Natural disasters, economic growth and armed civil conflict

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Abstract: Catastrophes such as floods, droughts and earthquakes have caused significant human and infrastructural losses throughout history. Nevertheless, researchers struggle to quantify macroeconomic impacts, and the existing literature is ambiguous in its findings. In this study I use econometric methods on panel data from Centre for Research on the Epidemiology of Disasters (CRED), and find that hydrometeorological, climatological and geophysical events all affect economic growth negatively in the short run. Second, while events typically linked to climate change tend to cause negative growth shocks the same year they occur, geophysical disasters do not alter overall economic performance before the next year. With respect to future global warming, these dynamic differences give important insights for the understanding of how economies might be affected by climate change. However, by means of two stage least square methods, I do not find that negative economic shocks caused by weather related disasters increase the likelihood of armed civil conflicts. This latter result is in contrast to conclusions in much of the seminal conflict literature, but similar to findings in other recent cross-country studies that use the instrument variable approach.

Preface:

First and foremost, I am grateful to post doc. Päivi Lujala (Department of Economics, University of Science and Technology) and senior researcher Halvard Buhaug (Centre for the Study of Civil War, Peace Research Institute Oslo) for their excellent guidance on this master thesis. Second, I want to thank participants at the "Young Scholars Forum" (February 2010 in Oslo), the "Climate Change and Security" conference (June 2010 in Trondheim) and the "Facts and Myths about Civil War" conference (June 2010 in Oslo) for very helpful comments and discussions. Finally, I thank Peace Research Center Oslo for financial and infrastructural support.

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1. Introduction

1.1 Background

"Pakistan is facing a slow-motion tsunami. Its destructive power will accumulate and grow with time... Make no mistake: This is a global disaster, a global challenge. It is one of the greatest tests of global solidarity in our times."

Secretary General Ban Ki-moon in remarks to the UN Assembly, 19th August 2010 (UN Department of Public Information 2010)

A heavy monsoon hit Pakistan late in July this year. As I write this, the situation has escalated dramatically, and floods ravage throughout the country. The destructive nature of this disaster seems to be of enormous scale, with severe impacts on homes, schools, plants, crops, roads and human livelihood. While only 1500 people are reported killed so far, an estimated 17.2 million, or nearly ten percent of the Pakistani population, have been affected according to Office of U.S. Foreign Disaster Assistance (OFDA 2010). It is overall economic impacts of such natural disasters that I am going to target in this study.

We might be able to grasp the gravity of some of the direct disaster damages in Pakistan through testimonies from victims, relief workers and journalists in media, but aftermaths of the ongoing event is by far unknown. How will such a natural disaster affect future development and everyday life in the region? What will happen to production and national income once the water masses have withdrawn? Further, with regards to ongoing transnational efforts to prevent armed civil conflicts and terrorism, how do large scale events like the Pakistani flood play out? These issues are relevant not only for Pakistan; natural disasters happen every year throughout the world. Only the last few weeks, another huge flood and multiple landslides have taken place in China, heat waves and wildfires have caused great losses in Russia, and Eastern Europe has just experienced heavy rainfall with significant material damages. Not to mention the Haiti Earthquake in January.

An additional concern with regard to economic consequences is the potential link between climate change on the one side, and the frequency and intensity of natural disasters on the other. As illustrated in figure 1.1 from the International Panel on Climate Change Fourth Assessment Report (IPCC 2007: 31), there is clear evidence that global temperatures and sea levels have increased significantly the past decades, while average snow cover on the northern hemisphere has decreased. Among potential outcomes of these trends are changing patterns of natural disasters. In fact, the IPCC Fourth Assessment Report suggests that future global warming will cause more frequent and intense heat spells, precipitation events, droughts, flooding, storms, cyclones and extreme sea levels, all of which might affect economic growth and development (IPCC 2007: 53). A quick glance at data seems to give support for this view. Figure 1.2 shows the historic frequency of different natural disaster groups between 1980 and 2007, based on data from the dataset used in this study (CRED 2010). The yellow line at the bottom tracks droughts, the green line in the middle represents earthquakes and volcanoes, while the blue line at the top shows the frequency of floods, storms, cyclones, hurricanes and other weather-related natural disasters. One interesting pattern emerges: Except from droughts, the frequency of disasters often linked to climate change have increased significantly over time in the dataset.[1]

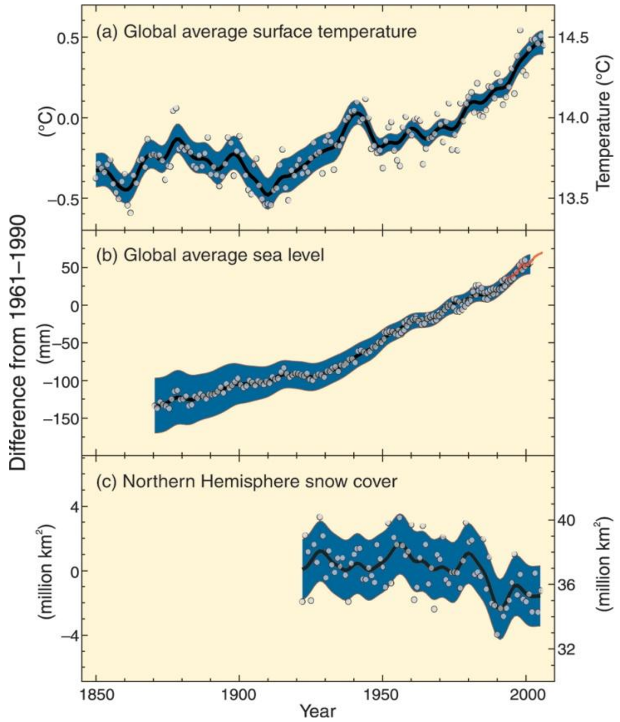

Figure 1.1: Trends in global temperatures, sea levels and snow cover (IPCC 2007: 31)

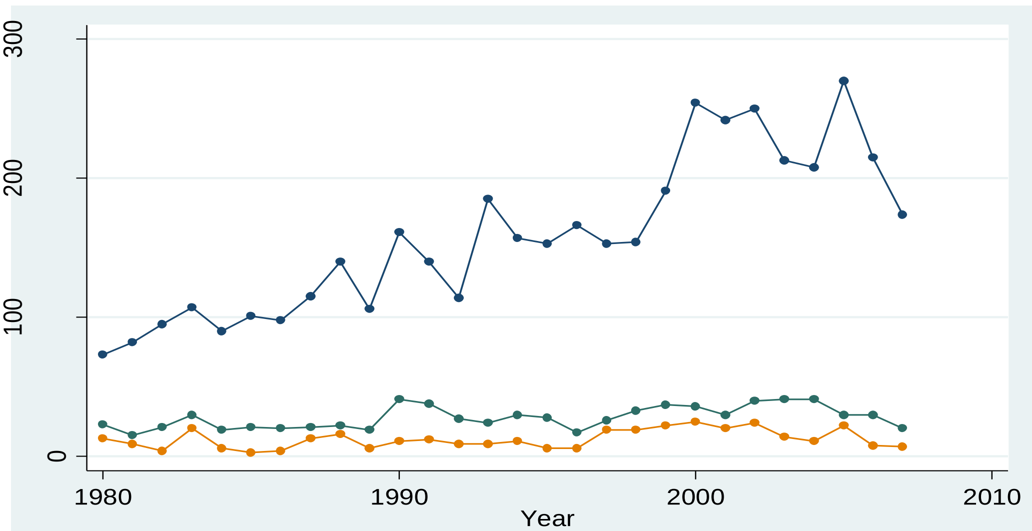

Figure 1.2: Frequency of droughts, geophysical and hydrometeorological events.

[1] A part of this increase might be explained by improved recording of hydrometeorological disasters.

As a reference, the frequency of earthquakes and volcanoes seems stable over the last thirty years. This can be seen as yet another indication that climate change might contribute to more natural disasters in the future, and hence stress the importance of quantifying economic effects.

1.2 Main contribution and findings in this study

It is evident that questions about the impacts of natural disasters are of great importance for the livelihood of a large number of people, and hence for international development agencies and policymakers throughout the global community. However, only a few studies have attempted to quantify these impacts using econometric methods. In this study, I explore global panel data[2] in order to shed light on two important research questions related to natural disasters: First, I seek to clarify how different disasters affect economic growth in the short run. Second, I investigate how changes in income caused by certain natural disasters are related to the risk of armed civil conflicts. Both these research questions are examined by means of different regression techniques.

One key element that is part of the identification strategy used in this study is a transformation of country-specific effects that do not vary in time; the so-called fixed effects transformation. This approach is motivated by the fact that natural disasters are not distributed randomly. For instance, it seems as poor countries tend to experience both higher frequency and intensity of natural disasters than rich countries. When such structural differences are unaccounted for, classic least squares regressions might produce incorrect estimates of economic effects, and hence lead to bad policy recommendations. As far as I know, this study is the first attempt to identify economic effects of natural disasters by means of the fixed effects transformation. Furthermore, much of the previous work has only looked at economic effects from large scale disasters, where definitions of “large scale” vary between studies. In contrast, this study also 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-scaled events.

With respect to natural disasters, I find that the number of people affected by them is significantly related to lower GDP per capita growth. This relation holds for both disasters linked to climate change and for geophysical events like earthquakes and volcanoes. Since the

[2] The data cover 165 countries between 1980 and 2007, although some observations are missing.

very nature of natural disasters should make them exogenous to economic growth, it is likely that my estimated relations express causal effects. The negative disaster effects on growth that this study comes up with contrast some of the research out there, including Albala-Bertrand (1993), Skidmore and Toya (2002) and Loyza et al. (2009). All of these studies find positive effects from natural disasters on economic growth.

Furthermore, my results indicate that different types of natural disasters have different effects on the economy: First, hydrometeorological events equal to one standard deviation predictably cause a growth reduction equal to .5 percentage points within the next year. Given the frequency of such disasters, this means that they are responsible for substantial economic losses in a global perspective.[3] Second, a typical drought is expected to reduce economic growth by almost one percentage point within the next year. Third, geophysical disasters equal to one standard deviation only reduce economic growth by .1 percentage points within next year.

This study also reveals that economic effects from natural disasters follow different dynamic patterns: While most economic losses caused by disasters related to climate change happen within the year the disaster occur, geophysical disasters primarily reduce economic growth the next year in my models. I suggest that a part of this latter result might be an artificial finding caused by the way economic data are constructed. It is also likely that geophysical disasters destroy infrastructure more directly, and therefore triggers immediate fiscal response which sets off growth reduction in the very short run.

This study further investigates how income changes caused by hydrometeorological disasters are related to the risk of new civil conflicts. In particular, I aim to overcome a simultaneity problem that previous literature has struggled to address: While economic growth arguably reduces conflict risk, the latter also decrease potential economic growth. Naive least squares models that ignore this simultaneous causality are likely to end up with biased estimates of growth effects. As an alternative, this study uses hydrometeorological disasters as an instrument for economic growth in order to impose arguably exogenous growth variation on the models. Meanwhile, I do not find that negative economic growth shocks caused by weather related disasters increase the likelihood of armed civil conflicts. This latter result contrasts earlier studies that find a negative causal link between growth and conflict risk, but is similar to findings in recent growth-conflict studies that take on the two-stage least squares approach.

[3] The average frequency of hydrometeorological disasters such as floods, storms, cyclones and mudslides is once each country-year observation in my data.

1.3 Summary of content

The rest of this paper goes as follows: Chapter two summarizes some of the preceding empirical research on relations between natural disasters, economic growth and armed civil conflict. Chapter three presents key hypotheses, identification strategies, econometric specifications and choice of method. Data and variable definitions are outlined in chapter four, and I also introduce the reader to simple descriptive statistics. The fifth chapter provides the econometric analysis of natural disasters and their impact on economic growth in the short run. Chapter six reports the instrumental variable analysis of the causal relation between economic growth and armed civil conflicts. I also touch upon possible methodological and data related caveats. Chapter seven summarizes this study and concludes.

2. Economics of natural disasters and armed civil conflict

As recent events demonstrate, natural disasters undoubtedly cause very real economic damages when they appear: Lives are lost, people are forced to leave their homes, buildings and other infrastructure collapse, and everyday business goes through serious setbacks. All of these damages can be defined as direct impacts in the sense that they arise as immediate outcomes of disasters. However, there are also a number of indirect impacts that follows in the aftermath of natural disasters, and these impacts are linked to economic activity. Examples are changes to production compositions, demand and supply shocks, shifting terms of trade, entry and exit of firms, inflation, etc. The net effect on overall economic performance is the sum of direct and indirect impacts.

These net effects by natural disasters are uncertain from a theoretical point of view. According to most benchmark growth models[4], (human and physical) capital intensity and technology both affect income level positively. Hence, when these measures are altered because of natural disasters, immediate negative growth shocks should follow. However, as soon as the economy is removed from long term equilibrium conditions, there are forces driving it back to the initial steady state path.[5] Consequently, short run effects on economic growth are really a matter of dynamics and selected time frame, and hence an empirical question.

Whit regard to economic growth and conflicts, the theory addressing this relation is mostly descriptive. A game-changing contribution was made by Collier and Hoeffler (2002; 2004): In contrast to much of the previous conflict theory which primarily looked at political, social and ethnic grievances, Collier and Hoeffler advocated the idea that civil conflicts are motivated by income opportunities. This approach treats people as rational, economic actors, which constantly compare expected income (broadly defined) from different activities. When joining rebel movements pays more than foregone salaries from legal activities, the economic actor lays down his plow and joins in. Consequently, high economic growth potentially reduces risk of armed civil conflict in the sense that foregone income from legal activity becomes high.

[4] These models are all part of curriculum in introductory growth economics throughout the world, so I will not go into detailed algebra here. See Heijdra and van der Ploeg (2002: 405-476) for a rigorous presentation of the most well-known growth models out there, including versions of the Solow-Swan model and models explain endogenous growth. See Benhabib and Spiegel (2002) for an updated version of the classic Nelson-Phelps model of technology diffusion. Schumpeterian growth and creative destruction hypotheses are discussed in Aghion and Howitt (2009). Finally, the role of natural disasters in growth models are discussed by Albala-Bertrand (1993) and Skidmore and Toya (2002).

[5] As an illustration; most economic growth rates are either stationary or trend-stationary.

Given the rather intuitive theory outlined above, the link between natural 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 put under comprehensive investigation. Especially, there are still much work to be done when it comes to natural disasters and their impacts in the short run. The rest of this chapter briefly presents some of the most important empirical studies regarding natural disasters, economic growth and armed civil conflicts.[6]

2.1 Empirical research on natural disasters and economic growth

Surprisingly little research has been done to identify the causal between natural disasters and economic growth. Particularly, only very few studies take advantage of variation in panel data.

In his seminal book about the economics of natural disasters, Albala-Bertrand (1993) performs a before-after analysis to investigate how 28 disasters in 26 countries between 1960 and 1979 relate to economic performance.[7] He treats the two years before any given natural disaster as reference years, and then uses statistical methods to compare economic growth rates (and other economic indicators) in reference years with growth rates in disaster years and years immediately after disaster years (Albala-Bertrand 1993: 62).[8] In contrast to the proposition that severe natural disasters alter economic conditions, Albala-Bertrand finds that they are actually followed by higher economic growth, higher agricultural and infrastructural output, plus increased capital formation.[9] The calculated increase in average growth rates before and after disaster events is .4 percentage points (Albala-Bertrand 1993: 66). Furthermore, Tol and Leek (1999: 311) notice that these results are qualitatively similar to findings in other contemporary work.

Skidmore and Toya (2002) use more comprehensive data that covers 89 countries over a 30-year period. The authors construct a cross-sectional dataset by calculating mean values of all variables by country, and then run ordinary least squares (OLS) regressions with estimated disaster effects (2002: 672). To my knowledge, this study is the first that takes advantage of regression techniques in order to examine causal relations between natural disasters and

[6] The methodology section offers a more detailed presentation of some statistical strategies and methods mentioned here.
[7] Albala-Bertrand is the only disaster-growth analysis described in this section that does not examine the EM-DAT database that I use.
[8] Albala-Bertrand distinguishes between short term and medium term impacts of natural disasters (1993: 62-63): The former are defined as impacts within the same calendar year, while the latter are defined as impacts within the disaster year, plus the two years after.
[9] At the same time, he also finds that government deficits and trade deficits increase.

economic growth. The findings in the Skidmore and Toya study is that even when a number of different growth factors (such as initial income, investment, government consumption and foreign trade) are controlled for, climatic disasters are positively related to economic growth, while the opposite is the case for geological disasters (2002: 673-675).[10,11] The authors argue that at least to some extent, the positive relation between climatic disasters and economic growth stems from substitution to human capital when physical capital is destroyed. According to their hypothesis, this substitution ultimately results in net growth. They also present empirical support for this claim (2002: 678).

In a more recent study, Raddatz (2007) uses a panel vector auto-regression (panel VAR)[12] approach to study short run effects of different external shocks[13] on economic growth in 40 low-income countries between 1965 and 1997. With respect to natural disasters, he traces growth effects from both geological and climatic disasters.[14] Raddatz also restricts the investigation to large disasters, i.e. natural events that either affect minimum .5 percent of the population, cause damages for at least .5 percent of GDP, or result in more than 1 per 10000 people killed (2007: 162). When some of these thresholds are satisfied, the corresponding disaster dummy takes the value of one. Raddatz finds that while large geological disasters do not have any significant impact on the economy (in low-income countries), large climatic disasters reduce economic growth by almost 2 percentage points within the year after the event (2007: 170-171).

Noy (2009) exploits panel data covering 109 countries from 1970 to 2003 in order to examine how effects of natural disasters on economic growth depend on governmental institutions and financial conditions. He uses a random effects approach in order to estimate

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[10] The authors classify climatic disasters as floods, cyclones, hurricanes, ice storms, snow storms, tornadoes, typhoons and storms. Geological disasters are classified as volcanic eruptions, natural explosions, avalanches, landslides and earthquakes. Disaster variables are measured both as number of disasters and as number of disasters per land area (Skidmore and Toya 2002: 671).

[11] For instance, in table 4 column 3, economic growth is predicted to increase by .44 percentage points ($.0022 * 1.988 = .004374$) when the number of climatic disasters (per land area) increase by one standard deviation. Summary statistics including standard deviations are reported in table C.1 at page 685 in the paper. When using numbers from the same regression model, an increase in geological disasters (per land area) by one standard deviation yields predicted growth loss equal to .38 percentage points ($-.0032 * 1.196$).

[12] Vector auto regressive (VAR) models include two or more (hence the term vector) time series where each variable is modeled as a linear function of past values of all variables. More details on vector auto regressive models in Wooldridge (2009: 647-651).

[13] Raddatz defines external shocks as those that are exogenous to country-level variables. To be specific, he examines fluctuations in terms of trade, international economic performance, international interest rates, aid inflow and in natural disasters (2007: 156).

[14] Raddatz follows a categorization similar to Skidmore and Toya (2002): He defines geological disasters as earthquakes, landslides, volcano eruptions and tidal waves. Climatic disasters are defined as floods, droughts, extreme temperatures and wind storms. Finally, Raddatz also includes humanitarian disasters (famines and epidemics). (Raddatz 2007: 162).

impacts from both time-variant and time-invariant control variables.[15] The disaster variable is made up by a large battery of different disasters which, depending on specifications, are measured by people killed, people affected and direct economic damage.[16] While no significant effects from people killed or people affected by natural disasters are found, effects from direct economic damage on economic growth is negative and significant in several specifications (2009; 225).[17] Interestingly, Noy also finds that a number of factors such as low literacy rates, high levels of public expenditures and large foreign exchange reserves seem to dampen negative growth effects from natural disasters.

Subsequent to the work by Noy, Raddatz (2009) uses panel data from 122 countries between 1975 and 2006 in order to trace both short and long run growth effects from climatic and geological disasters (these two disaster categories are defined in the same way as in the Raddatz 2007-study). By means of similar methods as in his previous paper, Raddatz finds that while climatic disasters reduce economic growth immediately by .5 percentage points, effects from geological disasters are insignificant (2009: 9). Another interesting finding is that 80 percent of the growth loss from climatic disasters are identified within the year of the event.[18]

Loayza et al. (2009) use panel data from 94 countries between 1961 and 2005 in order to estimate economic growth effects from droughts, floods, earthquakes and storms. They compute all variables as averages over 5-year periods, and thereafter take a generalized method of moment (GMM) approach in order to identify causal relations.[19] With people affected relative to population as the size of each disaster variable, floods seem to have a positive effect on economic growth (2009: 33-34). This result applies for both the whole sample (table 1, column 2) and for 68 developing countries (table 2, column 2). Furthermore,

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[15] The methodology used by Noy (2009) was first introduced by Hausman and Taylor (1981). See the methodology section for more details about random effects coefficients and time-invariant factors.

[16] To be specific; the disaster variable is the sum (by country-year observations) of impacts from floods, wave surges, storms, droughts, landslides, avalanches, earthquakes, tsunamis, volcanic eruptions, epidemics and insect infestations (Noy 2009: 222).

[17] For instance, using the world sample, economic growth is predicted to drop by .96 percentage points within same year (according to table 5, column 1, row 3), when the natural disasters variable increases by one standard deviation (Noy 2009: 225). This prediction is based on table 4, column 1 in the paper, readable with a disaster coefficient that is significant only at the ten percentage level. Furthermore, when disaggregating the world sample, short run disaster effects on economic growth is positive at the one percentage level in OECD-countries (table 4, column 2), negative at the ten percentage level in developing countries and in small economies (table 4, column 3 and 4), and insignificant in large economies (table 4, column5).

[18] Raddatz reports a .5 percentage point growth loss within the event year and .6 percentage points total growth loss (2009: 9). Immediate growth loss relative to total loss is therefore $.5/.6 = .83$.

[19] Loyza et al. choose this approach since they estimate models with dependent and independent variables from the same (5-year) time period, and thereby expose the analysis to simultaneous causality (2009: 9). Wooldridge offers a detailed introduction to GMM estimators (Wooldridge 2002: 188-205).

droughts seem to have a negative effect on economic growth in development countries (table 2, column 2).[20] The authors suggest that these results might be due to the importance of water (especially for agriculture) in many poor countries. Especially, if floods are associated with large water supply at the national level, they can be good for economic performance although local areas are negatively affected (2009: 21-22).

Finally, in addition to the studies described above, a number of scholars have estimated direct effects of natural disasters.[21] Generally, it seems to be that richer and more developed countries experience less direct damages from natural disasters (Kahn 2005; Toya and Skidmore 2007; Kellenberg and Mobarak 2008). Meanwhile, since these studies only look at direct damages instead of final output changes, they do not determine effects on overall economic performance. With regard to policy implications, indirect impacts such as loss of future income, migration shocks, etc. might be just as important as direct damages.

The overall picture seems to be that modern empirical literature on natural disasters and economic growth is ambiguous in its findings. Some papers report negative effects while others conclude the opposite. Also, those that separate between disaster types find that different disasters have different impacts, sometimes with opposite signs. Therefore, this strand of research clearly needs to be addressed in more detail before an overall conclusion can be drawn.

2.2 Economic growth and armed civil conflicts

In the following section, I briefly summarize the two empirical growth-conflict studies most relevant to mine. In their seminal papers on civil conflict, Collier and Hoeffler use several proxies for income opportunities, including GDP per capita growth. For instance, in the 2004-study they use ordinary least squares techniques on pooled panel data compiled in 5-year intervals between 1960 and 1999, and find a significant negative growth effect on the risk of civil conflict (Collier and Hoeffler 2004).

Fearon and Laitin use several different variables as proxies for state capacity, and test the hypothesis that state capacity is negatively linked to conflict risk (because strong states makes it less tempting to rebel) on panel data covering 161 countries between 1945 and 1999. By means of different LOGIT regressions, they find that GDP per capita (as proxy for relative state capacity) is negatively linked to the risk of armed civil conflict onset.

[20] Effects from earthquakes and storms were insignificant across specifications and samples in the dataset.
[21] These direct effects are most often defined as some normalized or transformed measure of people killed, people affected or economic damage (typically insurance expenditures).

Both the two papers mentioned are vulnerable to potential simultaneity between income and conflict that I want to address in this study: Because tensions and unrest might occur long before the conflict are qualified as such in traditional conflict datasets such as the UCPD/PRIO data, low income level might be a result of an approaching armed conflict as much as a result of an existing conflict.

2.3 Weather impacts on economic growth and armed civil conflict

This section describes some important contributions to the conflict literature that focus on different natural events such as rainfall and temperature. The seminal article by Miguel et al. (2004) is an early attempt to overcome potential simultaneity problems in conflict models by means of the 2SLS-approach instead of usual OLS-techniques. The researchers use rainfall in 41 countries in Sub-Saharan Africa between 1981 and 1999 as instrument for GDP per capita growth. They find that a 1 percentage point decrease in rainfall increases the likelihood of a country experiencing conflict by about 2 percentage points. The effect on conflict onsets is even stronger; 3 percentage points.[22] Given that rainfall cause exogenous economic growth shocks, this 2SLS-approach reveals not only how growth correlates with conflict, but also justifies causal assertions.

In a recent review of the study by Miguel et al., Ciccone (2010) has provided some strong criticism: Consider the conclusion that higher rainfall levels are associated with less risk of civil conflict. If rainfall levels are permanent, the Miguel et al. findings seem credible. However, rainfall levels are not only transitory; they are also highly mean reverting (ibid). Therefore, high rainfall growth could actually reflect low rainfall levels, the opposite of what Miguel et al. presume. Consequently, when rainfall is used as an instrument for economic growth, it is critical to determine whether rainfall shocks have a permanent or transitory effect on income. Ciccone finds the latter to be true, and concludes that higher rainfall levels actually seem to increase conflict risk (Ciccone 2010: 2).

Bernauer et al. (2010) uses change in rainfall as an instrument for economic growth in their study of global panel data that covers 130 countries over the period 1950-2000. Similar to Miguel et al., the study concludes that there is a positive and significant link between rainfall increase and GDP per capita growth. However, by means of a 2SLS-LOGIT approach, the researchers find no significant economic growth effect on the risk of conflict

[22] Jensen and Gleditsch (2009) point out that Miguel et al. (2004) erroneously include observations where countries participate in civil wars outside their own borders. When the authors replicate the analysis, they find that exclusion of these observations decrease the magnitude of the effects.

onsets, when the income change is instrumented by the rainfall. This conclusion remains robust not only in the world sample, but also in Africa alone.

In a recent contribution to the conflict literature, Burke et al. (2009) focus solely on the reduced form relation between temperature and the risk of conflict. They study panel data on African countries between 1981 and 2002 by means of fixed effects transformed models, and find that a one Celsius degree increase in temperature boosts the risk of armed civil conflict by as much as 4.5 percentage points within the same year (2009: 20670). Furthermore, they target previous 2SLS-studies and find that the temperature coefficients are robust to rainfall variables at the ten percentage significance level (2009: 20671).

Following in the footsteps of Miguel et al. and other conflict writers, I take on the 2SLS approach and instrument GDP per capita fluctuations with help from a defined set of natural events. Although much of the identification strategy relies heavily on similar arguments, this study differs from Miguel et al. and others in some important ways: Even while rainfall or precipitation events often are perceived as sudden shocks, the sum of rainfall levels throughout the year is a rather gradual phenomenon in most countries. To avoid potential expectation effects, and to be able to identify income fluctuations even in regions where rainfall shocks are unrealistic, I suggest a set of hydrometeorological events as instrument for economic growth.

3. Hypothesis and econometric identification strategy

3.1 Hypothesis

In order to identify causal effects between natural disasters, economic growth and armed civil conflict, this study includes two analytical stages: First, I examine the causal relationship between different natural disasters and economic growth in the short run. I suggest that natural disasters affect economic growth through their impact on production input: Regardless whether natural disasters come as sudden shocks with immediate impact or as more latent events such as drought, they cause damage to human capital, to infrastructure, to living conditions and to investment opportunities. Even in cases there is substantial international relief assistance, this destruction alter input that is used to create income and economic growth. I therefore set up the following hypothesis to be tested:

H_1: *Natural disasters have a negative effect on economic growth, i.e.* $\frac{\partial Economic\ growth}{\partial Natural\ disasters} < 0.$

Second, I investigate the growth effect on conflict onsets with help from assumingly exogenous variation in economic growth, caused by certain kinds of natural disasters. As economic growth stimulates prosperity, thus raising the alternative costs of joining a rebel group, negative economic shocks (caused by natural disasters) should make armed conflict more likely, and therefore be statistically related to conflict onsets. I therefore set up the following hypothesis:

H_2: *Negative economic growth shocks caused by natural disasters increase the likelihood of armed civil conflict onsets, i.e.* $\frac{\partial Conflict\ onset}{\partial Economic\ growth} < 0.$

3.2 Econometric specifications – natural disasters and economic growth

To investigate the causal effect from natural disasters on economic growth, I primarily estimate OLS regressions with fixed effects coefficients. Meanwhile, some of the regressions are estimated with random effects coefficients in order to explore characteristics of the data further. Analytical derivation of both fixed and random effects parameters are covered rigorously in learning books about panel data econometrics (see for instance Wooldridge 2002: 257-291), so I do not explain the algebraic details here.

The econometrical work horse applied in this study is specified by a theoretical population model given by:

$$y_{it} = \alpha_0 + \alpha_1 DM_{it} + \boldsymbol{\phi}\boldsymbol{\kappa}_{it} + \tau_t + u_{it} \tag{1}$$

where $u_{it} = \eta_i + \varepsilon_{it}$

For each country i in year t, y_{it} is GDP per capita growth; α_0 is a constant term; α_1 is the disaster coefficient for the aggregated disaster magnitude DM_{it}; $\boldsymbol{\kappa}_{it}$ is a vector of $1 \times K$ control variables frequently used in the growth literature; τ_t is the sum of all time specific and country-invariant factors; u_{it} is a composite error term that consist of unobserved country-specific factors that are independent of time, η_i, and an idiosyncratic error term ε_{it}. The explanatory variable DM_{it} is defined as $DM_{it} \equiv \sum_{l=1}^{L} DM_{ilt}$, that is the sum of all observed disasters $\{1,2, \dots L\}$ in that country-year observation, each weighted by their magnitude. Under the ordinary Gauss-Markov assumptions[23], including the zero conditional mean assumption that $E(u_{it}|DM_{it}, \boldsymbol{\kappa}_{it}) = 0$, estimating (1) by means of OLS will give unbiased pooled effects estimates of α_1, the parameter of interest.

In all regressions done in this study, I take a couple of precautionary steps in order to achieve credible inference testing: Generally, intra-country serial correlation is the case when $E(\varepsilon_{it}\varepsilon_{is}) \neq 0$ for $t \neq s$. This affects the formulas used for inference testing and therefore also causal assertions about the relation between natural disasters and economic growth. To relax this requirement, I correct for serial correlation between error terms within the same country by clustering standard errors around countries. I still assume that errors between countries are serially uncorrelated. All regressions are also estimated with Huber-White robust standard errors in order to allow for heteroscedasticity.[24]

In real life, η_i probably consists of factors that correlate with at least some included variables. In other words, the assumption that $E(\eta_i|DM_{it}, \boldsymbol{\kappa}_{it}) = E(\eta_i)$ seems unlikely, and therefore also the zero conditional mean assumption. There are several reasons for the time-

[23] The assumptions are: Linear population parameters (i.e. that model (1) is the true population model), panel data that reflects the population of country-years (this really means random sampling), no perfect collinearity and a zero conditional mean in the error term (Wooldridge 2009: 103-104).

[24] Wooldridge (2009: 265-269) explains the algebra behind Huber-White robust standard errors. Furthermore, he also shows how standard errors can be constructed in order to allow for both heteroscedasticity and serial correlation, and suggests that these errors should be used in large samples as a general rule (2009: 428-431). Hence, this is just what I do.

constant part of the composite error term to be correlated with natural disasters (and other variables). First, dependent of factors like coastline, climate and location on tectonic plates, countries might relate to natural disasters differently. Second, developed countries are probably less prone to human and infrastructural damages because of their ability to construct disaster secure buildings, etc. Finally, there are concerns among disaster researchers that poor countries have the tendency to exaggerate the magnitude of their natural disasters in order to get more aid from abroad (Skidmore and Toya 2002: 670). At least some existence of these phenomenon's seem likely and therefore lead to violation of the zero conditional mean assumption. This motivates for the use of fixed effects transformations (within transformations) to get rid of η_i. To achieve this transformation, I first define country-specific means of each variable in (1), so that

$$\bar{y}_i = \bar{\alpha}_0 + \alpha_1 \overline{DM}_i + \boldsymbol{\phi}\bar{\boldsymbol{\kappa}}_i + \bar{\tau} + \bar{\eta}_i + \bar{\varepsilon}_i$$

where

$$\bar{y}_i \equiv T^{-1}\sum_{t=1}^{T} y_{it}, \qquad \bar{\alpha}_0 \equiv \alpha_0, \qquad \overline{DM}_i \equiv T^{-1}\sum_{t=1}^{T} DM_{it}, \qquad \bar{\boldsymbol{\kappa}}_i \equiv T^{-1}\sum_{t=1}^{T} \boldsymbol{\kappa}_{it},$$

$$\bar{\tau} \equiv T^{-1}\sum_{t=1}^{T} \tau_t, \qquad \bar{\eta}_i \equiv \eta_i, \qquad \bar{\varepsilon}_i \equiv T^{-1}\sum_{t=1}^{T} \varepsilon_{it}.$$

Subtracting $\bar{y}_i$ from y_{it} gives the fixed effects transformed model:

$$y_{it} - \bar{y}_i = \alpha_1(DM_{it} - \overline{DM}_i) + \boldsymbol{\phi}(\boldsymbol{\kappa}_{it} - \bar{\boldsymbol{\kappa}}_i) + (\tau_t - \bar{\tau}) + (\varepsilon_{it} - \bar{\varepsilon}_i) \tag{2}$$

In model (2), all variables are expressed as deviations from their individual means. The very essence of this approach is that all unobserved factors that previously made up η_i in (1) are effectively transformed away in (2), since η_i by definition is equal to its mean. When estimating (2), we can relax the assumption that η_i is uncorrelated with included explanatory variables.[25] The fixed effects transformation just outlined is the key methodological difference between this study and other recent work on natural disasters and economic growth. Finally, suspecting that $E\big((\tau_t - \bar{\tau})|(DM_{it} - \overline{DM}_i), (\boldsymbol{\kappa}_{it} - \bar{\boldsymbol{\kappa}}_i)\big) \neq E(\tau_t - \bar{\tau})$, for instance because of some global economic crisis or time trends in variables, I include year dummies in all regressions with 1980 as the base year. By construction, these dummies should clearly be exogenous to the error term.

[25] The zero conditional mean assumption must still be satisfied, of course. Since the time constant variance σ_η^2 are taken care of by the within transformation, this means that we assume $E(\varepsilon_{it}|DM_{it}, \boldsymbol{\kappa}_{it}) = 0$ in model (2).

In cases where key explanatory variables are time-constant (or have very little variance), fixed effects models can obviously not be used. But since none of my natural disaster variables are constant over time, there is no a priori reason to prefer random effects coefficients instead of fixed effects coefficients[26]. Nevertheless, I still report random effects coefficients estimated by GLS in many of the tables because they can reveal some of the nature of biases that time-invariant factors represent. The random effects transformation comes in many shapes, but a popular version is given by model (3) (Wooldridge 2009: 490). See Wooldridge (2002: 257-288) for analytical derivation:

$$y_{it} - \lambda\bar{y}_i = (1-\lambda)\alpha_0 + \alpha_1(DM_{it} - \lambda\overline{DM}_i) + \boldsymbol{\phi}(\boldsymbol{\kappa}_{it} - \lambda\bar{\boldsymbol{\kappa}}_i) + (\tau_t - \lambda\bar{\tau}) + (u_{it} - \lambda\bar{u}_i) \tag{3}$$

where $u_{it} = \eta_i + \varepsilon_{it}$ and λ is defined as $\lambda \equiv 1 - \left[\sigma_\varepsilon^2\left(\sigma_\varepsilon^2 + T\sigma_\eta^2\right)^{-1}\right]^{1/2} > 0$.

Notice how $lim_{\sigma_\eta^2 \to \infty}\lambda = 1$. Therefore, even in cases with violation of the zero conditional mean assumption, the larger the cross-country variation in unobserved country-specific factors is relatively to variation in the idiosyncratic error, the closer are random effects parameters to fixed effects parameters. Contrary, when $\sigma_\eta^2 = 0$, the random effects parameters are identical to pooled effects parameters. The hypothesis that $\sigma_\eta^2 = 0$ can easily be tested by the Breusch-Pagan Lagrangian multiplier test for random effects.

3.3 Econometric specifications – disasters, economic growth and civil conflict

In order to identify and quantify the causal effect from economic growth on armed civil conflict onsets, I start out with a linear probability model of the population, given by the structural equation in (4):[27]

$$C_{it} = \beta_0 + \beta_1 y_{it} + \boldsymbol{\gamma\delta}_{it} + \tau_t + u_{it} \tag{4}$$

where $u_{it} = \eta_i + \varepsilon_{it}$

[26] Besides the ability to estimate effects of time-constant factors, the use of random effects transformations is generally motivated by the fact that η_i creates serial correlation in the error term when estimating pooled effects in panel data (Wooldridge 2009: 490). Because this serial correlation is removed in random effects models by subtracting $\lambda\bar{y}_i$ on both sides of the equation, random effects estimated by GLS is more efficient and generally preferred to pooled OLS. Nevertheless, since the pooled 2SLS estimates I report later in this study have standard errors that allow for intra-country serial correlation, I do not use random effects transformations there either.

[27] Although the letters τ, u, η and ε are identical to that in model (1), they naturally represent other factors and values in this conflict model.

For each country i in year t, C_{it} is a binary variable equal to 1 for observations with reported armed civil conflict onset; β_0 is a constant term; β_1 is the disaster coefficient for GDP per capita growth y_{it}; $\boldsymbol{\delta}_{it}$ is a vector of $1 \times K$ control variables frequently used in the conflict literature; τ_t is the sum of all time specific and country-invariant factors; u_{it} is a composite error term that consist of unobserved country-specific factors that are independent of time, η_i, and an idiosyncratic error term ε_{it}. The nature of this model implies that the binary variable depicts the probability of conflict onset, given all the right hand side variables; $P(C_{it} = 1|y_{it}, \boldsymbol{\delta}_{it})$. Once again, given the ordinary Gauss-Markov assumptions[28] including the zero conditional mean assumption $E(u_{it}|y_{it}, \boldsymbol{\delta}_{it}) = 0$, estimating (4) by means of OLS will give unbiased pooled effects estimates of β_1, the parameter of interest.

A naive OLS estimation of (4) has some important drawbacks in addition to general challenges in panel data that is already described (i.e. the unobserved country-specific effect). The most important, which I aim to address in this study, is the simultaneity issue: While economic growth is likely to reduce the risk of armed civil conflicts, expectations of the latter might also strangle opportunities for economic growth. Therefore, OLS estimation of (4) potentially adds in the effect from potential or approaching conflicts on economic growth, and thereby result in biased estimates of β_1. The bias can really be understood as an omitted variable problem: By omitting conflict relevant factors such as tensions between interest groups or income opportunities related to rebellion, these factors become part of the error term in (4) and the zero conditional mean assumption becomes violated.

In order to overcome the simultaneity between growth and conflict, I make causal assertions about β_1 by means of the instrumental variables 2 stage least squares method (2SLS). A rigorous outline of relevant restrictions and derivations can be found in most well established learning books about econometrics, including Wooldridge (2009: 506-545). The crucial assumption I make advantage of is that selected natural disasters DM_{it} from the disaster-growth study already outlined cause variation in economic growth that is exogenous to already existing risk of civil conflict. See figure 3.1 for an overall illustration of causal arrows.

[28] The assumptions are: Linear population parameters (i.e. that model (4) is the true population model), panel data that reflects the population of country-years (this really means random sampling), no perfect collinearity and a zero conditional mean in the error term.

Figure 3.1: Natural disasters, economic growth and armed civil conflict

From the assumingly negative causality between natural disasters and economic growth fluctuations, and from the supposed negative causality between economic growth fluctuations and the risk of civil conflicts, it follows that natural disasters might increase the likelihood of conflict trough disasters impact on economic growth. Analytically, civil conflict onsets can be written as a function of economic growth, and economic growth as a function of natural disasters. The chain rule of derivation and postulations made above yields:

$$\frac{\partial Civil\ conflict}{\partial Natural\ disasters} = \frac{\partial Civil\ conflict}{\partial Economic\ growth} * \frac{\partial Economic\ growth}{\partial Natural\ disasters} > 0$$

A critical concern is whether natural disasters qualify as a credible instrumental variable for economic growth. To do so, the instrument must fulfill two critical restrictions: First; natural disasters must be a relevant determinant for economic growth, i.e. there must be a significant relation between the two variables. Analytically; $E(y_{it}|DM_{it}) \neq E(y_{it})$. Naturally, I will not be able to impose the exogenous variation in economic growth without this criterion. Second; natural disasters must be uncorrelated with the error term in the structural equation, i.e. natural disasters should not have any significant effect on civil conflict onsets other than through economic growth. Analytically; the zero conditional mean assumption that $E(u_{it}|y_{it}, \boldsymbol{\delta}_{it}) = 0$ is replaced by $E(u_{it}|DM_{it}, \boldsymbol{\delta}_{it}) = 0$. This restriction is critical because I am interested in the variation in conflict onsets that is caused by variation in economic growth. While the first restriction can be tested statistically by OLS regressions, the second restriction cannot be defended by other means than theory and intuition. Given these two critical restrictions, the 2SLS method involves two stages. The first stage is an OLS estimation of the effect of natural disasters on economic growth. The second stage is an OLS estimation of the effect of economic growth on conflict onsets, instrumented with help from exogenous variation in disasters in the first stage. This results in an updated version of the linear probability model:

$$C_{it} = \beta_0 + \beta_1^{IV}\hat{y}_{it} + \boldsymbol{\gamma\delta}_{it} + \tau_t + u_{it} \tag{5}$$

where $u_{it} = \eta_i + \varepsilon_{it}$

The update is $\beta_1^{IV}\hat{y}_{it}$, where $\hat{y}_{it}$ is the predicted growth from the first stage and β_1^{IV} is the instrumented marginal effect of economic growth on the risk of conflict onset. Finally, to remove bias caused by unobserved country-specific factors, I do the fixed effects transformation of (5) that has been described already. Given the general Gauss-Markov assumptions and the additional IV-assumptions, β_1^{IV} is an unbiased estimator for the true β_1 in (4). Therefore, this approach should provide credible empirical results about the causality between economic growth and the risk of armed, civil conflict onsets. To say something about the bias when the simultaneity is ignored, I also estimate (4) by OLS fixed effects and LOGIT, and compare the results with the 2SLS estimates.

There are a couple of reasons to use LOGIT models estimated by maximum likelihood estimation (MLE) instead of linear probability models estimated by OLS when the dependent variable is binary. First, estimation of linear probability models can, for certain values on explanatory variables, yield predictions of the dependent binary variable that is outside the corner solutions 0 and 1. Second, the structure of (4) implicitly gives that partial effects of all explanatory variables (in level form) are constant. These two concerns can be overcome by using a more sophisticated binary response model; for instance the LOGIT model. Again, Wooldridge (2009: 575-587) provides an analytical outline and discussion of LOGIT models.[29]

[29] The reason that I use linear probability models instead of LOGIT models when using natural disasters as an instrument for economic growth is that the nonlinear structure of LOGIT models might provide wrong estimates of standard errors because the first stage analysis is linear, while the second stage is not. This is turn, implies problems in the inference testing. I have discussed the concern with a couple of researchers, and there seems to be some confusion about LOGIT and 2SLS. Professor Bjarne Strøm (Department of Economics, Norwegian University of Science and Technology) strongly recommended me to use linear probability models instead of LOGIT in order to achieve credible inference testing. This is also the approach that most 2SLS studies with binary left hand side variable have taken, including Miguel et al. (2004) and Ciccone (2010). Meanwhile, Professor Vally Koubi (Center for Comparative and International Studies, ETH Zurich and Department of Economics, University of Bern) suggested that I should use a LOGIT IV approach in order to gain on the benefits associated with LOGIT models. Indeed, she and colleagues used this approach themselves in Bernauer et al. (2010). There is no LOGIT IV command in Stata, so they used several days programming the command manually. Instead of this, I choose to calculate linear probability models estimated by 2SLS with ordinary pooled and fixed effects.

4. Data and variables

In order to study the disaster-growth-conflict relationship, I have constructed a dataset with statistics on 165 countries, covering the years 1980-2007. Raw data are taken from several different panel datasets. Most of these originally stretch further back in time. However, since I am concerned about poor quality on old disaster data, I only include data from 1980 and onwards. Among others, the Bureau for Crisis Prevention and Recovery indicate that the period after 1980 is the most reliable period of data from EM-DAT (Bureau for Crisis Prevention and Recovery 2004: 99).

The dataset that I have constructed is unbalanced, i.e. data are missing for certain country-year observations. Especially, time series differ in length between countries: While all countries but Bahrain have time series that end in 2007, most time series belonging to former Soviet Union countries start in 1993. To keep things simple, I follow main stream literature and assume that reasons for missing data are not correlated with the error term in the regression equations that I estimate.[30]

The following sections describe variables and data. First, I outline the construction of natural disasters data. Second, I explain economic growth data and control variables used in growth models. Third, I summarize the conflict data.

4.1 Natural disasters data

To study short run growth effects from natural disasters on economic growth, I have collected all natural disasters data from the Emergency Events Database (EM-DAT), developed by Centre for Research on the Epidemiology of Disasters (CRED) (CRED 2010). EM-DAT is a global dataset that records disasters since 1900, where disasters are defined as:

"A situation or event, which overwhelms local capacity, necessitating a request to national or international level for external assistance…" (Below et al: 2009: 15).

To qualify for inclusion, EM-DAT requires that an event has to fulfill at least one of the following four criteria: 10 or more casualties, 100 or more people affected, declaration of a state of emergency, or call for international assistance (Below et al: 2009: 3).

[30] For instance, this assumption is violated if natural disasters had another effect on economic growth in the Soviet Union than in other countries. See section 3.2 and 3.3 for an outline of critical assumptions about the idiosyncratic error term.

In order to relate estimated disaster impacts to climate change, I separate between three different groups of natural disasters, all defined in the EM-DAT classification system (Below et al. 2009: 5-14). Table 4.1 reports the full set of disaster types included in this study.

Table 4.1: Classification of natural disasters

Disaster group	*Disaster type*	*Disaster sub-type*
Hydrometeorological disasters	Floods	General floods River floods Coastal floods Storm surge
	Slides (wet mass movements)	Landslides Rockfalls Debris flows Snow avalanches Debris avalanches Subsidence
	Storms	Tropical storms Extra-tropical cyclones Thunderstorms/lightning Snowstorms/blizzards Sandstorms/duststorms Generic (severe) storms Tornadoes Orographic storms (strong winds)
Geophysical disasters	Earthquakes	Ground shaking Tsunamis
	Volcanoes	Volcanic Eruptions
Climatological disasters	Droughts	Droughts/lack of precipitation

The first disaster group is hydrometeorological disasters, which are defined as disasters caused by deviations in the normal water cycle, or by overflow of water caused by wind set-up, or by short-lived, atmospheric processes (in the spectrum from minutes to days) (Below et al. 2009: 12). In other words, these are floods, storms and wet mass movements. Among well-known hydrometeorological disasters are the landslides caused by heavy rain in northern Venezuela in December 1999, which led to destruction of thousands of homes and complete collapse of infrastructure (Lopez and Cortel 2007: 1). The 2005 hurricane Katrina in southern United States also classifies as a hydrometeorological disaster.

The second disaster group is geophysical disasters, which are disasters originating from solid earth. These disasters are triggered by either earthquakes or volcanoes.[31] Among devastating examples are the 2004 Indian Ocean Earthquake and the 1985 volcanic eruption on Nevado del Ruiz in Columbia.

[31] EM-DAT also operates with a third geophysical disaster type, namely dry mass movements. However, I have no observations of such disasters in my panel data. Economic effects of dry mass movements are therefore not included in this study.

The third disaster group is climatological disasters, which are caused by long-lived, macro scale processes in the atmosphere. Natural events that classifies as climatological disasters are droughts like the 2005 Amazon Basin drought, extreme temperatures and wild fires. With respect to dynamics and variable specification, droughts differ from extreme temperature events and wild fires in one important way: While droughts often last for several years, heat waves, cold waves and wild fires usually have a much shorter time span. In fact, the latter disaster types represent a real econometrical challenge: Some of them come and go as sudden shocks, just like hydrometeorological and geophysical disasters. Others last for several months or may be even years. This makes it difficult to specify empirical measures of different temperature and wild fire events, so these two disaster types are excluded from the dataset and left for future research.

The separation between different disaster groups is motivated by the fact that hydrometeorological and climatological disasters are linked to climate change, geophysical disasters are not. Another important thing to point out is that while main disaster types are considered as initial events, they tend to cause a number of sub-disasters such as tsunamis, avalanches, cyclones, lightings, tornados, blizzards and subsidence. These happenings are also included in the analysis. For instance, the 2004 tsunami in the Indian Ocean is classified under geophysical disasters since the root cause was an earthquake.

With respect to disaster magnitude, EM-DAT reports information on number of people killed and people affected by each event, as well as the total direct damage (measured in current US dollars). Meanwhile, how a disaster affects national economy is likely to depend both on relative disaster magnitude and the timing of the event (Noy 2009: 223; Noy and Vu 2009: 10-11).

To control for the former, I normalize each event and divide the EM-DAT numbers on people killed and people affected by total country population, while the economic damage is divided by national GDP (both measured in nominal US dollars). By definition, nominators and denominators are directly correlated when reporting from the same year. Therefore, I follow Noy (2009: 223) and use lagged figures for total population and GDP. Since United Nations Statistics Division (UNSD) is the source for most real economic data calculated in Penn World Table (the dataset I use for economic growth), I aim for stable data and use population and nominal GDP numbers from UNSD as well (UNSD 2009).

To control for the timing of natural disasters, I take into account that economic growth is measured annually. This is important since natural events that happen in January potentially have larger effects on current year's income than events happening towards the end of the year (all other things being equal). With that in mind, I impose time weights on each disaster: The disaster effect of the jth disaster is depreciated through the year by the rate $\frac{12-Event\ month_{ijt}}{12}$, in country i in year t. Also, disasters that happened last year are appreciated through the year by the rate $\frac{Event\ month_{ijt}}{12}$. For instance, this time appreciation allows disasters happening in December last year to have a larger impact on current economic growth than disasters happening in January last year. My empirical measures of the disaster variables of interest are thus calculated like this:

People killed, t: $$dmkt_{ijt} = \frac{\#killed_{ijt}}{population_{it-1}} * \frac{12-Event\ month_{ijt}}{12}$$

People killed, $t-1$: $$dmkt_{ijt-1} = \frac{\#killed_{ijt-1}}{population_{it-2}} * \frac{Event\ month_{ijt-1}}{12}$$

People affected, t: $$dmat_{ijt} = \frac{\#affected_{ijt}}{population_{it-1}} * \frac{12-Event\ month_{ijt}}{12}$$

People affected, $t-1$: $$dmat_{ijt-1} = \frac{\#affected_{ijt-1}}{population_{it-2}} * \frac{Event\ month_{ijt-1}}{12}$$

Economic damage, t: $$dmd_{ijt} = \frac{\$damage_{ijt}}{GDP_{it-1}} * \frac{12-Event\ month_{ijt}}{12}$$

Economic damage, $t-1$: $$dmdt_{ijt-1} = \frac{\$damage_{ijt-1}}{GDP_{it-2}} * \frac{Event\ month_{ijt-1}}{12}$$

where $dmkt$ is weighted number of people killed in any given event, $dmat$ is weighted number of people affected, and $dmdt$ is the weighted direct economic damage.[32] Finally, the individual values for all disasters within the same country-year observation are summed up and used as the final value for the magnitude of natural disasters. This explicitly takes into account both the intensity and frequency of natural disasters in any given (country-year) observation. Because a person is defined as affected every time he or she fulfills the criteria set by CRED, persons can be counted as affected several times within a country-year observation. Consequently, the people affected variables can take values higher than one.[33] As stated already, droughts last for up to several years, so it makes little sense to weigh them by event timing within a given year. Therefore, I use a binary variable equal to one for drought years in most drought-growth specifications. Table 4.2 reports descriptive statistics for the

[32] This construction assumes that disaster's effect on growth is linear. As it is possible that natural disasters alter production only for a couple of months – for example, an event in January may have same effect on growth as a disaster in June, I also report regressions where time weights are excluded.

[33] The same goes for variables expressing economic damage relative to GDP, but obviously not for people killed variables (the highest possible number of killed is the total population).

natural disaster variables. Standard deviations reported are based on overall variation, not only variation within or between countries.

Table 4.2: Descriptive statistics – Natural disasters

Variable	*Mean*	*Standard Deviation*	*Minimum*	*Maximum*	*Observations*
Hydrometeorological events:					
Number of hydrometeorological disasters per country-year	1.02	2.32	0	30	4314
Population affected by hydrometeorological disasters	.0047	.0274	0	.6247	4314
Population affected by hydrometeorological disasters (with time weights for year t)	.0021	.0140	0	.3219	4314
Population affected by hydrometeorological disasters (with time weights for year t-1)	.0029	.0209	0	.3092	4314
Population killed by hydrometeorological disasters	$2.03 * 10^{-6}$	.00002	0	.00128	4314
Economic damage from hydrometeorological disasters relative to GDP	.0019	.0155	0	.5083	4314
Geophysical events:					
Number of geophysical disasters per country-year	.18	.65	0	11	4314
Population affected by geophysical disasters	.0004	.0057	0	.2675	4314
Population affected by geophysical disasters (with time weights for year t)	.0002	.0042	0	.2416	4314
Population affected by geophysical disasters (with time weights for year t-1)	.0009	.0095	0	.1341	4314
Population killed by geophysical disasters	$1.62 * 10^{-6}$	.00003	0	.00078	4314
Economic damage from geophysical disasters relative to GDP	.0006	.0130	0	.5471	4314
Climatological events (droughts):					
Drought years	.08	.27	0	1	4314
Number of climatological disasters per country-year	.08	.29	0	3	4314
Population affected by climatological disasters	.0062	.0508	0	1.0788	4314
Population killed by climatological disasters	$3.56 * 10^{-6}$	.00016	0	.00824	4314
Economic damage from climatological disasters relative to GDP	.0003	.0052	0	.3037	4314

The top panel in table 4.2 shows descriptive statistics for hydrometeorological disasters. As reported in the first row, there is a little more than one hydrometeorological disaster per country-year observation in the dataset, with 30 as the maximum. The second row shows the (summarized) number of people affected by hydrometeorological disasters relative to total population. Although this variable can take values higher than 1, the highest “affected share” observation in my data is .62.[34] Because disaster variables in current and last year with time weights are used for predictions later in the study, the third and fourth row show data for these two variables. Because an average disaster is likely to occur sometimes in the middle of the year, it is no surprise that the people affected variable with time weights is approximately half the size of the corresponding variable without time weights on average (.0021 and .0047). The fifth and sixth row show (summarized) number of people killed relative to population and economic damage relative to GDP (both without time weights). According to data, .08 percent of the population was killed in the deadliest hydrometeorological country-year, while damages for the observation with highest economic losses constituted more than half of GDP.

The second panel in table 4.2 shows descriptive statistics for geophysical disasters. As indicated by figure 2 in the introductory chapter, these disasters are much less frequent than hydrometeorological disasters: It is only .18 geophysical disasters per country year in the data. As a consequence, the panel shows that the average population share that is affected and killed, as well as the average damage share of GDP, is only a fraction of corresponding values for hydrometeorological disasters.

The third panel in table 4.2 shows descriptive statistics for droughts. The numbers show that 8 percent of the observations are drought years. Also, according to the third row in the panel, more people than the whole population was affected in the worst drought year, indicating that this year had more than one drought.

Finally, it should be said that concerns have been expressed about the reliability of EM-DAT data. Indeed, as mentioned earlier, while most scholars explore observations all the way back to 1950 or so, I suspect that old disaster data are less trustworthy and limit the study to 1980-2007. The selected time period should still be sufficiently long with respect to reliable findings.

[34] Since I have excluded all hydrometeorological observations that last more than one month, I suspect that a disproportionate share of the very large scale disasters is not included in my analysis (given that these disasters often last longer). Hence the low maximum value on people affected relative to population. The same goes for maximum values of people killed and economic damage in my data. If anything, I suspect that this exclusion of certain large-scale disasters from the data results in smaller coefficients (in absolute values).

4.2 Economic growth data

The key economic variable of interest is the growth rate of real GDP per capita, defined as $\frac{(GDP/capita)_{it}-(GDP/capita)_{it-1}}{(GDP/capita)_{it-1}}$. The variable is taken from Penn World Table (version 6.3), a comprehensive effort done by researchers at the University of Pennsylvania to provide purchasing power parity and national accounts from countries all around the world (Heston, Summers and Aten 2009). The PWT-team takes nominal economic data from major statistical sources such as the World Bank and OECD, and converts them into real economic measures. The PWT project reports real GDP based on several different techniques. I have chosen to use data calculated with an updated Laspeyre technique (called Laspeyre 2)[35] because these growth data are preferred by statisticians that construct PWT (Heston 2009: 2).[36]

Table 4.3 shows descriptive statistics for economic variables. The average growth in real GDP per capita is 1.68 percentage points, but the variation is substantial. The most extreme outliers on the down side are Iraq in 1991 (down 65.1 percentage points) and Liberia in 1990 (down 62.4 percentage points). These two observations have one thing in common; devastating war and civil suffering. Equatorial Guinea has the highest GDP per capita growth rate observed in my data; 123.3 percentage points in 1997. This observation is probably because of the huge oil and gas export that Equatorial Guinea has undertaken since 1995 (EIA 2009). The second largest growth observation is identified in Liberia in 1997, with a growth in GDP per capita on 88.7 percentage points. I include all the observations mentioned above.

4.3 Control variables in growth models

In order to control the estimated growth effects of natural disasters, I take advantage of a large battery of control variables often used in the short run growth literature such as Noy (2009) and Raddatz (2009). Summary statistics are reported in table 4.3. All control variables in the growth models are lagged one year because of expected delay between most macro-factors and economic growth. This is in line with other short run empirical research (Noy 2009: 225; Burke et al. 2009: 20674).

[35] Laspeyre 1 is derived based on fixed shares of domestic components; consumption, investments and public spending. The share of domestic components in the base year (2005 in PWT 6.3) is assumed to be equal to domestic component shares in all other years. The total of these components plus the net foreign balance gives the GDP per capita Laspeyre 1. Laspeyre 2 allows for changing shares of domestic components by summing them together each year and then adding the net foreign balance. The Laspeyre 2 growth rates are assumed to be more stable between different version of PWT (Heston, Summers and Aten 2009b: 2)

[36] I also explored real GDP per capita data calculated by Laspeyre 1 and the Chain index. Results were mainly similar (not reported).

Table 4.3: Descriptive statistics – Economic growth

Variable	*Mean*	*Standard Deviation*	*Minimum*	*Maximum*	*Observations*
Dependent variable:					
Real GDP per capita growth	1.68	7.41	−65.08	123.27	4299
Classic growth variables:					
Gross capital formation relative of GDP (%)	22.52	8.50	1.76	113.58	3986
Life expectancy (in years) at birth	64.41	10.87	26.41	82.51	4218
Real variables:					
Account balance (%)	−3.02	10.12	−240.50	102.70	3678
Government share of GDP per capita (%)	18.86	9.85	1.44	83.35	4314
Trade relative to GDP (%)	77.53	48.62	1.09	456.56	4314
Net FDI inflow relative to GDP (%)	3.23	15.20	−82.89	524.88	3901
Natural resource export relative to merchandise export (%)	24.59	28.99	.00	100.00	2931
Financial variables:					
Inflation in consumer prices (%)	51.35	644.12	−17.64	24411.03	3655
Changes in net reserves relative to GDP	−.01	.05	−1.11	.29	3649
M2 relative to GDP	42.33	36.61	.92	668.10	3525

First and foremost, I take the same approach as Islam (1995: 1138) and most subsequent empirical models of short run growth and include a lagged GDP per capita growth variable in all regressions.[37] There are some good reasons for the use of a lagged dependent variable in my specifications: One is that it allows for prediction of more dynamic natural disaster effects. To be specific; a lagged growth variable allows me to estimate both the direct effect of assumingly exogenous disaster shocks (on current growth) and the indirect effect through lagged growth. Indeed, to the extent that current economic growth is determined by the growth last year, natural disasters that happen today can also affect economic growth in the future. Another advantage is that inclusion of lagged economic growth indirectly controls for omitted variables, at least to the extent that they embody information that was important in determining the dependent variable last year (Andersen 2002: 117).

[37] According to Wooldridge, there is a widespread understanding that "OLS is inconsistent in the presence of lagged dependent variables and serially correlated errors" (Wooldridge 2009: 411), and that this assertion results in claims of possible bias caused by lagged dependent variables. As s a general statement, Wooldridge rejects this opinion both mathematically and with intuition. Furthermore, I explored a variety of different lags of the dependent variable, but only the first lag was significant across specifications. Also, as stated by Noy (2009: 223), recent empirical research including Raddatz (2007: 166-167) support the use of only one lag of the (dependent) growth variable.

Next, I control for two of the key growth determinants in seminal growth literature; physical capital assets and human capital. Neoclassical growth theory like the benchmark model developed by Solow and Swan focus on physical capital such as plants, buildings, roads and machinery as providers of economic growth in the short run (Heijdra and van der Ploeg 2002: 405-417).[38] The argument is very simple: For given levels of technology and labor, higher capital intensity leads to more effective production and hence to higher output growth. In other words; when a group of farmers share one tractor, another tractor will, ceteris paribus, increase production per farmer. The story is similar when it comes to human capital: Either human capital creates growth through productivity development domestically (Mankiw, Romer and Weil 1992: 407-437) or through technology adoption from abroad (Benhabib and Spiegel 2002: 1-50), higher educated and better trained workers should be able to produce more, even in the short run. To measure short run growth effects of physical capital, I follow Noy (2009) and include physical capital formation as a percentage share of GDP. Data comes from the World Bank (World Bank 2010). According to their definition, capital formation is expenditures on additions to the fixed assets[39] of the economy plus net changes in the level of inventories.[40] The average capital formation share of GDP is equal to 22.5 percentage points. It is more difficult to find good proxies for human capital, but I follow Barro (1996: 15) and include the (natural) logarithm of life expectancy at birth as a proxy for human capital.[41] It has to be said that life expectancy might be a poor measure on human capital, especially in the short run. First, life expectancy might be loosely correlated with human capital; it is probably a better proxy for health conditions. Second, the life expectancy variable is only based on prospects made by specialists at UN agencies and other institutions. Still, it is the best proxy for human capital that I have available. The average life expectancy in my country-year data is 64.4 years. Data comes from the World Bank (World Bank 2010).

I also control for a variety of real economic factors: First, Noy finds that current account surplus (lagged one year) has a stable and positive impact on economic growth in the short run (Noy 2009: 225). Since governments with large economic surpluses might be better able

[38] It is important not to confuse this statement with the long run conclusion that follows from the Solow-Swan model, namely that countries with low capital intensity experience higher growth (and therefore catching up) than capital abundant countries.

[39] Fixed assets are defined by the World Bank as land infrastructure (such as fences, ditches and drains), plants, machinery, roads and railways, as well as all public and private buildings including schools, offices, hospitals, private homes and industrial buildings (World Bank 2010).

[40] “Inventories are defined as stocks of goods held by firms to meet temporary or unexpected fluctuations in production or sales, including "work in progress"” (World Bank 2010).

[41] I also estimated models with literacy rate as proxy for human capital, but I had two few observations (and hence to few degrees of freedom) to run reliable inference tests. Anyway, the main results were qualitatively similar to those in specifications with life expectancy (results not reported).

to respond to natural disasters, I control for current account balance, measured as the sum of net export, net income and net transfers relative to GDP. The average observation is an account deficit equal to 3 percent of GDP. Data comes from the World Bank Development Indicators (World Bank 2010).

My second real economic control variable is government consumption share of real GDP. In theory, economies with large governments might have an advantage when it comes to post-disaster relief work. Toya and Skidmore (2007: 3) find support for this hypothesis when they use people killed and economic damage as left hand side variables. Furthermore, Noy (2009: 226) finds that countries with high government share of GDP experience smaller economic growth losses than other countries. The average government share of GDP is 18.9 percent. Data comes from Penn World Table version 6.3 (Heston, Summers and Aten 2009).

Previous studies have shown that open economies with high levels of foreign trade generally experience higher economic growth than economies with domestic oriented markets (Skidmore and Toya 2002: 665). Also, when it comes to natural disasters, Noy (2009: 228) finds that countries with more export are less prone to negative impacts, assumingly because foreign demand remains largely unaffected. I use the same specification as Skidmore and Toya (2002) and include a trade openness variable measured as the sum of export and import relative to total real GDP. The average observation in the dataset consists of foreign trade equal to 77.5 percent. Data comes from PWT version 6.3 (Heston, Summers and Aten 2009). Intuitively, I suggest that if natural disasters cause negative demand shocks wherever they occur, domestic disasters should have less negative impact on the economy when export is high (since foreign demand is largely unaffected) or when import is high (since this improves the trade balance through reduced import).

Similar to the reasoning of foreign demand and trade, foreign investments might be less prone to domestic natural disasters than domestic investments. Noy (2009: 225) finds that foreign direct investments have a positive impact on economic growth. Therefore, I control for net inflow of foreign direct investments as share of GDP. The average value is equal to 3.2. Data are from the World Bank Development Indicators (World Bank 2010).

The final real economic control variable is natural commodities export. In their seminal work, Sachs and Warner (1995: 1-47) highlighted the resource curse theory that economies with more export of natural resources tend to experience less economic growth. Furthermore, Torvik (2001: 290) argues that positive natural resource shocks might worsen terms of trade, even in the short run. It could also be the case that countries with significant export of natural resources suffer because their supply sectors are more vulnerable to natural disasters. I control for certain export sectors by including the rate of fuel, ore and metal export relative to total (merchandise) export. These products constitute almost a quarter of total export on average. Data are once again from the World Bank Development Indicators (World Bank 2010).

In addition to the real economic variables, I also control for three financial factors: First, I control for inflation in consumer prices, measured by the consumer price index (World Bank 2010). In theory, unstable and high price growth is likely to dampen domestic and foreign demand, and thereby economic growth. However, Noy (2009) finds no significant relation between inflation and economic growth in his specifications. The average inflation rate is equal to 51.4 percentage points, probably driven by some outliers.

Second, since foreign reserves could be used to dampen impacts of natural disasters, I control for net reserve changes relative to GDP with data from the World Bank Development Indicators (World Bank 2010). While Noy (2009: 228) find empirical support for this hypothesis, Albala-Bertrand (1993: 1424) actually identify increased reserves in the aftermath of natural disasters. The average reserve changes constitute 1 percent of GDP.

Third, Burnside and Dollar (2000: 859) use money and quasi-money (M2)[42] relative to GDP as a proxy for development of financial systems, and find limited support for a positive growth effect of this variable. Therefore, I also control for M2 relative to GDP (World Bank 2010). M2 is 42.3 percent of GDP on average.

4.4 Armed civil conflict data

In order to study growth effects on armed civil conflicts, I use armed civil conflict data from the annually updated UCDP/PRIO Armed Conflict Dataset, version 4-2010 (Gleditsch et al. 2002, Harbom and Wallensteen 2010).[43] This dataset has a relatively low inclusion criterion, 25 battle-related deaths during a year. Therefore, low-intensity conflicts are included in the analysis in addition to high-intensity conflicts (1000 battle-related deaths). From the dataset, all internal and internationalized internal conflicts are included and merged together. My interest lies in disaster effects on the risk of internal conflicts, so intra-state wars are excluded from the data. Also, I follow modern conflict literature and study the onset of conflicts rather

[42] Money and quasi-money (M2) is the sum of currency outside banks, demand deposits other than those of the central government and the currency deposits of resident sectors other than the central government (World Bank 2010).

[43] To be exact, I use the onset version of the UCDP/PRIO dataset. These onset data are available online at http://www.pcr.uu.se/research/UCDP/data_and_publications/datasets.htm.

than conflict presence since the latter are hampered with more serious endogeneity problems.[44]

The conflict variable is a dummy variable that takes the value of 1 when at least one new conflict emerges in that country-year observation, or when at least one previous conflict with at least two years break starts up again. Since countries with an existing armed conflict still can experience outbreak of new conflicts, I do not delete the observations following the conflict onset. This allows me to include all conflict onsets in the dataset. I have identified 141 onsets in the dataset, which is a little more than 3 percent of all observations.

Finally, as a country that already is experiencing a conflict might be more likely to experience another conflict, I correct for this by including a variable that counts the years since the last year of conflict, as suggested by Beck, Katz and Tucker (1998).[45]

Table 4.4: Descriptive statistics – Conflict onsets

Variable	*Mean*	*Standard Deviation*	*Minimum*	*Maximum*	*Observations*
Dependent variable:					
Conflict onset	.03	.18	0	1	4314
Control variables in conflict models					
Population	$3.44 * 10^7$	$1.23 * 10^8$	149207	$1.32 * 10^9$	4314
Polity index	11.50	7.27	0	20	4007
Ethnic fractionalization	.46	.26	0	.93	4295
Peace years	8.77	8.10	0	27	4314

Notes: The peace years variable do not express observed time since last conflict, but number of continuous peace years with 1980 as the base year.

4.5 Control variables in conflict models

A set of the most common conflict controls are included in the conflict models. Descriptive numbers are reported in table 4.4. First, because of the simple statistical reality that countries with large populations are more likely to experience some kind of a conflict, I control for population size by including the logarithm of the population. The average population size is equal to 34.4 million people. Data are extracted from Penn World Table version 6.3 (Heston, Summers and Aten 2009).

[44] Conflict duration is often believed to depend on other factors than conflict onsets.
[45] This variable is generated by the Stata extension "btscs" programmed by Tucker (Tucker 1999). Included are three spell-identification cubic spline variables that are related to the time since last conflict. This controls for time dependence and correct for bias in standard errors (Sasieni 1994).

Second, I control for democracy and autocracy characteristics by using the panel data version of the Polity IV variable (Marshall et al. 2009). This variable is constructed as an index from -10 to 10, where -10 indicates that the country is totally autocratic, and 10 indicates that the country is fully democratic. Following Hegre et al. (2001), I include both the linear and the squared measure in order to control for the possibility that countries somewhere in between are more exposed to conflicts. I do this by converting the original variable to a new version varying from 0 to 20, in which 0 denotes the most autocratic and 20 the most democratic state. The squared measure therefore has a maximum on 400. According to the descriptive statistics, the average observation is equal to 11.5.

To control for fractionalization within countries, I use ethnic fractionalization data from Alesina et al. (2003). Such fractionalization potentially stresses tensions between groups of people within a country, and thereby increases risks of conflict. Ethnic fractionalization is a continuous variable constructed by the formula $eth_i = 1 - \sum p_i^2$, where p is the population share that belongs to any given ethnic group in country i. This variable does not vary in time, so it is not included in fixed effects transformed models. The average fractionalization in a country is equal to .46. In other words, when two persons are randomly drawn in that country, they belong to the same ethnic group in 46 percent of the cases. Finally, as stated earlier, I include number of peace years as a control for latency of conflicts. Just as in the growth models, I follow subsequent short run empirical research such as Noy (2009: 225) and Burke et al. 2009: 20674), and use one year lags for all control variables in order to correct for potential simultaneity within the same year. Now that data have been outlined and summarized, and variable definitions are established, it is time to start with the regressions analyses.

5. Analysis – Natural disasters and economic growth

This chapter reports the regression analysis of different natural disaster effects on economic growth. I follow the approach by Noy (2009) and start with an examination of how people affected, people killed and economic damage by natural disasters relate to growth. After that, I explicitly investigate each disaster group (hydrometeorological, geophysical and climatological disasters). The use of natural disasters as an instrument for economic growth is presented in the subsequent chapter.

5.1 Pooled effects of hydrometeorological and geophysical events

First, I analyze how different measures of hydrometeorological and geophysical disasters relate to economic growth (for instance, if economic damages are more closely linked to economic growth than people killed). Main results are reported in table 5.1.[46] Besides different disaster measures, only lagged economic growth is included in order to track dynamic effects (see the data and variables chapter for motivation). As stated already, events like earthquakes, floods and storms are similar in the sense that they tend to come as sudden shocks, and that they exist only for a short period of time (while impacts on the economy typically last longer). Therefore, all natural disaster variables in the table are constructed as the sum of both hydrometeorological and geophysical events. Climatic events are left out of the equations for time being (droughts do not behave as sudden shocks). Naturally, the underlying assumption is that a given number of people affected or killed, as well as a given size of the monetary costs, should have the same impact on the economy whether the disaster is a hydrometeorological disaster like floods, or a geophysical disaster like an earthquake. The time weights described in detail in the previous chapter are also included.[47]

According to the model in the first column, there seems to be a negative and highly significant effect from people affected on GDP per capita growth. Testing the hypothesis that both disaster coefficients are equal to 0 gives a computed F-value on 8.33 and a p-value equal to .0004. In other words, H_0 (there is no joint impact of natural disasters happening this year and last year on economic growth) is clearly rejected. Furthermore, the effect from lagged

[46] Throughout the tables, OLS-FE stands for ordinary least squares estimation of a fixed effects transformed model like the one described in the methodology section. Similarly, OLS-RE stands for ordinary least squares estimation of a random effects transformed model. Also, R^2 throughout tables report variation within countries in fixed effects models, and overall variation in random effects models.

[47] Remember that time weights imposed on disaster variables reduce the importance of disasters happening late the current year as well as disasters happening early the previous year.

economic growth is positive and highly significant, meaning that increased economic growth last year statistically relates to increased economic growth this year as well. This is no surprise with respect to traditional theory on economic cycles.[48]

Table 5.1: Measures of natural disasters (with time weights) and economic growth

	Dependent variable: Real GDP per capita growth					
Model	OLS-FE (1)	OLS-FE (2)	OLS-FE (3)	OLS-FE (4)	OLS-RE (5)	OLS-RE (6)
People affected (time weights), t	-19.43^{***} (4.78)			-18.21^{***} (5.40)	-18.95^{***} (5.52)	-17.06^{***} (6.03)
People affected (time weights), t-1	-6.28^{**} (2.73)			-7.34^{**} (3.39)	-2.70 (3.47)	-1.81 (4.70)
People killed (time weights), t		-6366.33 (11012.78)		5737.33 (14735.37)		2234.60 (14468.54)
People killed (time weights), t-1		-1242.37 (790.72)		-391.18 (1349.64)		-1288.83 (1387.96)
Economic damage (time weights), t			-20.36^{*} (11.76)	-15.95 (17.90)		-15.60 (15.61)
Economic damage (time weights), t-1			6.83 (6.20)	11.33^{*} (6.02)		-1.83 (3.17)
Real GDP per capita growth (%), t-1	$.16^{***}$ (.06)	$.16^{***}$ (.06)	$.16^{***}$ (.06)	$.16^{***}$ (.06)	$.24^{***}$ (.06)	$.24^{***}$ (.06)
R^2	.07	.07	.07	.07	.10	.10
Observations	4279	4279	4279	4279	4279	4279
Clusters	165	165	165	165	165	165

*Notes: All models include fixed year effects. Regression disturbances are clustered around countries with Huber-White robust standard errors in parentheses. Significance at the 1, 5, and 10 percentage levels are indicated by ***, ** and *, respectively.*

Let us take a look at how the estimates should be interpreted, i.e. how dynamics of natural disasters are predicted to play out according to the model in column 1: Because of the time weights, interpretation of natural disaster coefficients is not totally straight forward. In fact, marginal effects are best expressed by standard deviations. The standard deviation on the people affected variable current year (hydrometeorological and geophysical disasters combined) is .015. Therefore, when a given hydrometeorological or geophysical disaster this year leads to an increase in the disaster variable by one standard deviation (.015), economic growth is predicted to drop by $19.43 * .015 = .29$ percentage points. Furthermore, the standard deviation on the people affected variable last year (hydrometeorological and geophysical disasters combined) is .023. Consequently, if the respective disaster is observed previous calendar year, the direct effect on economic growth this year is predictably $-6.28 *$

[48] A second growth lag (GDP per capita growth two years ago) was far from significant (p-value equal to .95 if included in the model reported in column 1) throughout specifications (results not reported). With that in mind, I follow Raddatz (2007) and Noy (2009), and assume that only one lag of economic growth should be included (as discussed in the data and variables chapter).

$.023 = -.14$ percentage points.[49] Finally, since natural disasters readably reduce economic growth within the year they occur and economic growth last year increase economic growth this year (lagged dependent variable is significant), there is also an indirect effect from lagged disasters through lagged economic growth. According to results in column 1, this indirect effect is .16 times the direct effect of disasters current year (based on the coefficient in front of lagged economic growth). The total predicted effect of a hydrometeorological or geophysical natural disaster on one standard deviation is the sum of the two direct effects on current growth (coefficients belonging to the two disaster variables) plus the indirect effect through lagged growth:[50]

$$\Delta y_{it} = -.29\Delta DM_{it} - .14\Delta DM_{it-1} - .16 * .29\Delta DM_{it-1}$$

$$\Rightarrow \quad \frac{\Delta y}{\Delta DM} = -.48$$

In words, a disaster with the scope of one standard deviation (of hydrometeorological and geophysical disasters) is expected to make economic growth fall by almost 0.5 percentage points.

The next model looks at how fatal disasters affect economic growth. I use the same fixed effects transformations as in model 1, and included in the model are people killed by natural disasters this year and last year, as well as economic growth last year. Results are reported in column 2: While the average relationship between people killed and economic growth is negative for both current and lagged disasters, neither of them are significant at a ten percentage level. The p-value for the H_0, the hypothesis that current and lagged disaster variables are jointly insignificant, is calculated to be .21 by means of the F-test (F-value equal to 1.57). The null-hypothesis is therefore not rejected. Lagged economic growth effects remain significant and stable. Turning to the effect of economic damages in column 3, disaster events that happen within the same calendar year have significant impact only at the 10 percentage level, while lagged disasters are insignificant (and positively related to economic growth on average). The p-value of joint significance is 0.12.

Theoretically, it could be the case that some measures on natural disasters (people affected, people killed and economic damage) are driving estimated impacts of other disaster

[49] I tried to explore longer lags of the disaster variables than one year, but the coefficients were never significant (results not reported). In other words, I found no evidence for the hypothesis that hydrometeorological and geophysical natural disasters have direct effects on economic growth beyond a two year time period.

[50] This is of course given that the model is correctly specified.

measures. For instance, if the number of people killed is closely related to the number of people affected, it is important to control for a potential spurious effect from people affected on growth (caused by people killed).[51] To check whether estimates are robust to multiple disaster measures, model (4) includes all three of them; people affected, people killed and economic damage. The results for people affected remains stable, while most of the other measures have relatively large changes in coefficients. I take this as support for the argument that people affected by natural disasters are a relevant determinant for economic growth in the short run.

This finding is interesting on its own and contrasts some of the recent short run growth literature out there. For instance, Loyza et al. (2009) find a positive relation between people affected by floods and economic growth (floods are an important share of the disasters included in the pooled hydrometeorological and geophysical disaster variable that I use here), and Noy (2009) finds no effect from people affected by a pooled set of disasters (including droughts, epidemics and insect infestations) and economic growth.[52]

Model (5) and (6) (reported in column 5 and 6 in the table) are random effects transformed versions of model (1) and (4), respectively. As discussed in the methodology chapter, these two models are more restrictive since the random effects transformation generally leads to biased coefficients when country specific effects are correlated with included explanatory variables (for instance, if poverty is correlated with natural disaster impacts, and at the same time is a static burden that belongs to certain countries). Again, the current proportion of people affected relative to population in the country seemingly has a very significant and negative impact on economic growth. Meanwhile, the lagged measure of people affected becomes insignificant. F-tests of joint significance for the people affected variables produce p-values on .0105 and .0006 in model (5) and (6), respectively. I also performed pooled OLS regressions and the results were similar to the random effects regressions (results not reported). In order to investigate if the fixed effects transformations in model (1)-(4) are preferable over random effects transformations (because of unobserved and time-invariant country-effects), I repeated the estimation of model (1) and (5) without country-clusters and Huber-White robust standard errors,[53] and then performed a Hausman

[51] The calculated correlation between the two is only .27 when hydrometeorological and geophysical disasters are pooled together.

[52] It is however important to note that both studies use identification strategies and samples that differ substantially from those used here. Furthermore, Loyza et al. (2009) only look at 5-year intervals. See the previous research chapter for more on these two studies.

[53] As discussed by Imbens and Wooldridge (2007: 4), the classic Hausman test cannot be performed with robust standard errors or clusters.

test on the hypothesis that the estimated coefficients are equal (results not reported).[54] The null-hypothesis was strongly rejected (p-value practically equal to zero), an indication that the fixed effects parameters in table 5.1 are preferred over the random effects parameters.

Next, I check how different measures of hydrometeorological and geophysical disasters perform without time weights.[55] The validity of such weights depends on the assumption that disaster impacts are continuous through time, even while the events themselves are instant or discrete. This assumption is not necessarily true. If disasters included in this analysis have a very time-limited impact on the economy, the specified time weights could be misleading and add in disturbance rather than precision to the estimates. For instance, if an average flood affects aggregated production in the economy for, let's say two months only, it would clearly be wrong to emphasize disasters happening in Mars any higher than disasters happening in August.

Table 5.2: Measures of natural disasters (without time weights) and economic growth

	Dependent variable: Real GDP per capita growth					
Model	OLS-FE (1)	OLS-FE (2)	OLS-FE (3)	OLS-FE (4)	OLS-RE (5)	OLS-RE (6)
People affected (no time weights), t	-8.82^{**} (4.14)			-6.95 (4.39)	-8.39^{**} (4.06)	-6.22 (4.21)
People affected (no time weights), t-1	3.36 (2.37)			2.94 (2.47)	4.91^{**} (2.18)	4.71^{**} (2.33)
People killed (no time weights), t		-5125.94^{*} (2733.14)		-3355.72 (2957.37)		-3721.15 (3222.08)
People killed (no time weights), t-1		2730.91 (1853.95)		2435.25 (1716.49)		2371.62 (2015.33)
Economic damage (no time weights), t			-10.04^{*} (5.21)	-5.98 (6.36)		-6.95 (6.17)
Economic damage (no time weights), t-1			1.23 (4.34)	$-.88$ (4.17)		-1.84 (3.86)
Real GDP per capita growth (%), t-1	$.16^{***}$ (.06)	$.16^{***}$ (.06)	$.16^{***}$ (.06)	$.16^{***}$ (.06)	$.24^{***}$ (.06)	$.24^{***}$ (.06)
R^2	.07	.07	.07	.07	.10	.11
Observations	4134	4134	4134	4134	4134	4134
Clusters	165	165	165	165	165	165

*Notes: All models include fixed year effects. Regression disturbances are clustered around countries with Huber-White robust standard errors in parentheses. Significance at the 1, 5, and 10 percentage levels are indicated by ***, ** and *, respectively.*

[54] If the difference between fixed and random effects coefficients is insignificant, many econometricians prefer random effects models because of efficiency. A rejection of the null-hypothesis is an indication on bias in at least some of the random effects coefficients because of unobserved individual effects. See Wooldridge (2002: 288-291) for more on the Hausman test statistics.

[55] The size of a disaster j in country i in year t is thereby defined in the following three ways: $\frac{\#affected_{ijt}}{population_{it-1}}$, $\frac{\#killed_{ijt}}{population_{it-1}}$ and $\frac{\$damage_{ijt}}{GDP_{it-1}}$.

The main results without time weights are reported in table 5.2, with fixed effects transformed variables in model (1)-(4) and random effects transformations in model (5) and (6). Since the disaster variables have higher values without time weights, the parameter values are naturally lower compared to table 5.1.[56] People affected by natural disasters are still significantly related to economic growth within the same year, according to model (1). Meanwhile, people affected last year become an insignificant disaster measure with positive signs. In model (2), people killed have a negative effect at the ten percentage level the current year, while the lagged variable remains insignificant at all acceptable significance levels. The results are qualitatively similar for the effect from economic damage in model (3); i.e. significant negative coefficients at the ten percentage level for current disasters, but insignificant coefficients for lagged disasters. Furthermore, when all three disaster measures (and their lags) are included in model (4), none of them are significant.

Interestingly, the random effects transformations in model (5) and (6) lead to positive and significant coefficients for the lagged measure of people affected.[57] These results are not intuitive, but some general thoughts can be made based on the reasoning in the methodology chapter: Since country-specific factors are likely to be correlated with either natural disaster measures or lagged economic growth (or both) in the random effects models, it could be the case that there exist some country-factor that correlates both with people affected last year (or some other included explanatory variable) and with current economic growth.

In total, none of the natural disaster variables seem sufficiently significant without time weights. I take this as support for the argument that hydrometeorological and geophysical disasters seem to have continuous rather than very discrete time effects.

The main point up until now have been to find a stable and significant measure of natural disasters, if such a measure exists (similar to what Noy 2009 does). In sum, it seems as people affected relative to total population is the only significant determinant of economic growth in my data. The two other variable definitions fail to meet any credible threshold for relevance (for instance significance at the five percentage level), and their coefficients change a lot between specifications in the two tables above. From now on, I only use people affected with time and population weights to measure the magnitude of hydrometeorological and geophysical disasters.

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[56] Given that the average timing of a natural disaster is in the middle of the year, the expected disaster measures without time weights should be twice as large as them with time weights. Consequently, estimated coefficients of variables without time weights should be approximately half the size. When comparing the two regression tables (and also when looking at the descriptive statistics), we see that this is roughly the case.

[57] The Hausman test still rejects these two models in favor of the corresponding fixed effects models.

5.2 Hydrometeorological disasters and economic growth

The next step is to disaggregate the pooled disaster measure that I have used so far in order to check if hydrometeorological and geophysical disasters differ with respect to economic growth. Especially, it might be of interest to identify the growth effects of hydrometeorological disasters. In contrast to geophysical events such as earthquakes and volcanoes, the frequency of hydrometeorological events like floods, storms and surges are, as mentioned earlier, probably linked to climate change. While the very nature of natural disasters should make them relatively exogenous to economic growth, it is still of interest to test how robust the parameters are to different control variables. Therefore, a set of controls frequently used in the growth literature are introduced as well.

The estimated results that link hydrometeorological disasters to economic growth are reported in table 5.3. The explanatory variable is people affected by natural disasters relative to total population, and every disasters event timing is taken into consideration by use of time weights. Both disasters in current and previous year are included. Model (1) reproduces the simplest specification with only lagged economic growth in addition to disaster variables. Coefficients are once again estimated by means of OLS on fixed effects transformed variables. The estimated results are remarkably similar results in the previous section. In other words; people affected by hydrometeorological disasters like floods, mudslides, storms and cyclones reduce economic growth in the short run. The computed F-value for current and lagged hydrometeorological disasters is 8.62, the p-value is 0.0003.

In the previous section, I found that a disaster equal to one standard deviation in size reduced economic growth by .29 percentage points within the same year, and by 0.48 percentage points in total (within two years). The standard deviation for people affected by hydrometeorological disasters is equal to .014, according to descriptive statistics in the data chapter. This gives that hydrometeorological disasters equal to one standard deviation in size (.014) predictably reduce economic growth within same year by $20.75 * .014 = .29$ percentage points. Furthermore, the standard deviation on hydrometeorological disasters (with time weights) last year is .021. Consequently, if the respective disaster is observed last year, the direct effect on current economic growth is $-6.33 * .021 = -.13$ percentage points. The indirect effect through economic growth last year is $-.16 * .29 = -.05$ percentage points.[58]

[58] As explained in the previous section; the indirect effect is the effect that comes from reduced growth last year caused by a disaster last year.

The total reduction in economic growth (given by the model in column 1) is the sum of direct and indirect effects:

$$\Delta y_{it} = -.29\Delta DM_{it} - .13\Delta DM_{it-1} - .16 * .29\Delta DM_{it-1}$$
$$\Rightarrow \quad \frac{\Delta y}{\Delta DM} = -.47$$

In words; a hydrometeorological disaster by the size of one standard deviation is predicted to reduce economic growth with a little less than .5 percentage points in the short run. This result is almost identical to predictions from the previous section, an indication that those results are driven by hydrometeorological disasters (as demonstrated in the next section, geophysical disasters have growth effects that are different).

Table 5.3: Hydrometeorological disasters and economic growth

	Dependent variable: Real GDP per capita growth					
Model	OLS-FE (1)	OLS-FE (2)	OLS-FE (3)	OLS-FE (4)	OLS-FE (5)	OLS-RE (6)
People affected (time weights), t	-20.75^{***}	-25.65^{***}	-23.23^{***}	-25.53^{***}	-26.47^{***}	-20.76^{***}
	(5.00)	(7.53)	(5.18)	(4.42)	(6.25)	(5.79)
People affected (time weights), t-1	-6.33^{**}	-4.81	-4.30	-6.74	-4.37	$-.99$
	(3.10)	(4.35)	(10.69)	(4.34)	(11.68)	(4.23)
Real GDP per capita growth (%), t-1	$.16^{***}$	$.15^{***}$	$.13^{***}$	$.23^{**}$	$.15^{***}$	$.24^{***}$
	(.06)	(.05)	(.04)	(.11)	(.03)	(.06)
Capital formation relative to GDP (%), t-1		.10			$-.07^{**}$	
		(.07)			(.03)	
Life expectancy at birth (ln), t-1		$-.04$			1.04	
		(3.44)			(3.85)	
Account balance (%), t-1			$-.01$		$-.06$	
			(.04)		(.05)	
Government share of GDP per capita (%), t-1			.09		.05	
			(.06)		(.04)	
Trade openness (%), t-1			$.020^{**}$		.012	
			(.007)		(.008)	
Foreign direct investment (net inflow) as share of GDP (%), t-1			.005		.02	
			(.013)		(.05)	
Natural commodities export (%), t-1			$-.003$		$-.003$	
			(.012)		(.010)	
Inflation, consumer prices (%), t-1				$-.0002$	$-.0003^{***}$	
				(.0002)	(.0001)	
Changes in net reserves (%), t-1				-10.08^{***}	-15.64^{***}	
				(3.67)	(3.87)	
Money and quasi money (M2) as share of GDP (%), t-1				$-.0006$	$-.02^{***}$	
				(.0004)	(.01)	
R^2	.07	.09	.12	.17	.16	.10
Observations	4279	3823	2706	2922	2147	4279
Clusters	165	163	150	135	128	165

*Notes: All models include fixed year effects. Regression disturbances are clustered around countries with Huber-White robust standard errors in parentheses. Significance at the 1, 5, and 10 percentage levels are indicated by ***, ** and *, respectively.*

Model (2) introduces the two proxies for physical capital and human capital. Since country-year observations with less abundance of these two production factors might have lower growth, it is of interest to test whether negative effects from natural disasters are sensitive to them. Interestingly, while the effect of hydrometeorological disasters happening within the same year remains stable and significant, the lagged disaster measure becomes insignificant when capital stocks are controlled for. The computed F-value for the two disaster variables decreases to 5.91, corresponding to a p-value equal to .0033. The null-hypothesis that hydrometeorological disasters this year and last year are jointly insignificant is in other words still rejected at a one percentage level. One could speculate that lagged disasters become insignificant because countries with abundance of physical and human capital are better able to absorb negative disaster effects. Meanwhile, neither capital formation nor life expectancy is significant in column 2. It is also worth mentioning that since lagged disaster effects are insignificant, aggregated predicted effects from hydrometeorological disasters on economic growth become smaller. Based on descriptive statistics and the coefficients in column 2, the total direct growth effect (within the same year) is equal to $-25.65 * .014 = -.36$ percentage points, while the indirect effect through lagged economic growth is $-.15 * .36 = -.05$ percentage points. The overall effect is consequently a growth reduction equal to $.36 + .05 = .41$ percentage points.[59]

Next, I follow Noy (2009: 226) and control for different real economic variables that are used in various short run growth models: Countries with positive account balances last year might absorb natural disaster effects more easy. Countries with large governments (measured as government share of GDP) might be in better shape to set up proper disaster responses. Countries with high degrees of foreign trade might be less dependent on domestic markets and their vulnerabilities to natural disaster shocks. Similar for foreign direct investments: Countries with substantial inflow of FDI might overcome natural disasters easier since such investments possibly are less prone to internal shocks. Finally; countries that are highly dependent on primary resource exports might experience more adverse effects on the economy when natural disasters occur. Column 3 reports estimated results from the model with real economic control variables. With respect to these controls; only the trade openness variable has a significant coefficient: When import and export as share of GDP per capita last year increases by one percentage point, current economic growth is predicted to be .02

[59] There is of course potential indirect effects through investment changes, etc. that is uncounted for in the simple specifications that I set up, which comes in addition.

percentage points higher. This might seem as a small change, but compared to the typical hydrometeorological shock, it is not: From the descriptive statistics we see that the trade openness variable has a (overall) standard deviation equal to 48.62. A change in this variable equal to one standard deviation consequently relates to a $.02 * 48.62 = .97$ percentage points growth increase.[60] Compared to model (2), the hydrometeorological disaster variable in model (3) that represents current year remains stable and significant, while disasters last year remain insignificant for economic growth (F-test of joint significance yields F-value equal to 10.77 and p-value practically equal to 0). Compared to the significant coefficients in model (1), it therefore seems as once selected real economic factors are controlled for, hydrometeorological disasters happening last year do not play an important role for current economic growth.

As in Noy (2009: 227), I also test for robustness against different financial control variables: Countries with high inflation might be more vulnerable to further economic instability, for instance caused by natural disasters. Countries with large reserves held by the central bank can use this as a buffer against economic shocks. Finally, a similar argument can be used for private money: Countries with large amounts of foreign deposits and private currency might be better able to absorb exogenous shocks caused by hydrometeorological disasters. Column 4 shows the results. Natural disasters still have a negative and significant effect on current economic growth, and just as in the last model, they do not have a significant direct effect on growth next year. Among the financial control variables, only changes in net reserves are significant. It is not very clear why net reserves are negatively related to economic growth in model 4, but it could be the case that increased reserves last year lead to less economic growth through depreciation of the real exchange rate.[61]

Model (5) (in column 5) is a richer fixed effects model with all control variables included. The people affected by natural disasters are once again negatively related to current economic growth, while disasters last year are insignificant. With regard to control variables; capital formation, inflation, net reserve changes and private money deposits are all significant.

Finally, model (6) is a random effects transformed version of model (1). While hydrometeorological disasters within current year have almost identical coefficients, disasters last year loose all relevance in model (6). With respect to the critical assumptions for random

[60] This statement comes with one important modification: While almost all variation in the "people affected by natural disasters" variable are identified within countries, most variation in the trade openness variable is because of differences between countries. The within country standard deviation in trade openness is equal to 21.01. Therefore, a "within country shock" equal to one standard deviation in trade openness only results in a change in economic growth equal to $.02 * 21.01 = .42$ percentage points.

[61] See Rødseth (2000: 63-78) for more on possible foreign reserves effects on economic growth.

effects models (presented in the methodology chapter), model (6) is the most restrictive of the two.[62] Nevertheless, since the two coefficients representing current disasters are very similar in the two models, model (6) does not indicate that the current hydrometeorological disasters variable is correlated strongly with country-specific factors (such as structural poverty, geographic location, etc.). With respect to goodness of fit; the overall R^2 is equal to .10 in both models. Meanwhile, since the variables are transformed in different ways, it is not straight forward to compare their explanatory power either.[63]

I also ran regressions with a large set of other control variables, such as governmental debts, GDP per capita (ln), value added production variables, ethnic fractionalization, degree of democracy (the polity2 index), etc. The results were mostly the same, although effects from hydrometeorological disasters last year became significantly negative in some of the specifications (results not reported). As a final robustness check, I explored other measures of hydrometeorological disasters (see table A in the appendix for results). That is, I removed time weights (model (1)), I took the logarithm of the people affected variable with time weights (model (2)), and I simply counted the number of hydrometeorological disasters (model (3)). Except from the count measure, these alternative specifications gave the same qualitative results, namely a very significant and negative effect on current economic growth. Nevertheless, I follow the approach by Noy (2009) and Noy and Vu (2009), and stick to the measure of people affected relative to population (with time weights) in this analysis. This specification seems to give the most stable estimates.

In total, it clearly seems to be the case that natural disasters such as floods, storms, surges and slides have a negative impact on current economic growth. Meanwhile, it is not very clear that these disasters also affect economic growth next year, other than through the indirect growth effect (the lagged dependent variable). This might be an indication that disasters such as floods, storms and cyclones are relatively quickly absorbed by the economy, although they alter overall performance for a short while. Estimates in the models reported here suggest that a disaster event on one standard deviation reduce real GDP per capita growth by somewhere between .29 (model (1)) and .37 (model (5)) percentage points (confidence intervals not taken into consideration) immediately, while the total effect is a growth reduction somewhere

[62] In the methodology chapter, I showed that since the fixed effects transformation eliminates all country-specific factors (that do not vary in time), it allows these factors to be correlated with included variables. In contrast, the random effects transformation does not.
[63] Reported R^2 in columns with fixed effects models are within R^2. Hence, when the table reports that R^2 for the estimation of model (1) is equal to .07, it is not overall R^2. As pointed out in Wooldridge (2009: 484), it is not perfectly clear which R^2 to report in fixed effects estimations (he reports within R^2 in the example).

between .37 (model (3)) and .47 (model (1)) percentage points. These results are remarkably stable when typical determinants for short run economic growth are added into the equation.

5.3 Geophysical disasters and economic growth

I now turn to geophysical events, which are earthquakes and volcanoes. Just as with hydrometeorological disasters, I only look at events that last one month at maximum. These events come and go as sudden shocks, and they are suitable for the constructed time weights. It is also important to emphasize that I include sub-disasters caused by geophysical phenomenon in this analysis, including tsunamis, rockslides, subsidence and volcano-related fires. If these sub-disasters were excluded from the analysis, I would overlook important elements of geophysical processes and their effects on economic performance. Since control variables have been explained already, I will not go into their effects in detail here. Table 5.4 reports the results. As in the previous section, key explanatory variables are people affected relative to population with imposed time weights.

Model (1) is once again the simplest fixed effects model. Here, the story seems to be a little different than for hydrometeorological disasters: While people affected current year by geophysical disasters have a negative effect on economic growth on average, this effect is far from significant at the 10 percentage level (p-value equal to .287). Furthermore, the lagged disaster variable (people affected last year) has a negative and very significant effect on current growth, even at the one percentage level (p-value practically equal to 0). The F-test that current and lagged disaster variables (jointly) have no effect on economic growth is rejected at the one percentage level (F-value equal to 7.28, p-value equal to .001). Lagged economic growth has a significant and positive impact, just as in all the previous estimations.

From the descriptive statistics table, we see that the variable for people affected by geophysical disasters in previous year (with time weights) have a standard deviation equal to .0095. Consequently, a geophysical disaster on one standard deviation last year has a direct effect on current economic growth equal to $-6.08 * .0095 = -.06$ percentage points. This is only one half of the predicted direct effect from a hydrometeorological disaster last year (which I found to be $-.13$ percentage points in the corresponding model in the previous section).

Model (2) includes selected control variables for physical and human capital. The lagged disaster variable is still significant at the five percentage level, but not at the one percentage level. The respective coefficient readably drops one third in absolute value (from -6.08 to

-3.96). Negative effects from people affected by geophysical disasters last year are also robust to the set of real economic control variables in model (3), to the set of financial control variables in model (4), and to the specification with all control variables in model (5). Control variables have similar coefficients to corresponding specifications in the previous section.

Table 5.4: Geophysical disasters and economic growth

	Dependent variable: Real GDP per capita growth					
Model	OLS-FE (1)	OLS-FE (2)	OLS-FE (3)	OLS-FE (4)	OLS-FE (5)	OLS-RE (6)
People affected (time weights), t	-6.73 (6.30)	-6.66 (5.55)	-11.29 (10.08)	-5.14 (8.14)	-7.89 (9.75)	-4.84 (5.75)
People affected (time weights), t-1	-6.08^{***} (1.63)	-3.96^{**} (1.56)	-5.91^{***} (1.55)	-4.32^{**} (1.92)	-6.40^{***} (1.96)	-10.24^{***} (1.72)
Real GDP per capita growth (%), t-1	$.16^{***}$ $(.06)$	$.15^{***}$ $(.05)$	$.13^{***}$ $(.04)$	$.23^{**}$ $(.11)$	$.15^{***}$ $(.03)$	$.23^{***}$ $(.06)$
Capital formation relative to GDP (%), t-1		$.10$ $(.07)$			$-.07^{**}$ $(.03)$	
Life expectancy at birth (ln), t-1		$.25$ (3.43)			$.91$ (3.93)	
Account balance (%), t-1			$-.01$ $(.04)$		$-.06$ $(.05)$	
Government share of GDP per capita (%), t-1			$.09$ $(.06)$		$.05$ $(.04)$	
Trade openness (%), t-1			$.021^{***}$ $(.008)$		$.013^{*}$ $(.008)$	
Foreign direct investment (net inflow) as share of GDP (%), t-1			$.004$ $(.013)$		$.02$ $(.05)$	
Natural commodities export (%), t-1			$-.003$ $(.011)$		$-.003$ $(.010)$	
Inflation, consumer prices (%), t-1				$-.0002$ $(.0002)$	$-.0004^{***}$ $(.0001)$	
Changes in net reserves (%), t-1				-10.09^{***} (3.66)	-15.58^{***} (3.88)	
Money and quasi money (M2) as share of GDP (%), t-1				$-.0006$ $(.0004)$	$-.03^{***}$ $(.01)$	
R^2	$.07$	$.09$	$.10$	$.17$	$.15$	$.10$
Observations	4279	3823	2706	2922	2147	4279
Clusters	165	163	150	135	128	165

*Notes: All models include fixed year effects. Regression disturbances are clustered around countries with Huber-White robust standard errors in parentheses. Significance at the 1, 5, and 10 percentage levels are indicated by ***, ** and *, respectively.*

Turning to the random effects model in column 6, it seems as the (significant) marginal effect on growth increases in absolute value (from -6.08 to -10.24), an indication that country-specific factors might be correlated with people affected by geophysical disasters, alternatively with growth last year.

I also ran these regressions without time weights, but just as in the first section in this chapter, the disaster effects were less significant (results not reported). Further, I changed the disaster measure to people killed (relative to population, with and without time weights), economic damage (relative to GDP, with and without time weights), and to a simple count measure.[64] Meanwhile, estimated effects were insignificant and coefficients were sensitive to variable and model specifications (results not reported).

In total, I find no evidence for the hypothesis that geophysical disasters reduce economic growth the year they occur, but it seems to be a small reduction the next calendar year. It is not to say that geophysical disasters don’t cause immediate economic shocks. Instead, as discussed by Tol and Leek (1999: 311), it could be the case that such shocks are offset in the very short run by typical governmental and international responses to earthquakes and volcanoes. I will discuss the results from all three disaster groups in more detail after the examination of climatological disasters.

5.4 Climatological disasters and economic growth

In the study of hydrometeorological and geophysical disasters, the use of time weights have been motivated by an assumption that these events appear as sudden shocks which disappear after a short time period. This is obviously not the reality for droughts. In contrast, they have rather slow onsets, act as more long-lasting phenomenon and slowly strangle living conditions (Below et al. 2007: 329). Indeed, the very characteristic of a drought is not the high temperature or lack of water alone, but the drought in interaction with time. For that reason I cannot rely on time weights used up until now. To measure the effects from droughts on economic growth, I follow the approach suggested by Pandey and Bhandari (2007: 34-35), and define a dummy variable equal to one in country-year observations with reported drought in the EM-DAT data. Also, as a specification test, I report results from a model with people affected relative to the population (without time weights). Table 5.5 reports the main results.

Model (1) is once again the simple fixed effects transformed model with only lagged economic growth as a control variable (in addition to the usual year dummies). From the table we see that a drought year is expected to have .75 percentage points lower GDP per capita growth than country-year observations without reported droughts. This result is significant at the five percentage level. Droughts last year do not have significant effects; they are even positively related to current economic growth on average. The F-test for joint significance of the two drought dummies just fails to reject the null-hypothesis at a five percentage level (F-value equal to 3.02, p-value equal to .0513). Furthermore, economic growth last year (the lagged dependent variable) has a similar coefficient to previous results. When indirect effects

[64] Equal to the number of geophysical disasters current year, as well as a lagged version.

are taken into account (effects on current growth trough economic growth last year), the total reduction in GDP per capita by a drought-year is given by:

$$\Delta y_{it} = -.75\Delta DM_{it} - .16 * .75\Delta DM_{it-1}$$

$$\Rightarrow \quad \frac{\Delta y}{\Delta DM} = -.87$$

In words; an average drought-year is expected to reduce economic growth by .90 percentage points within the two years specified in the model. This is considerable given the average economic growth rate in the dataset, which is 1.68 percentage points.

Table 5.5: Climatological disasters and economic growth

	Dependent variable: Real GDP per capita growth					
Model	OLS-FE (1)	OLS-FE (2)	OLS-FE (3)	OLS-FE (4)	OLS-FE (5)	OLS-FE (6)
Drought (dummy), t	$-.75^{**}$ (0.33)	$-.91^{***}$ (.29)	$-.83^{***}$ (.29)	$-.87^{***}$ (.29)	$-.75^{**}$ (.32)	
Drought (dummy), t-1	.47 (.48)	.45 (.54)	.48 (.51)	$.87^{*}$ (.48)	.48 (.51)	
People affected (no time weights), t						-2.74 (1.84)
People affected (no time weights), t-1						.14 (1.91)
Real GDP per capita growth (%), t-1	$.16^{***}$ (.06)	$.15^{***}$ (.05)	$.13^{***}$ (.04)	$.23^{**}$ (.11)	$.15^{***}$ (.03)	$.16^{***}$ (.06)
Capital formation relative to GDP (%), t-1		.10 (.07)			$-.07^{**}$ (.03)	
Life expectancy at birth (ln), t-1		.12 (3.44)			.44 (3.94)	
Account balance (%), t-1			$-.01$ (.04)		$-.06$ (.05)	
Government share of GDP per capita (%), t-1			.09 (.06)		.05 (.04)	
Trade openness (%), t-1			$.020^{***}$ (.008)		$.013^{*}$ (.008)	
Foreign direct investment (net inflow) as share of GDP (%), t-1			.005 (.013)		.02 (.05)	
Natural commodities export (%), t-1			$-.003$ (.012)		$-.003$ (.010)	
Inflation, consumer prices (%), t-1				$-.0002$ (.0002)	$-.0004^{***}$ (.0001)	
Changes in net reserves (%), t-1				-10.07^{***} (3.61)	-15.54^{***} (3.87)	
Money and quasi money (M2) as share of GDP (%), t-1				$-.0006$ (.0004)	$-.03^{***}$ (.01)	
R^2	.07	.09	.10	.17	.15	.10
Observations	4279	3823	2706	2922	2147	4279
Clusters	165	163	150	135	128	165

*Notes: All models include fixed year effects. Regression disturbances are clustered around countries with Huber-White robust standard errors in parentheses. Significance at the 1, 5, and 10 percentage levels are indicated by ***, ** and *, respectively.*

Model (2) includes the two control variables for physical and human capital. Here we see that the negative effect from drought years on economic growth becomes even more negative and significant. The direct effect on current economic growth is a reduction on .91 percentage points, and the total effect is predicted to be a $.91 + .15 * .91 = 1.05$ percentage point growth loss. Capital controls are insignificant as before. When I control for real economic factors as in model (3), financial factors as in model (4), and all factors together as in model (5), estimated effects from drought year observations are significantly negative. Furthermore, coefficients are relatively stable across specifications.

In model (6), I replace the drought dummies by people affected relative to total population. This is the same measure as described in the data and variables section for hydrometeorological and geophysical disasters, only without time weights. Estimated disaster coefficients in model (6) have the same signs as the dummy coefficients, but they are small (in absolute values) and insignificant. This is no surprise given the nature of droughts and how they are registered in the EM-DAT data: Since droughts can last for years, the people affected variable is likely to be severely hampered by measurement errors.[65] It can be shown that such measurement errors in OLS models generally lead to estimated coefficients that are biased against zero (Wooldridge 2009: 318-322), and that the fixed effects transformation in some cases exaggerate this bias severely (Wooldridge 2002: 311-312). Therefore, to the extent that there is measurement errors in the people affected variables for droughts, the unbiased coefficient for droughts in current year is likely to be more negative than the estimate given in column 6. In total, I therefore take the results represented here as relative robust support for the hypothesis that country-year observations with drought have less economic growth. With that in mind, I provide an overall discussion of natural disasters and their effects on economic growth in the next section.

5.5 Notes about natural disasters and their economic impacts

The work presented in this chapter provides quantitative evidence for a negative causal effect from different natural disasters on economic growth in the short run. Respective coefficients are very significant in most specifications, and the results are robust to different control

[65] The nature of droughts can make it very difficult to define exactly when a person became affected, not to say if the criteria for being affected are fulfilled at all. Although recent attempts have been made to improve drought data in EM-DAT, there are still considerable drawbacks related to quantitative measures such as people affected (Below et al. 2007). Please see the data and variables chapter for the definition of being affected used in EM-DAT data.

variables often used in the literature. If anything, these results can be taken as support for the argument that natural disasters alter abundance of factors important for production and income in economies, and hence reduce overall economic performance. The creative destruction hypothesis on the other hand is not supported by this analysis.

One aspect which is interesting on its own, is that different disasters seem to have different impact on the economy. While effects from disasters linked to weather and climate are identified within the year these events occur, geophysical events typically affect the economy next year. Furthermore it seems as compared to geophysical events, a given number of people affected by hydrometeorological disasters has a more adverse effect in my estimations. It is not perfectly clear why this is the case, but I suggest a couple of possible stories: First, one has to understand the nature of different disasters. My suspicion is that floods, droughts and other climatic events are relatively more destructive for human life than for infrastructure, compared to geophysical events. In particular, earthquakes and volcanoes tend to represent devastating consequences for fixed assets such as buildings. It is not to say that climatic disasters do not cause infrastructural damage. Indeed, as is the case in Pakistan and China these days, massive weather-related events can destroy buildings and other manmade structures severely. Also, as demonstrated in Haiti earlier this year, earthquakes can kill thousands of people within very short periods of time. Nevertheless, it might be that the typical climatic disaster has a higher ratio of human damage to infrastructural damage, compared to the typical earthquake or volcano. For instance, it seems likely that droughts are bad news for local farmers, but at the same time have little to say for their houses.

Now, if we accept that climatic disasters are relatively worse for human capital than for physical capital compared to geophysical events, it can further be the case that infrastructural damage are badly captured in economic data. As discussed by Tol and Leek (1999: 309-315), GDP measures generally capture flows of capital, while damages to infrastructure represent stock reductions. Consequently, it could be that growth specifications in empiric analyses fails to capture the real impacts building collapses and other physical damages represent. If geophysical events cause relatively more damage to buildings than to humans, this would result in a disproportional underreporting of economic costs by geophysical events (played out as small coefficients in regression models). A further concern is related to governmental responses when different natural disasters occur. In particular, earthquake damages might trigger intense efforts by governments and international development agencies to restore buildings and other fixed assets. Such efforts might stimulate aggregated economic activity to the extent that initial losses are offset for a short while.[66] If this is the case, the insignificant coefficients that I found for current geophysical events seem more intuitive. A long-lasting drought on the other side, seldom initiates large-scale economic activity, and hence has negative economic impacts right away.[67]

With regard to variables that are omitted from this analysis, there is of course a possibility that poor countries with low growth rates exaggerate the scope of their natural disasters in order to get more aid from abroad. Nevertheless, to the extent that exaggerating disaster impacts is some country-specific characteristic, the fixed effects transformations that I do effectively removes bias caused by these characteristics. Another concern is that poor countries often have less resources and knowledge when it comes to collecting and interpreting statistics on natural events. This might lead to measurement errors that are correlated with poor countries, and therefore with economic growth. To the extent that such errors exist, it can be shown that estimated parameters are biased towards zero (Wooldridge 2009: 315-320). Therefore, the true effect of sudden natural shocks on current income might be even more negative than estimates reported here.[68] In total, I am relatively confident that the negative relationship between natural disasters and economic growth should be regarded as a causal effect, not only as simple correlations.

[66] After some time, the negative impacts on overall economic performance that stems from lower aggregate demand, reduced investment flows, etc., is likely to dominate. Consequently, the effect from geophysical events last year becomes negative in my regressions.

[67] One exception might be the humanitarian aid that is often needed because of droughts, which dubiously kick the economy back on track.

[68] As a robustness check, I also switched the growth variable with logarithm of GDP per capita. This was done in order to test if natural disasters explain low income generally, and not just income fluctuations. Meanwhile, I found no support for this hypothesis.

6. Analysis – Disaster triggered growth shocks and armed civil conflicts

The second major task in this study is to investigate how disaster related income fluctuations affect the risk of armed civil conflict. This task is motivated by the fact that such conflicts have ended with disastrous humanitarian outcomes throughout history. Hence, and in light of the ongoing climate change, it is of great importance to target the role of natural disasters for future conflicts.

As explained in previous chapters, economic performance and conflict risk might very well be determined simultaneously in the sense that causal arrows run both ways. My strategy is to identify arguably exogenous variation in economic growth with help from natural disaster effects on growth. To be a valid instrument, natural disasters must have a strongly significant link to economic growth. Therefore, I take advantage of the seemingly clear relationship between people affected by hydrometeorological disasters and economic growth. The other critical restriction is that the instrument only affects armed civil conflicts through growth; i.e. that there is no such thing as a direct causal relationship between disasters and conflict onsets. I will investigate these two restrictions more closely in the next section, but first it is of interest to do an informal test of the connection between economic growth and civil conflict onsets.

Table 6.1: Sample differences – t-test

		Mean	Standard error	Observations
GDP per capita growth	Non-onset sample	1.735	.113	4161
	Onset sample	−.017	.868	138
	Combined	1.679	.113	4299
	Difference	1.752	.876	
H_0: Non-onset and onset observations have equal economic growth rates	t-value			2.001
	Significance level			.047**
	Degrees of freedom			141.752

Notes: Students t-test of population differences in GDP per capita growth. Degrees of freedom are obtained from Welch's formula (1947) in order to correct for different population variances. H_0: The two populations have equal GDP per capita growth.

Table 6.1 reports results from a simple t-test on sample differences between observations with and without conflict onsets in my data. The null-hypothesis is that country-year observations without armed civil conflict onsets have the same economic growth rate as observations with conflict onsets. From the table, we see that average GDP per capita growth in the sample with non-onsets is equal to 1.735 percentage points, while it is less than zero in the onset sample. The difference, which is 1.752 percentage points, is significant at a five percentage level, i.e. the two-sided null-hypothesis is rejected. This informal exercise therefore gives support to previous literature on conflicts, which concludes that economic growth is linked to less conflict risk. Now, in order to examine the causal relationship between economic growth and armed civil conflict onsets, I next turn to the two-stage least squares (2SLS) analysis.

6.1 Instrument validity – the first stage

First, I check how robust the disaster-growth relation is when conflict determinants are introduced. Table 6.2 reports selected first stage regressions with different control variables often used in the conflict literature. Model (1) is a fixed effects transformed regression estimated without any conflict controls. The independent variable is people affected by hydrometeorological disasters relative to total population, and time weights are imposed on each disaster. The estimated coefficient is similar in size to those previously reported and clearly significant (p-value equal to .0002).

Table 6.2: Economic growth and armed civil conflict onsets – first stage

	Dependent variable: Real GDP per capita growth					
Model	OLS-FE (1)	OLS-FE (2)	OLS-FE (3)	OLS-PE (4)	OLS-FE (5)	OLS-PE (6)
People affected by hydrometeorological disasters (time weights), t	-19.80^{***} (5.18)	-18.77^{***} (5.21)	-17.29^{***} (5.29)	-20.73^{***} (4.92)	-17.30^{***} (5.28)	-19.91^{***} (5.18)
Population (ln), t-1		.13 (2.16)			−.78 (2.36)	−.11 (.16)
Polity2, t-1			.04 (.17)		.06 (.17)	.01 (.12)
Polity2 (squared), t-1			−.0006 (.0078)		−.0016 (.0081)	.0006 (.0056)
Ethnic fractionalization (%)				-1.72^{*} (.96)		-1.99^{*} (1.12)
R^2	.06	.06	.06	.08	.06	.08
H_0: Instrument is insignificant for economic growth (F-test)	14.61^{***}	12.98^{***}	10.71^{***}	17.73^{***}	10.75^{***}	14.76^{***}
Observations	4299	4161	3855	4281	3855	3837
Clusters	165	165	156	164	156	155

*Notes: Fixed year effects and the decay function developed by Beck et al. (1998) are included in all specifications. Models based on pooled effects transformations include fixed region effects. Regression disturbances are clustered around countries with Huber-White robust standard errors in parentheses. Significance at the 1, 5, and 10 percentage levels are indicated by ***, ** and *, respectively.*

Model (2) includes the logarithm of countries population size. In the second stage, this variable is included to control for the simple statistical reality that countries with large populations are more likely to experience some kind of a conflict. Model (3) includes the polity index and its square measure. These two variables are included in the second stage in order to control potential linkages between democratic and autocratic regimes and conflict risk. Finally, model (4) is a pooled effects model with the ethnic fractionalization measure from Alesina et al. (2003). Such fractionalization potentially increases tensions between groups of people within a country. In all these models, the disaster effect is very significant with p-value equal to .0004, .0013 and .0000, respectively. Model (5) includes all second stage control variables that vary in time[69], and model (6), which is a pooled regression, also includes the fractionalization variable. The overall picture is that my natural disaster measure proves robust. Estimated coefficients are relatively stable, with (negative) point estimates between 17.29 and 20.73. In other words, hydrometeorological disasters seem to be strongly relevant for short term growth fluctuations in GDP per capita, even when controlling for typical conflict variables.[70]

Besides being relevant for economic growth in the first stage equations, hydrometeorological disasters should also be exogenous in the second stage. A potential problem is that they might affect the risk of conflict through other channels than economic growth. If this is true, I could get biased second stage regressions. Theoretically, there are ways in which hydrometeorological disasters might affect conflict propensity other than through economic growth. For instance, if hydrometeorological disasters tend to destroy communication and transportation systems such as roads, they could make it harder for insurgents to convey weapons and other important equipment that is necessary to carry out armed conflict. In fact, severe catastrophes like floods, storms and hurricanes could even make it difficult to bring rebel soldiers to the front. Of course, the same problem applies for government forces as well. Net consequences of these mobility constraints are in theory ambiguous. On one side, hydrometeorological disasters might cut conflict parties away from each other, and thereby temporarily force truce or even peace. On the other side, if government forces depend heavily on road systems, while rebellions mainly take advantage of the wilderness, natural disasters might shift the conditions asymmetrically and thereby increase conflict risk.

Although it was related to geophysical activities, the Indian Ocean Tsunami on 26 December 2004 can serve as an example. Shortly after the event, two remarkably similar conflicts went through braking changes, but with different signs: Sri Lanka experienced the

[69] Since the fixed effects transformation effectively removes all time invariant factors, the fractionalization variable cannot be included in fixed effects regressions.
[70] Random effects models produced results similar to the pooled effects models (results not reported).

outbreak of civil war between LTTE and the Sri Lankan government, ending nearly three years of cease fire. In Aceh however, GAM and the Indonesian government signed a peace treaty after twenty nine years of civil war. Case studies (Le Billion and Waizenegger 2007, Beardsely and McQuinn 2009) suggest that these divergent outcomes are partly explained by factors that have little to do with economic shocks. Most important, prior to the tsunami GAM managed its activities in comprehensive interaction between military fractions and the local community, LTTE did not. Taking this structural difference into account, Beardsely and McQuinn (2009) argue that ceteris paribus, the tsunami increased conflict risk in Sri Lanka, and at the same decreased conflict risk in Aceh.

Table 6.3: Economic growth and armed civil conflict onsets – reduced form equations

	Dependent variable: Conflict onset					
Model	OLS-FE (1)	LOGIT-MLE (2)	OLS-FE (3)	LOGIT-MLE (4)	OLS-FE (5)	LOGIT-MLE (6)
People affected (time weights), t	$-.09$ $(.08)$	-10.51 (9.40)	$-.10$ $(.10)$	-10.30 (9.42)	$-.04$ $(.11)$	-7.80 (11.11)
Real GDP per capita growth, t			$-.0009^{*}$ $(.0005)$	$-.02^{*}$ $(.01)$		
Population (ln), t-1					$.03$ $(.03)$	$.36^{***}$ $(.11)$
Polity2, t-1					$.007^{*}$ $(.004)$	$.16^{*}$ $(.09)$
Polity2 (squared), t-1					$-.0003$ $(.0002)$	$-.008^{*}$ $(.004)$
Ethnic fractionalization (%)						1.27^{***} $(.46)$
R^2	$.02$	$.11$	$.03$	$.11$	$.03$	$.15$
Observations	4314	4066	4299	4051	3720	3480
Clusters	165	161	165	161	155	150

*Notes: Fixed year effects and the decay function developed by Beck et al. (1998) are included in all specifications. Regression disturbances are clustered around countries with Huber-White robust standard errors in parentheses. Significance at the 1, 5, and 10 percentage levels are indicated by ***, ** and *, respectively.*

It is not possible to prove that natural disasters affect conflict risk only through economic growth, a requirement for the instrument to be valid. In particular, since I have no quantitative data on how different insurgency groups are organized or achieve legitimacy among civilians, I am not able to set up an interaction term to test if such factors determine the role of hydrometeorological disasters. Nevertheless, a reduced form equation can at least give some hints about the general relation between natural disasters and armed, civil conflict. Table 6.3 reports estimates of different reduced form equations, i.e. the (short run) effects from natural disasters on conflict onset. Model (1), (3) and (5) are fixed effects transformations, while model (2), (4) and (6) are maximum likelihood estimations (MLE) of LOGIT regressions.[71] According to the results, it seems as natural disasters have no significant direct effect on the risk of conflict onset in my data. Economic growth is added in model (3) and (4), but the results are similar.

Finally, I estimated regressions with each of the second stage control variables as dependent variables. This was done in order to check if hydrometeorological disasters could influence conflict risk through other channels than economic growth in the second stage. None of the regressions produced significant disaster coefficients (results not shown). In total, I find no support in my data for the hypothesis that people affected by hydrometeorological disasters have any impact on conflict onset. With that in mind, I now turn to the instrumental variable (second stage) analysis.

6.2 Economic growth and conflict onsets – the second stage

Table 6.4 reports the main findings on how economic growth fluctuations caused by natural disasters affect the risk of civil conflict onsets. All regressions with instrumented economic growth include a version of the F-test developed by Kleibergen (2007). This is essentially a test on weak identification of the endogenous explanatory variable; in this case economic growth. The Kleibergen-Paap test is preferred because it explicitly takes into account that regression disturbances are clustered around countries with Huber-White robust standard errors.

The first model (column 1) is a linear probability model (since the dependent variable is binary) with the usual fixed effects transformed variables. Similar to results in a number of previous studies, it indicates that economic growth is negatively related to the risk of conflict onset. According to the growth coefficient, when economic growth increase by one percentage point, the risk of armed civil conflict onset is reduced by .13 percentage points. This result is significant at the five percentage level. While all control variables have expected signs, only the linear polity variable is significant at the ten percentage level. Model (2) is a LOGIT model that also includes ethnic fragmentation. The growth coefficient is less significant in this model, but still negatively related to conflict onset at the ten percentage level. All control variables are also significant and with expected signs.

Model (3) and (4) are the simplest 2SLS-models, with all control variables excluded. Economic changes caused by hydrometeorological disasters are clearly far from significant

[71] Ordinary least squares estimations of pooled and random effects models give similar results.

for conflict onsets, the coefficient signs are even positive. The Kleibergen-Paap statistics indicate that the instrument is a strong determinant for economic growth.

Table 6.4: Economic growth and armed civil conflict onsets – second stage

	Dependent variable: Conflict onset					
Model	OLS-FE (1)	LOGIT-MLE (2)	2SLS-FE (3)	2SLS-PE (4)	2SLS-FE (5)	2SLS-PE (6)
Real GDP per capita growth, t	$-.0013^{**}$	$-.028^{*}$	$.004$	$.007$	$.002$	$.004$
	$(.0005)$	$(.015)$	$(.005)$	$(.005)$	$(.006)$	$(.004)$
Population (ln), t-1	$.03$	$.37^{***}$			$.03$	$.012^{***}$
	$(.03)$	$(.11)$			$(.03)$	$(.004)$
Polity2, t-1	$.008^{*}$	$.16^{*}$			$.007$	$.004$
	$(.004)$	$(.09)$			$(.005)$	$(.003)$
Polity2 (squared), t-1	$-.0003$	$-.008^{**}$			$-.0003$	$-.0002$
	$(.0002)$	$(.004)$			$(.0002)$	$(.0001)$
Ethnic fractionalization (%)		1.23^{***}				$.03$
		$(.45)$				$(.02)$
R^2	$.04$	$.12$				
Kleibergen-Paap Wald F-statistic of weak identification. H_0: Equation is weakly identified			14.61^{***}	16.47^{***}	10.75^{***}	14.76^{***}
Observations	3855	3708	4299	4299	3855	3837
Clusters	156	155	165	165	156	155

*Notes: Fixed year effects and the decay function developed by Beck et al. (1998) are included in all specifications. Models based on pooled effects transformations include fixed region effects. Regression disturbances are clustered around countries with Huber-White robust standard errors in parentheses. Significance at the 1, 5, and 10 percentage levels are indicated by ***, ** and *, respectively.*

Inclusion of control variables in model (5) and (6) changes little. Disaster triggered growth fluctuations are still not significant for conflict onsets. Furthermore, when time invariant effects are transformed away as in model (5), none of the variables have significant coefficients. Note that both the population variable and the two polity variables have very similar coefficients in model (1) and model (5). In fact, the only large difference between the two models is the effect from economic growth. This can arguably be seen as a further indication that economic growth (caused by hydrometeorological disasters) really does not affect conflict onset. Various inclusion of other controls produced similar results. I also substituted the onset variable with a dummy for conflict incidence in order to test whether disaster-triggered economic growth shocks affect the likelihood of conflict presence. Once again, economic growth had no significant effects on the risk of armed civil conflicts when estimated by 2SLS (results not reported). In total, the a priori expected negative effect from current economic growth on the risk of armed civil conflict onset is not present in my 2SLS-models.

6.3 Notes about the disaster triggered growth-conflict relationship

Compared to other empirical studies, these results differ from seminal work such as Collier and Hoeffler (2004) and Miguel et al. (2004), who all find significant negative effects from economic growth on the risk of civil conflict onset. However, recent 2SLS investigations by Bernauer et al. (2010) and Ciccone (2010) produce results that are more similar to the numbers presented here. Neither studies find significant effects from economic growth on civil conflict onsets. Ciccone actually declare that if anything, economic shocks seem to cause less civil conflicts (Ciccone 2010: 12). I choose a more modest statement and suggest that if anything, these results support the view that economic growth, when instrumented by hydrometeorological disasters such as floods, storms and hurricanes, does not relate systematically to conflict onsets. Compared to Ciccone, my conclusion is less restrictive because it does not rule out growth impacts on conflict in general. It might very well be the case that income shocks caused by rainfall (see Miguel et al. 2004) change likelihood of civil conflicts in other ways than income shocks caused by sudden floods and storms.

Now, there are alternative stories that might explain my insignificant results in the second stage. To be perfectly clear, I have not rejected the possibility that my instrument is endogenous. Regardless of the insignificant disaster effects presented in the reduced form equations, I still suspect that at least to some degree, hydrometeorological disasters might determine conflict risk through other channels than economic growth. Also, the econometric specifications that I have put up are rather superficial. It might be the case that dynamics between economic growth and conflict onsets have been specified wrongly,[72] or that the variable definitions are poor statistical proxies for their theoretical counterparts. In reality, a combination of these three stories can be true.

Nevertheless, the 2SLS exercise that I have undertaken here reveals some important new insights. First, as shown in table 6.2 (and in the previous chapter), it seems to be the case that hydrometeorological disasters, when they are proxied by the number of people affected relative to population, are strongly relevant for economic growth. To the extent that this disaster variable does not influence the risk of civil conflicts through other channels, it fulfills the criteria for valid instruments. Now, even if it should be the case that hydrometeorological disasters are endogenous in my conflict models, they might still appear as exogenous

[72] However, I tried a variety of different disaster lags, but the results were the same.

instruments for economic growth in other studies. In that sense, this analysis adds to a growing body of literature that is in constant search for instrumental variables.

Second, and regardless of disaster effects on economic growth; the reduced form equations in table 6.3 can be seen as an indication that climate change not necessarily leads to more violent conflicts in the future. This view contrasts findings by Burke et al. (2009) and should really inspire to further research.

7. Concluding remarks

In light of ongoing events such as the Pakistani flooding, and in a wider perspective, the global climate change, the main objective of this study has been to empirically investigate social impacts caused by different natural disasters. I have shed light on two key research questions, and the conclusions can be summarized as this:

1. *Natural disasters seem to cause less economic growth in the short run.*
2. *Economic growth reductions triggered by (hydrometeorological) disasters do not seem to be of importance for the risk of new armed civil conflicts.*

As follow-ups to these two research questions, several other interesting findings have been brought to daylight: First, while people affected by economic disasters are important for economic growth, people killed and direct economic damage is of less importance. Second, disasters typically linked to climate change have a statistically larger impact than geophysical disasters, and they hit the economy faster. Third, while previous literature shows that rainfall and temperature might be of importance for future conflict risk, this study indicates that weather-related disasters are not.

For the sake of future research, economics of natural disasters should really be considered a promising field the next decades. Central research questions with important policy implications remain unanswered. Especially, while much of the disaster literature up until now has examined impacts on overall economic performance, channels which disasters might work through have not yet been put under comprehensive investigation. Also, the direct link between natural events and armed civil conflict is an almost untouched ground.

Finally, although the most important findings in this study are related to direction of effects rather than the quantitative sizes, one can still do a simple exercise and predict real life impacts. I introduced the paper by reporting that 17.2 million people, or ten percent of the population, so far have been affected by the current flood in Pakistan (OFDA 2010). What does this mean for overall economic performance in my models? Given that reported numbers are correct, and that the flood started late in July this year, economic growth rates in Pakistan are predicted to decrease by approximately 1.5 percentage points within next year.[73] At first sight this might seem as a small impact, and a large number of important factors are obviously

[73] This prediction is based on numbers in table 5.3, column 1, as well as definitions of disaster variables in the data and variables chapter.

unaccounted for. Nevertheless, a 1.5 percentage point growth reduction is enough to throw 44 percent of the 4314 country-observations that I have examined into recession. We should also remember that Pakistan is a large economy given its 170 million inhabitants. Consequently, such a growth reduction really represents huge economic values. Civil conflicts however, should be of little concern in the aftermath of the Pakistani flooding.

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Appendix:

Table A: Hydrometeorological disasters and economic growth – alternative measures

	Dependent variable: Real GDP per capita growth		
Model	OLS-FE (1)	OLS-FE (2)	OLS-FE (3)
People affected (no time weights), t	-9.77^{**} (4.20)		
People affected (ln) (time weights), t		$-.16^{***}$ (.06)	
Number of disasters, t			.04 (.07)
Real GDP per capita growth (%), t-1	$.16^{***}$ (.06)	.06 (.07)	$.16^{***}$ (.06)
R^2	.10	.06	.10
	.07	.06	.07
Observations	4279	1357	1270
Clusters	165	150	108

*Notes: All models include fixed year effects. Regression disturbances are clustered around countries with Huber-White robust standard errors in parentheses. Significance at the 1, 5, and 10 percentage levels are indicated by ***, ** and *, respectively.*

Table B: Frequently used regression commands in STATA

Model	*Command*
OLS-FE	*xtreg dep_var var_list t2-t28, fe robust cluster(country)*
OLS-RE	*xtreg dep_var var_list t2-t28, re robust cluster(country)*
OLS-PE	*reg dep_var var_list t2-t28, robust cluster(country)*
LOGIT-MLE	*logit dep_var var_list t2-t28, fe robust cluster(country)*
2SLS-FE	*xtivreg2 dep_var (end_var = iv) var_list t2-t28, fe robust cluster(country)*
2SLS-PE	*ivreg2 dep_var (end_var = iv) var_list t2-t28, robust cluster(country)*