skidmore & Toya, 2002). To reduce biases caused by these concerns, we estimate country fixed effects models, i.e. with variables transformed to deviations from their country-specific means. This effectively removes time-independent growth-factors, contained in the vector $\boldsymbol{\eta}_i$. We also include fixed year dummies to control for global shocks, the vector $\boldsymbol{\tau}_t$. Hence, both levels and trends in economic growth are picked up in a non-parametric fashion.[14]

Table III reports the results on the effects of climate-related disasters on per capita economic growth. As an introductory estimation, Model 1 includes a simple dummy variable noting whether a large-scale disaster took place in the country. The model also includes lagged economic growth for the previous year and the other control variables: openness to foreign trade, investment, government expenditure, FDI, and inflation, all lagged by one year. The results show a negative effect on current economic growth, significant at the 10% level.

Table III about here

We next study the effect of our more sophisticated climatic disaster variable that also explores variation in the smaller disasters. Model 2 includes our main variable of interest, the time-weighted *population affected* together with the controls from Model 1.[15] As can be seen from

[13] Other subsequent growth studies suggest that this AR(1) specification should be used (Raddatz, 2007; Noy, 2009).

[14] As robustness checks we also include country-specific time trends in the models in Table III. Use of these does not change the results (not shown).

[15] Including other controls such as current account balance, life expectancy at birth, etc. does not affect the results regarding our variable of interest.

the results, the effect of climatic natural disasters on current economic growth is negative and highly significant. When the weighted *population affected* increases by one standard deviation (0.014), economic growth is predicatively reduced by 0.38 percentage points (26.8*0.014) within the same year. The long-run growth reduction, calculated by evaluating Equation 2 in steady state with y_{it} equal to y_{it-1}, is predicatively 0.46 percentage points (0.38/(1–0.18)).

In Model 3 we include floods and storms separately to compare their impact on growth. The coefficients are similar and highly significant, and a F-test rejects the hypothesis that the marginal effects are different (F-value is 0.31; p-value is 0.58). This result holds across all specifications in the article. Thus, we use the combined measure for floods and storms in subsequent models.

We conduct several robustness checks of which some are reported in Table IV. Model 4 in Table IV shows that the results remain similar when all controls except for lagged growth are removed. As a control for other natural disasters, Model 5 shows the results using *earthquakes*, *volcano eruptions*, and *droughts* as additional regressors (earthquakes and volcanos are also measured by the number of people affected while drought is modeled by a dummy for the relevant country-years). Our climatic disaster variable proves robust to these controls and only drought seems to be significantly related to economic growth. Model 6 adds *lagged population affected* to the Model 2 from Table III. The lagged disaster variable has a positive sign, but fails to attain conventional significance level. It does not have any effect on our main variable of interest. Model 7 uses *logged population affected* and returns a strong negative impact on economic growth. Model 8 extends the time series to 1970 (the first year with available population data from UNSD), returning the same results as for the shorter time-span. Model 9 reruns the model with *population affected without time weights*. As expected, we get a negative coefficient about half of the size compared to the time weighted *population affected*.

Table IV about here

So far we have used the fixed effects estimator to control for time- and country-independent growth factors. Country-years probably also differ with respect to fixed conflict risk factors, so we use this estimator in the section about civil conflicts as well. However, fixed effects regressions based on Equation 2 might yield biased results because y_{it-1} is correlated with the country-specific *averaged* error ε_i by construction. As a final robustness check we adress this concern in Model 10 where the Arellano & Bond (1991) estimator is applied instead.[16] The empirical results confirm our previous findings: an increase in population affected by one standard deviation now corresponds to a total growth reduction of 0.56 percentage points.[17]

In total, the work presented so far provides quantitative evidence of a negative causal effect on short-run economic growth from the number of people affected by climatic disasters. The respective coefficients are significant and the results are robust to different model specifications and control variables used in the economic literature. If anything, these results can be taken as support for the argument that climate-related disasters alter factors that are important for production and income, and hence reduce overall economic performance.

Armed civil conflict

The second goal of this study is to analyze how growth changes triggered by climatic disasters determine the risk of armed civil conflict onset. Previous studies have shown that low income levels and slow economic growth increase the risk of armed civil conflict onset. From this, it follows that climate-related disasters may increase the likelihood of conflict through their negative impact on income growth. Analytically, we can define civil conflicts as a function of economic growth, and economic growth as a function of climatic disasters. According to advocated postulations and the chain rule, the dynamics are then given by:

(3)

The first term on the right-hand side of Equation 3 can be understood as a structural equation describing the growth effects on conflicts. It is empirically specified as:

(4)

For each country *i* at time *t* we denote the following: c_{it} is a dummy variable equal to one for all observations with new armed civil conflict onset; β_1^{IV} is the coefficient for the

[16] The estimator builds on a GMM-framework. It is obtained by differencing Equation 2 once, using all past values of economic growth in *levels* as instruments for present values in *first-differences* (this generates 71 instruments). Country-specific effects are eliminated by the differentiation, and the instruments remove correlation between lagged growth and error terms.

[17] Arellano-Bond tests (in first differences) suggest that the error term follows an AR(1) process (p-value is 0.000), but not an AR(2) (p-value is 0.337). The Hansen test of overidentifying restrictions does not reject the null (p-value is 0.275). All these numbers provide support for our model specification. The system GMM-estimator initially developed by Arellano & Bover (1995) gives similar results (not shown).

instrumented income growth $\hat{y}_{it}$;[18] $\boldsymbol{\gamma}$ is the coefficient vector for a vector of lagged control variables $\boldsymbol{\delta}_{it-1}$; and v_{it} is the error term.[19] Because the dependent variable is binary, the model in the second stage is a linear probability model. The parameter of interest in the structural equation is β_1^{IV}.

Table V summarizes key results from our instrumental variable analysis. First, we check how robust the disaster-growth relation is to commonly used conflict determinants. Model 11 includes controls for population size, regime type, and length of peace prior to the onset. The key explanatory variable as defined in Equation 1 is unchanged. The results confirm that our measure for climatic disasters is robust. The estimated growth reduction is 0.18 percentage points per percentage point increase in the disaster variable. The computed F-value is 11.48 (p-value < 0.001). In other words, climatic disasters seem to be strongly relevant for short-term growth fluctuations in GDP per capita, even when controlling for typical conflict variables.

Table V about here

As well as being relevant for income growth in the first-stage equation, climatic events should be exogenous in the second stage. A potential problem is that climate-related disasters might affect the risk of conflict through channels other than income. If this is true, we could get biased coefficients in the second-stage regression. Theoretically, weather-related disasters may affect conflict propensity in ways other than through income growth. For instance, if such events destroy communication and transportation systems, they may affect the mobility of the military and potential rebel groups. Net consequences of these mobility constraints are in theory ambiguous. On the one hand, climate-related disasters might separate conflict parties from each other, and thereby temporarily postpone an onset. On the other hand, if government forces depend more heavily on roads and conventional communication systems, climatic disasters might shift the conditions to wage war asymmetrically and thereby increase conflict risk as potential rebels' opportunity to emerge and survive may increase.

Thus, it is not feasible to rule out the possibility that sudden climatic disasters determine the probability of new conflicts only through income, a requirement for the instrument to be valid. Nevertheless, a reduced-form specification can at least provide some hints about the general relation between climate-related events and armed civil conflict. Model 12 in Table V

[18] The hat above *y* indicates that we use the instrumented rather than the observed values.

[19] Again we estimate country and time fixed effects models.

reports results from a reduced-form equation, i.e. the (short-run) effect from climate-related disasters on conflict onset. Current economic growth is also included in order to illustrate the typical negative growth effect found in previous studies.[20] As the model shows, climate-related disasters have no significant direct effect on the risk of conflict onset in our data. In fact, the average relation between population affected and conflict onset is negative (point estimate equal to -0.083), i.e. the opposite of our a priori hypothesis.

The other results presented by Model 12 are similar to the results in a number of previous studies. Economic growth is negatively linked to the risk of conflict onset: when economic growth increases by one percentage point, the risk of armed civil conflict onset is predicatively reduced by 0.11 percentage points. This result is significant at the 5% level. While all control variables have their expected signs, none of them are significant at the 10% level. In total, we find no support in our data that climatic disasters affect conflict onset other than through income fluctuations.

Model 13 shows results from the 2SLS analysis (Model 11 provides the first-stage results). Here, the link between current growth and conflict onset has changed from being negative and significant to being (positive and) clearly insignificant. In other words, growth changes caused by climatic disasters do not seem to affect the likelihood of experiencing a conflict onset. This is a further indication that changes in economic growth triggered by climatic disasters do not affect the probability of conflict onset.

To test sensitivity of the results, we run several alternative specifications. Table VI reports some of these: Model 15 repeats the baseline specification (Model 13 in Table V) with country-specific time-trends in addition (Model 14 shows results from the first stage). While the instrument gain in strength (F-value is 17.7), the second stage results remain unchanged. In Models 16 and 17 we use the two disaster classes floods and storms as separate instruments.[21] As expected, the results are almost identical to Models 14 and 15 although the statistics suggest weaker identification in the first stage. The same is the case with Models 18 and 19 that use the natural logarithm of *population affected* as instrument. Model 21 substitutes the onset variable with a dummy for conflict incidence to test whether disaster-triggered growth shocks affect the likelihood of conflict presence (reduced form is provided

[20] We also estimated conflict models with one and two year time lags for economic growth, but these did not affect the conflict propensity.

[21] We cannot reject the null-hypothesis that both instruments are valid (Hansen J statistic equal to 0.182; p-value is 0.67). Country-specific time trends are included here as well to gain power in the first stage.

in Model 20; the first stage is the same as Model 11 in Table V). Models 22 and 23 examine onset of war (conflict onset that accumulated at least 1000 battle-related deaths during the course of conflict). As earlier, the second-stage results are insignificant. Taken together, the a priori expected negative effect from current economic growth on the risk of armed civil conflict onset is not present in our 2SLS models.[22]

These results differ from those in the empirical studies of Collier & Hoeffler (2004) and Miguel et al. (2004), who find significant negative effects from economic growth on the risk of civil conflict onset. Our results support the view that economic growth, when instrumented by climatic phenomena, does not relate systematically to armed civil conflict onset (Bernauer et al. 2012). This finding, however, may be specific to climate-related natural disasters and does not necessary rule out growth impacts on conflict in general.

CONCLUSIONS

Climate change may well be the most serious and wide-ranging future challenge facing our planet. Not only will it change the living conditions for people and animal and plant life on a permanent basis when it comes to temperature and precipitation, it may also increase the number or intensity of various climate-related disasters. To explore how these latter changes may play out for countries affected by such disasters, this article examines how climate-related disasters affect economic growth and armed civil conflicts during the period 1980–2007.[23]

Our results show that an increase by one standard deviation in the number of people affected by sudden climatic disasters leads to a total aggregate income growth reduction of about 0.5 percentage points. Arguably, storms and floods adversely affect people and production inputs such as land, infrastructure, and factories, which in turn have a negative impact on the aggregate economy.

Interestingly, these negative income shocks do not increase the risk of armed civil conflict as predicted by prominent studies in the field (Collier & Hoeffler, 2004; Fearon & Laitin, 2003; Miguel et al., 2004). However, our results primarily justify assertions about income

[22] As further robustness checks, we run several alternative specifications of the base model: generalized least squares models without country fixed effects, logit models, expand the time period to 1970–2007, and add other controls. None of these change the results.

[23] For an attempt to predict the future, see Devitt and Tol (2012) who simulate a model with climate change, civil war and development.

changes caused by climatic disasters. It might still be the case that growth shocks caused by rainfall (see Miguel et al., 2004) change the likelihood of civil conflicts in ways other than growth shocks caused by sudden floods and storms, although analyses conducted on a more local scale indicate that short-term variations in climate do not seem to provoke land-related conflicts (Benjaminsen et al., 2012) and that drought periods see fewer episodes of violent cattle raiding (Roba et al., 2012).

There could be several possible reasons why we find, based on historical data, that economic downturn caused by climatic hazards does not seem to come with increased conflict risk on a year-by-year basis. First, it may matter what has caused economic hardship in the country. A natural disaster may be viewed by the population as outside the government's control and thus the economic consequences are not blamed on the government. Second, people hit by such a disaster may consider economic consequences as transitory; after the houses have been rebuild and next harvest is in, the life is expected to return back to normal in economic terms. Third, as disasters can have unifying effects on the population that diverts attention from other grievances, they might, at least transitionally, reduce the likelihood that a rebel movement emerges (Slettebak, 2012).

Finally, our results may indicate that economic growth and income level may not be such important sources of conflict as previous studies imply. We find our results appealing because the traditional economic approach with rebels as rational utility-maximizing individuals does not necessarily yield a negative income-conflict relationship. Indeed, higher income growth could make it more attractive to take up arms as long as higher national income means that there is more to grab. In other words, the argument that higher growth represents higher alternative costs associated with rebellion is not as straightforward as generally thought, even if one accepts the rather restrictive definition of rebels as rational and utility-maximizing individuals. This is in line with economic theory that suggests a positive relationship between economic growth and crime rates (Mehlum, Moene & Torvik, 2004).

Hence, our insignificant 2SLS estimates might be an indication that the linkage between economic conditions and conflict risk is far more complex or heterogeneous than suggested by earlier country-year analyses. When it comes to climate change and increased frequency and severity of climate disasters, our study indicates that in the past, the *short-term* negative effect of climate-induced disasters on economic growth does not increase the risk of conflict onset in the following two year period. Thus, there is a need for studies that look at the long-term economic effects of disasters and how these relate to the risk of armed civil conflict.

Replication data

The dataset and do-files for the empirical analysis in this article can be found at http://www.prio.no/jpr/datasets. All analyses was done using Stata 11.

Acknowledgements

We are grateful to our colleagues at the Department of Economics, Norwegian University of Science and Technology (NTNU), Department of Economics, Norwegian Business School (BI) and the Centre for the Study of Civil War, PRIO, for their comments and discussions. We also thank the editor and three anonymous referees for constructive comments and suggestions.

References

Andersen, Lykke E. (2002) *The Dynamics of Deforestation and Economic Growth in the Brazilian Amazon*. Cambridge: Cambridge University Press.

Arellano, Manuel & Olympia Bover (1995) Another Look at the Instrumental-Variable Estimation of Error-Component Models. *Journal of Econometrics* 68(1): 29–52.

Arellano, Manuel & Steve Bond (1991) Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *Review of Economic Studies* 58(2): 277–97.

Barro, Robert J. & Xavier Sala-i-Martin (2004) *Economic Growth* (Second edition). Cambridge, MA: MIT Press.

Beck, Nathaniel; Jonathan N. Katz & Richard Tucker (1998) Taking time seriously in binary time-series-cross-section analysis. *American Journal of Political Science* 42(4): 1260–1288.

Benjaminsen, Tor A.; Koffi Alinon, Halvard Buhaug & Jill Tove Buseth (2012) Does Climate Change Drive Land-Use Conflicts in the Sahel? *Journal of Peace Reseach* 49(1), in press.

Bernauer, Thomas; Vally Koubi, Anna Kalbhenn, & Gabrielle Spilker (2012) Climate Variability, Economic Growth, and Civil Conflict. *Journal of Peace Reseach* 49(1), in press.

Besley, Timothy & Torsten Persson (2011) The Logic of Political Violence. *Quarterly Journal of Economics*, 162(3): in press.

Brancati, Dawn (2007) Political aftershocks: The impact of earthquakes on intrastate conflict. *Journal of Conflict Resolution* 51(5): 715–43.

Brückner, Markus & Antonio Ciccone (2010) International commodity prices, growth and the outbreak of civil war in sub-Saharan Africa. *Economic Journal* 120 (5): 519–534.

Buhaug, Halvard (2010) Climate not to blame for African civil wars. *Proceedings of the National Academy of Sciences of the USA* 107(38): 16477–16482.

Burke, Marshall B.; Edward Miguel, Shanker Satyanath, John A. Dykema & David B. Lobell (2009) Warming increases the risk of civil war in Africa. *Proceedings of the National Academy of Sciences of the USA* 106(49): 20670–20674.

Ciccone, Antonio (2011) Economic shocks and civil conflict: A comment. *American Economic Journal: Applied Economics*, in press.

Collier, Paul & Anke Hoeffler (2004) Greed and grievance in civil war. *Oxford Economic Papers* 56(4): 563–596.

CRED (2011) 2010 Disasters in Numbers. Press release from Centre for Research on the Epidemiology of Disasters. http://cred.be/sites/default/files/PressConference2010.pdf

Devitt, Conor & Richard S. J. Tol (2012) Civil war, climate change and development: a Scenario study for Sub-Saharan Africa. *Journal of Peace Research* 49(1): 000–000.

Fearon, James D. & David D. Laitin (2003) Ethnicity, insurgency, and civil war. *American Political Science Review* 97(1): 75–90.

Gallup, John L.; Jeffrey D. Sachs & Andrew D. Mellinger (1999) Geography and Economic Development. *International Regional Science Review* 22(2): 179–232.

Gleditsch, Nils Petter; Peter Wallensteen, Mikael Eriksson, Margareta Sollenberg & Håvard Strand (2002) Armed conflict 1946–2001: A new dataset. *Journal of Peace Research* 39(5): 615–637.

Harbom, Lotta & Peter Wallensteen (2010) Armed conflicts, 1946–2009. *Journal of Peace Research* 47(4): 501–509.

Hegre, Håvard & Nicholas Sambanis (2006) Sensitivity analysis of the empirical literature on civil war onset. *Journal of Conflict Resolution* 50(4): 508–535.

Hegre, Håvard; Tanja Ellingsen, Scott Gates & Nils Petter Gleditsch (2001) Towards a democratic civil peace? Democracy, political change, and civil war, 1816–1992. *American Political Science Review* 95(1): 17–33.

Heston, Alan; Robert Summers & Bettina Aten (2009) Penn World Table version 6.3. Center for International Comparisons at the University of Pennsylvania (CICUP) (http://pwt.econ.upenn.edu/).

IPCC (2007) *Climate Change 2007: Synthesis Report*. Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Rajendra Pachauri & Andy Reisinger (eds.). Geneva: Intergovernmental Panel of Climate change. (http://www.ipcc.ch/publications_and_data/publications_ipcc_fourth_assessment_report_synthesis_report.htm).

Loyza, Norman; Eduardo Olaberria, Jamele Rigolini & Luc Christiaensen (2009) Natural disasters and growth – Going beyond the averages. *World Bank Policy Research Working Paper* (4980).

Marshall, Monty G & Keith Jaggers (2009) Polity IV Dataset. College Park, MD: Center for International Development and Conflict Management, University of Maryland (http://www.systemicpeace.org/polity/polity4.htm).

Mehlum, Halvor; Karl Moene & Ragnar Torvik (2004) Crime induced poverty traps. *Journal of Development Economics* 77(2): 325–240.

Miguel, Edward; Shanker Satyanath & Ernest Sergenti (2004) Economic shocks and civil conflict: An instrumental variables approach. *Journal of Political Economy* 112(4): 725–754.

Nel, Philip & Marjolein Righarts (2008) Natural disasters and the risk of violent civil conflict. *International Studies Quarterly* 52(1): 159–185.

Noy, Ilan (2009) The macroeconomic consequences of disasters. *Journal of Development Economics* 88(2): 221–231.

OFDA (2010) Pakistan – Floods. Fact Sheet #3. (www.usaid.gov/our_work/humanitarian_assistance/disaster_assistance/countries/pakistan/template/fs_sr/fy2011/pakistan_fl_fs03_10-22-2010.pdf).

Raddatz, Claudio (2007) Are external shocks responsible for the instability of output in low-income countries? *Journal of Development Economics* 85(1): 155–187.

Raddatz, Claudio (2009) The wrath of God: Macroeconomic costs of natural disasters. *World Bank Policy Research Working Paper* (5039).

Roba, Adano; Karen Witsenburg, Ton Dietz & Fred Zaal (2012) Climate change, violent conflict and local institutions in Kenya's drylands. *Journal of Peace Reseach* 49(1), in press.

Skidmore, Mark & Hideki Toya (2002) Do natural disasters promote long-run growth? *Economic Inquiry* 40(4): 664–687.

Slettebak, Rune (2012) Don't blame the weather! Climate-related natural disasters and civil conflict. *Journal of Peace Reseach* 49(1), in press.

UNSD (2010) *United Nations Statistical Database* (http://unstats.un.org/unsd/databases.htm).

Vos, Femke; Jose Rodriguez, Regina Below & D. Guha-Sapir (2010) *Annual Statistical Disaster Review 2009 – The numbers and trends*. Brussels: Centre for Research on the Epidemiology of Disasters.

World Bank (2010) *World Development Indicators*. Washington, DC: World Bank. (http://data.worldbank.org/data-catalog).

Bio

Drago Bergholt, b. 1984, PhD candidate in Economics (BI Norwegian Business School, 2010–) . Main research interests: economic growth, monetary policy and business cycles.

Päivi Lujala, b. 1975, PhD in Economics (Norwegian University of Science and Technology (NTNU), 2008); Associate Professor at the Department of Geography, NTNU (2011–). Main research interests: natural resources and conflict, natural resource governance, vulnerability and exposure to climate change. Most recent book: High-Value Natural Resources and Post-Conflict Peacebuilding (Earthscan, 2012).

Table I. Descriptive statistics for data used in the analysis

Variable	#	Mean	Std. Dev.	Min	Max
Dependent variables					
Conflict onset (> 25 battle deaths)	4,455	0.035	0.183	0	1
Real GDP per capita growth (%)	4,354	1.726	7.415	-65.1	123.3
Climatic disasters					
Large disaster (> 10,000 affected)	4,417	0.171	0.376	0	1
Population affected (%)	4,279	0.448	2.689	0	62.5
Population affected (%), time weights	4,279	0.201	1.388	0	32.2
Affected by floods (%), time weights	4,279	0.110	0.946	0	23.5
Affected by storms (%), time weights	4,279	0.090	1.012	0	32.2
Control variables (all lagged by one year)					
Openness of economy (%)	4,356	77.4	49.1	1.086	456.6
Real investment share of GDP (%)	4,342	20.1	11.8	-18.9	90.3
Real government share of GDP (%)	4,342	19.0	10.0	1.438	83.3
FDI inflow relative to GDP (%)	3,876	3.608	19.7	-82.9	564.9
FDI outflow relative to GDP (%)	3,468	1.129	14.2	-10.4	570.4
Inflation	3,630	46.0	505.3	-100.0	23,773.1
Population size ('000)	4,369	33,444	120,500	149.8	1,313,974
Democracy index	4,065	11.2	7.33	0	20

FDI=Foreign direct investment

Table II. Climate-related disasters included in the study

Disaster class	*Disaster type*
Floods	General floods
	River floods
	Flash floods
	Coastal floods
	Storm surge
Storms	Tropical storms
	Extra-tropical cyclones
	Thunderstorms/lightning
	Snowstorms/blizzards
	Sandstorms/dust storms
	Generic (severe) storms
	Tornadoes
	Orographic storms (strong winds)

Table III. Climate-related disasters and economic growth, 1980–2007

	(1) GDP/capita growth	(2) GDP/capita growth	(3) GDP/capita growth
Population affected (time weights), t		-26.8***	
		(-6.75)	
Affected by floods (time weights), t			-31.0***
			(-3.10)
Affected by storms (time weights), t			-24.0***
			(-4.47)
Climatic disaster (dummy), t	-0.53*		
	(-1.91)		
GDP/capita growth, t-1	0.17***	0.18***	0.18***
	(3.89)	(3.94)	(3.93)
Trade openness, t-1	0.015**	0.014*	0.014*
	(2.00)	(1.92)	(1.92)
Real investment share of GDP, t-1	0.031	0.031	0.031
	(0.75)	(0.76)	(0.76)
Real government share of GDP, t-1	0.025	0.025	0.025
	(0.29)	(0.28)	(0.29)
FDI inflow, t-1	0.36*	0.36*	0.36*
	(1.90)	(1.92)	(1.92)
FDI outflow, t-1	-0.30**	-0.30**	-0.30**
	(-1.98)	(-1.99)	(-1.99)
Inflation (ln), t-1	-0.075	-0.069	-0.068
	(-0.72)	(-0.66)	(-0.65)
Observations	2,940	2,904	2,904
Countries	149	145	145
R-squared	0.18	0.18	0.18

Robust t-statistics, clustered on countries, in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Fixed country and year effects are included in all analyses. Models are estimated with STATA 11.

Table IV. Climate-related disasters and economic growth – Robustness tests

	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	GDP/capita growth	GDP/capita growth	GDP/capita growth	GDP/capita growth	GDP/capita growth	GDP/capita growth	GDP/capita growth
Population affected (time weights), t	-22.6***	-26.5***	-26.6***		-25.7***		-32.8***
	(-4.27)	(-6.65)	(-6.71)		(-6.56)		(-5.12)
Population affected (time weights), t-1			4.72				
			(0.91)				
Population affected (ln) (time weights), t				-0.55***			
				(-4.14)			
Population affected (no time weights), t						-12.4**	
						(-2.28)	
Earthquakes (time weights), t		-3.11					
		(-0.31)					
Volcanoes (time weights), t		-25.0					
		(-0.10)					
Droughts (dummy), t		-0.62*					
		(-1.94)					
GDP/capita growth, t-1	0.16***	0.18***	0.18***	0.17***	0.18***	0.17***	0.18***
	(2.79)	(3.93)	(3.96)	(3.92)	(4.28)	(3.91)	(3.47)
Trade openness, t-1		0.014*	0.014*	0.014*	0.013*	0.014*	0.034
		(1.91)	(1.93)	(1.88)	(1.67)	(1.91)	(1.26)
Real investment share of GDP, t-1		0.031	0.031	0.032	0.023	0.032	-0.042
		(0.76)	(0.76)	(0.78)	(0.60)	(0.77)	(-0.46)
Real government share of GDP, t-1		0.024	0.025	0.025	0.015	0.023	0.052
		(0.28)	(0.29)	(0.29)	(0.20)	(0.26)	(0.26)
FDI inflow, t-1		0.36*	0.36*	0.36*	0.34*	0.36*	0.053
		(1.92)	(1.91)	(1.92)	(1.82)	(1.91)	(0.61)
FDI outflow, t-1		-0.30**	-0.30**	-0.30**	-0.29*	-0.30**	-0.050
		(-1.99)	(-1.99)	(-1.99)	(-1.88)	(-1.99)	(-0.68)
Inflation (ln), t-1		-0.071	-0.072	-0.055	-0.041	-0.069	0.15
		(-0.68)	(-0.68)	(-0.52)	(-0.40)	(-0.65)	(0.77)
Observations	4,210	2,904	2,904	2,904	3,256	2,904	2,731
Countries	162	145	145	145	145	145	143
R-squared	0.07	0.18	0.18	0.18	0.18	0.18	–
Time period	1980–2007	1980–2007	1980–2007	1980–2007	1970–2007	1980–2007	1980–2007

Robust t-statistics, clustered on countries, in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1. Fixed country and year effects are included in all analyses. Models are estimated with STATA 11.

Table V. Climatic disasters, economic growth, and armed civil conflict, 1980–2007

	(11) GDP/capita growth	(12) Conflict onset	(13) Conflict onset
GDP/capita growth, t		-0.0011**	0.0035
		(-2.01)	(0.65)
Population affected (time weights), t	-18.02***	-0.083	Instrument
	(-3.39)	(-0.84)	
Population (ln), t-1	-2.02	0.053	0.062*
	(-0.98)	(1.65)	(1.74)
Democracy index, t-1	0.055	0.0052	0.0049
	(0.32)	(1.14)	(1.04)
Democracy index (squared), t-1	-0.0020	-0.00020	-0.00019
	(-0.25)	(-0.94)	(-0.87)
Observations	3,894	3,894	3,894
Countries	153	153	153
R-squared	0.05	0.03	–
F-test of instrument	–	–	11.48***

Robust z-statistics (t-statistics in first stage columns), clustered on countries, in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1. Fixed country and year effects are included in all analyses. Coefficients for time since last onset and cubic splines are not shown. Models are estimated with STATA 11.

Table VI. Armed civil conflict – Robustness tests

	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
	GDP/capita growth	Conflict onset	GDP/capita growth	Conflict onset	GDP/capita growth	Conflict onset	Conflict incidence	Conflict incidence	War onset	War onset
GDP/capita growth, t		0.0045		0.0045		0.0020	-0.0020***	-0.012	-0.00025	-0.0020
		(0.96)		(0.96)		(0.29)	(-2.67)	(-1.28)	(-1.55)	(-0.90)
Population affected (time weights), t	-20.1***	Instrument					0.18	Instrument	0.031	Instrument
	(-4.20)						(1.10)		(0.82)	
Affected by floods (time weights), t			-20.4**	Instrument						
			(-2.21)							
Affected by storms (time weights), t			-19.7***	Instrument						
			(-4.40)							
Population affected (ln) (time weights), t					-0.38***	Instrument				
					(-2.70)					
Population (ln), t-1	-14.9**	0.065	-14.9**	0.065	-2.04	0.059*	0.045	0.025	0.0032	-0.00025
	(-2.05)	(0.43)	(-2.05)	(0.43)	(-0.99)	(1.66)	(0.75)	(0.35)	(0.46)	(-0.03)
Democracy index, t-1	-0.24	-0.0054	-0.24	-0.0054	0.059	0.0050	0.010	0.011	0.0029**	0.0030**
	(-1.02)	(-0.93)	(-1.02)	(-0.93)	(0.35)	(1.07)	(1.22)	(1.30)	(2.04)	(2.14)
Democracy index (squared), t-1	0.012	0.00031	0.012	0.00031	-0.0023	-0.00019	-0.00056	-0.00058	-0.00013**	-0.00013**
	(1.07)	(1.18)	(1.07)	(1.17)	(-0.28)	(-0.89)	(-1.42)	(-1.47)	(-2.06)	(-2.13)
Observations	3,894	3,894	3,894	3,384	3,894	3,894	3,894	3,894	3,894	3,894
Countries	153	153	153	153	153	153	153	153	153	153
R-squared	0.13	–	0.13	–	0.05	–	0.27	–	0.01	–
F-test of instrument	–	17.65***	–	13.87***	–	7.31***	–	11.48***	–	11.48***
Country-specific year trend	Yes	Yes	Yes	Yes	No	No	No	No	No	No

Robust z-statistics (t-statistics in first stage columns), clustered on countries, in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1. Fixed country and year effects are included in all analyses. Coefficients for time since last onset and cubic splines are not shown. Models are estimated with STATA 11.