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NATURAL DISASTERS AND GROWTH: EVIDENCE USING A WIDE PANEL OF COUNTRIES

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Abstract

Large natural disasters (LNDs) are ubiquitous phenomena with potentially large impacts on the infrastructure and population of countries, and on their economic activity in general. I examine the occurrence pattern of several types of disasters on a panel of 113 countries and its relationship with economic growth using data ranging from 1960 to 1996. The disasters are earthquakes, floods, slides, volcano eruptions, tsunamis, wind storms, wild fires and extreme temperatures. The country sample is partitioned in two ways: small, medium and large population; and low, medium and high income. The results suggest a heterogeneous pattern of short and long-term impact of LNDs, depending on the per capita GDP, the size of the countries studied and the type of LND. Overall, and contrary to previous research, LNDs appear to have persistent effects on the rate of GDP growth in the period between 1960 and 1996. These effects range from a decrease of 0.9% to an increase of 0.6%, depending on the type of disaster.

Keywords: Natural disasters, catastrophes, growth, foreign aid, panel data.

JEL Classification: O11, O19, Q54.

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DESASTRES NATURALES Y CRECIMIENTO: EVIDENCIA DE UN PANEL DE PAÍSES

Resumen

Las catástrofes naturales son fenómenos frecuentes con efectos potencialmente grandes sobre la infraestructura y la población de los países, y sobre su actividad económica en general. Este trabajo explora los patrones de ocurrencia de varios tipos de desastres en un panel de 113 países, y su relación con el crecimiento económico en el periodo 1960-1996. Los desastres considerados son terremotos, inundaciones, avalanchas, erupciones volcánicas, tsunamis, huracanes y tormentas de viento, incendios forestales, y temperaturas extremas. La muestra de países se divide de dos maneras: países con poblaciones pequeñas, medianas y grandes; y países de ingresos per cápita bajos, medios y altos. Los resultados sugieren patrones heterogéneos de efectos de corto y largo plazo según el tipo de desastre, la población del país y su nivel de ingreso per cápita. En general, y en contraste con la evidencia previa, las catástrofes tienen efectos persistentes sobre la tasa de crecimiento del PIB per cápita en el periodo de análisis. Estos efectos oscilan entre una disminución de 0.9% y un aumento de 0.6% en el crecimiento de largo plazo, según el tipo de desastre.

Palabras clave: Desastres naturales, catástrofes, crecimiento, ayuda externa, datos en panel.

Clasificación JEL: O11, O19, Q54.

1. Introduction

Large natural disasters (LNDs for short) are ubiquitous events with potentially large impact on the infrastructure and population of countries, and on their economic activity in general. While case studies of disasters abound and there are some small-panel studies,[2] I am not aware of any work that uses time-series data from a large number of countries to examine the importance of this impact.

In this paper, I explore the relationship between disasters and growth using panel data on recorded disaster events and macroeconomic variables of 113 countries over a 36-year span. I test for the effect of a disaster on current and next-year GDP growth (short-run effects). I also test for cumulative effects of disasters, which are interpreted as long-run effects, and compare the results to previous research that suggests small to non-existing long-term effects.

The data is a panel from different sources, including disaster measures and national accounts for a wide sample of countries. The data on disasters comes from EM-DAT: The OFDA/CRED International Disaster Database. It contains records of estimated damages, people killed, injured, homeless and affected for occurrences of natural, technological and political disasters, as well as dates of occurrence and the countries affected. The data are a compilation from different sources, among them the UN, OFDA, reinsurance firms and several NGOs and humanitarian institutions, and it includes events starting 1900 through the present.

The time series data on macroeconomic variables comes from several sources. Whenever available, I use the Penn World Tables 6.0. These contain data from 1950-1998, albeit most countries start reporting in 1960. This period seems to coincide with the more reliable data in the EM-DAT database. Foreign aid data is from the OECD's DAC/GEO database.

[2] See Auffret (2003a), Albala-Bertrand (1993).

The next section presents the theoretical framework. Section 3 describes the data in detail, emphasizing various aspects that require special attention. In section 4 I present the empirical specifications for the econometric analysis and the estimation results. Section 5 concludes.

2. Theory and Evidence of the economic Impact of Disasters

How may a catastrophe influence a country's economy? Macroeconomic theory allows for several types of possible impacts of a LND. First, a disaster destroys capital stock and labor. Insofar as this raises the rates of return to these factors, one should expect increased investment activity in the economy. This should be an effect of limited duration, and it should concern the level of GDP rather than its long-term growth path. A priori, this effect should be negative on the level of GDP. Nevertheless, because capital losses due to LNDs do not show up in national accounting but the surge in investment does, one might find a positive net effect in the recorded data. In this respect, the existing literature is based on individual cases, and it argues that substitution in production limits the size of the negative effects (Horwich 2000). For a sample of 28 disasters that took place between 1960 and 1979 in 26 developing countries, Albala-Bertrand (1993, Ch. 4) finds that GDP level does not suffer after a disaster and inflation does not rise. Auffret (2003a), in contrast, finds that disasters lead to a fall in output in a sample of 16 countries in latin America and the Caribbean for the period 1970-1999.[3]

A second and potentially more important avenue for LND impact has to do with per capita GDP growth rather than its level. One could think of a number of scenarios, all involving market imperfections, where the post-LND growth rates are different from the pre-disaster ones. Unfortunately, the literature on GDP growth suggests that one must take some subjective stand on what one views as the long run to address this question, since a

[3] See also Raddatz (2005, no effects), Crowards (1999, short-term effects, as cited in Charvériat 2000). Charvériat (2000) and Albala-Bertrand (1993) provide and extensive discussions on the theory and evidence of the economic impact of natural disasters. Also, the Economic Comission for Latin America and the Caribbean has numerous case studies and policy analyses on disaster prevention, preparedness and relief (http://www.eclac.cl).

definitive empirical answer cannot be obtained from a finite time series of data (Christiano and Eichenbaum 1989). What does the evidence say about these long-run effects? Albala-Bertrand reports small positive effects on GDP growth thanks to large increases in construction and smaller ones in agricultural output. The trade deficit increases, however. Whether these increases are persistent is not clear.

In view of the loss accounting issue, a country's reaction to LNDs would perhaps be best judged on the basis of its investment activity, both in absolute levels and as a share of its GDP. This investment must be financed either through current consumption cuts (private or governmental) in the case of a credit-constrained economy, or through borrowing (which entails a smaller but permanent decrease in consumption) and foreign investment. Thus, the country will substitute away from consumption, and this level effect will be smaller but more persistent if the country's economy has access to international credit. Here the evidence is sometimes in agreement and sometimes at odds with the predictions, and different studies contradict each other. Albala-Bertrand (1993) reports that gross fixed-capital formation tends to increase, financed with a small increase in public deficits and large inflows of capital. Auffret (2003a) adds a decrease in private and (inconsistent with the larger public deficits) public consumption growth, and confirms also the deterioration of the current account. Crowards (1999) reports sharp increases in GDP the years after the disaster due to investment.

Of course, this is not an exhaustive list of interesting economic questions related to LNDs.[4] Institutions matter in the face of catastrophe risk. The depth of insurance markets plays a fundamental role (Auffret 2003b, Charvériat 2000). So do informal insurance mechanisms (Fafchamps and Lund 2003, Jalan and Ravallion 2001), and more generally the households' strategies to cope with risk, which may help to explain the persistent effects on growth through human capital investment (Rosenzweig and Stark 1989, Jensen 2000, Jacoby and Skoufias 1997). The effectiveness of foreign aid as a tool to mitigate disaster

[4] Their impact on aggregate consumption patterns and on trade, or the institutional aspects of disaster responses, are examples of macroeconomic issues with no clear-cut theoretical predictions. There's also a wide range on microeconomic questions: sustitution in production, formal and informal insurance and household impact, to name a few.

impact depends on the quality of policies and institutions (Burnside and Dollar 2000, Easterly 2003), albeit it is not clear that its true aim is indeed this (Alesina and Dollar 1998).

Finally, asymmetric information and institutional factors may be a source of persistence in the effects of LNDs. For instance, the modes of investment that take place a country, in particular the role of foreign direct investment (FDI), may be affected by a disaster either directly, or indirectly through the disaster impact on other economic variables and government policies. Or the foreign aid flows may alter the institutions prevalent in the affected countries (Weder 2000). There's no unambiguous prediction regarding these matters, as it is unclear how the aftermath of a LND or the attention a country may get from it will affect –if at all– the determinants of the choice of FDI versus other types of capital flows or the quality of institutions.

Ultimately, none of the answers in the macroeconomic literature predicts long-term growth effects of LNDs except in extreme market failure cases. The focus of this paper is to determine whether the evidence shows robust long-term effects in spite of macroeconomic predictions.

3. Data

The data for the yearly panel of countries comes from several sources. I use country macroeconomic time series from the Penn World Tables 6.0 (PWT).[5] International data on official foreign aid is self-reported by the members of Development Assistance Commitee (DAC) of the Organisation for Economic Cooperation and Development (OECD). It is available in the DAC/GEO database of Geographic Distribution of Financial Flows to Aid Recipients, 1960-1998, included in the OECD publication International Development

[5] The PWT can be found at the Center for International Comparisons, University of Pennsylvania. http://pwt.econ.upenn.edu/

Statistics (IDS), edition 2000. The data on disaster events comes from EM-DAT: The OFDA-CRED International Disaster Database.[6]

In the remainder of this section I describe the regression variables obtained or constructed from each data source. With the exception of EM-DAT, the sources are standard and of common use in the literature. Therefore, I concentrate my comments on the EM-DAT data.

3.1 Penn World Tables 6.0

I use the following macroeconomic time series from the PWT country data:

y:	Real per-capita GDP (Chain Index) in constant dollars. Throughout this paper, this is the basic summary measure of a country's economic performance.
dln_ypc:	Percentage per-capita GDP growth, based on the above measure of GDP. It is computed as the change in the natural logarithm of *y*.
open:	Index of openness, calculated as (X+IM)/GDP. I control for openness prior to the occurrence of a disaster using lagged values of this indicator.

I also use the PWT country population time series.

3.2 DAC/GEO

The DAC/GEO database keeps separate records for two types of aid recipients: Developing Countries (part I, covers 1960-1998) and Countries in Transition (part II, 1990-1998). We do not distinguish between these two groups, so our measure of foreign aid accounts for aid received under any of these labels:

[6] This data can be found at \EM-DAT: The OFDA/CRED International Disaster Database." Université Catholique de Louvain- Brussels - Belgium. http://www.cred.be/emdat.

aid: Net total foreign official aid flow to a recipient country in a given year, expressed as a fraction of its current GDP.

As net total foreign official aid flow, we use the DAC/GEO time series on Total Official Net flows of aid by recipient. This data is the sum of Official Development Assistance (ODA) and Other Official Flows (OOF) for part I countries, and of Official Assistance (OA) and Other Official Flows (OOF) for part II countries. It represents the total net disbursements by the official sector at large to the recipient country in either case.

While the flows recorded in the DAC/GEO data are only those of OECD origin, they account for most of the international flows of official foreign aid in any given year from 1960-1998 for part I and 1990-1998 for part II. The countries of origin covered are the DAC Donor Countries: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Luxembourg, the Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom, and the United States.

3.3 EM-DAT

EM-DAT records the occurrence and effects of mass disasters in the world since 1900. It compiles data from several sources, and its main objective is to assist in humanitarian action in response and prevention of mass disasters. It has entries for approximately 12,800 events, and among its sources are UN agencies, non-governmental organizations, insurance companies, research institutes and press agencies.

The disaster-event entries in EM-DAT are individual occurrences in chronological order and include date, type of disaster, several measures of affected population, damage estimates and notes about the main sources of data for any particular event. A typical event entry is depicted in Table A1 in appendix A, along with more detailed information on each of the variables.

EM-DAT groups disasters in three broad categories (natural, technological and conflict) with several types, as listed in Table 1 below. In order for an event to qualify for the registry, it must satisfy at least one of several minimum requirements concerning the number of victims and the damage amounts.[7]

My focus is on events that can be unambiguously interpreted as exogenous. Thus, I concentrate on natural disasters. Moreover, I consider only those types of natural disasters that can be viewed as occurring at a point in time, rather than those that build up or develop through extended periods, so I discard droughts and famines. Finally, due to endogeneity concerns, I drop insect infestations and epidemics from the sample.

The remaining disaster events are earthquakes, floods, wild fires, wind storms, waves and surges, extreme temperatures, volcano episodes and slides. Figure 1 shows the geographic distribution of the disasters in our panel. As one should expect, the amount and types of disasters that occur vary across regions.

From the data in EM-DAT, I construct four types of measures of disaster impact normalized by the relevant country "size". These measures concentrate on the disruptive effect of a LND rather than its physical dimension:

XXtaff: People affected by XX in a given year as a fraction of the current country population.

XXkill: People killed by XX in a given year as a fraction of the current country population.

XXdama: Damages due to XX as a fraction of current GDP.

XXdisd: Number of disasters XX in a given year.

[7] See appendix A.

where XX may be EQ (earthquake), FL (flood), VC (volcano), SL (slide), WS (windstorm), WF (wildfire), WA (wave/surge) or XT (extreme temperature). Thus each of these measures exists for each type of disaster considered. For example, there exist *EQdisd, FLdisd, VCdisd, SLdisd, WSdisd, WFdisd, WAdisd* and *XTdisd*.

Additionally, I create aggregate measures as the sum over the eight types of disasters for a given country in a given year. The correlations among these aggregate measures are reported in Table 2. Not surprisingly, they are positively correlated, although one would have perhaps expected a higher coefficent.

If no disasters of any type are recorded for a given country in a certain year, *disd* has a value of zero for that observation. Whenever *disd* > 0, there exists a recorded event that has a non-zero value in at least one among the other three variables. If, for example, *kill* > 0, the other two variables may be positive, zero or missing.

Suppose *dama* is missing. There is no way to decide whether this is the result of misreporting of *kill*, unavailability of damage estimates, or actual absence of significant capital losses. My approach to this is straightforward: I replace all missing values of the three variables *taff*, *kill* or *dama* with zeros. In the cases where missing values are present but the true value is positive, this approach will generate bias in the estimation. However, it is likely that in the vast majority of cases missing data values just reflect zero values, or at most very small ones.

Additionally, I calculate for each type of event and for the aggregate measures the following cumulative measures of disasters:

cum_taff: Cumulative fraction of people affected, since the first year in the data. It is calculated as $cum\_taff_{it} = \sum_{\tau=0}^{t} taff_{i\tau}$.

cum_ kill: Cumulative fraction of people killed by LND's since the first year in the data. This measure and the previous one are based on the country's population in the year the LNDs take place. $cum\_kill_{it} = \sum_{\tau=0}^{t} kill_{i\tau}$.

cum_dama: Cumulative damages as a fraction of GDP, based on GDP at the year of LND occurrence. $cum\_dama_{it} = \sum_{\tau=0}^{t} dama_{i\tau}$.

cum_disd: Cumulative number of disasters since the first year in the data. $cum\_disd_{it} = \sum_{\tau=0}^{t} disd_{i\tau}$.

Several concerns besides the missing data must be addressed with EM-DAT. First, it is difficult to assess and compare the quality of the sources, especially for earlier events. The multiple sources also account for occasional repeated entries for events, and it is not always obvious whether two entries with small differences are indeed duplicate. Moreover, different sources emphasize different data: reinsurance firms likely provide better damage estimates, but they are based on claims, while UN agents have more encompassing assessments of damages and affected population. Thus, different data sources have different strengths (and perhaps systematic biases). Additionally, some data series may be more informative than others about the true dimension of the event. This is especially the case if measurement error differs across measures.

Fortunately, this first type of concern, although difficult to address directly, is likely to be of less importance as the number and scope of international institutions that deal with LNDs increases. For the time period of our panel, we are confident that this type of noise does not systematically affect our results.

A second concern, also related to the variety of the sources, is bias over time. The institutional infrastructure for disaster aid has evolved throughout the 20th century. It is reasonable to presume that events are more likely to be registered by the authorities in any given country later in the century, and conditional on this, they are also more likely to be reported to international agencies.

The total number of disasters reported in each year by all countries in the sample is reported in Figure 2. A log-linear fit with country-specific intercepts shows a yearly increase of some 1.1% in the period 1960-1998. Since it's reasonable to believe that the actual number of cataclismic events per year is roughly steady, the increase in events reported must come, at least in part, from these reporting biases. Another part of these numbers is certainly a result of increases in population and economic activity: other things equal, the more people in a country the higher the probability of having 10 deaths in an earthquake, and the higher the GDP the larger the expected damages from a given disaster. During the period, a log-linear fit for population growth yields a 2% yearly increase; and the correlation between the total number of disasters *disd* and per capita GDP, plotted in Figure 3, is positive.

Nor is the trend in disaster reports homogeneus across types of disasters. Figure 4 below shows the number of yearly events reported for each type of disaster.

The largest increases in reports stem thus from floods and windstorms. However, almost all types of disasters exhibit higher reported frequency over the period. Moreover, these increases are accompanied with increases in the amounts of damages (as a fraction of GDP) and affected people (as a fraction of the population, and again especially for floods and windstorms), albeit not in the amount of killed (Figure 5).

On the other hand, the number of affected and casualties per disaster has remained roughly steady with a notorious exception: floods, each of which affect more people nowadays. The average amount of damages has also increased for all disasters, especially in the last ten years of the sample.[8]

[8] This may be in large part a result of the deepening of insurance markets and the resulting increased incentives to estimate and report damages.

One must wonder whether the increased reporting is also a result of a strategic improvement in record-keeping. It seems that foreign aid as a response to LNDs has risen in the period of analysis. Could it be that the countries pay more attention to these events because it pays in terms of getting aid for disaster relief?

The regressions in Table 3 suggest that this is indeed the case: the odds ratio of a country reporting at least an event increases on average 0.063 each year (column 1).[9] Even after controlling for per capita GDP and population, this effect is correlated strongly with the world being more generous the year before (columns 3-5).[10] However, it may simply be that reporting improved exogenously and is settling into a new, better standard of accuracy, as attested by the quadratic trend in columns (6-7). No definitive indictment is thus possible.

Columns (1-4) in Table 4 show estimates of negative binomial fixed-effects regressions for the expected number of disaster reports by a country in a year. As before, a quadratic trend swamps the effect og the lag of world AID, making it difficult to place the blame on strategic reporting behavior by the countries.

Bias stemming from the failure of a country's authorities to observe and register a disaster is not likely a grave concern, since an unregistered event is probably one of little impact on economic activity to begin with. LNDs may be inaccurately measured, but it's difficult that they go unnoticed. To the extent that it is present, however, this usually downward error in *disd* is likely to generate upward bias in our estimates. Thus the trend in reporting, if due to better record-keeping, is not a major concern provided that one controls with the quadratic trend.

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[9] If p is the probability of reporting, the coefficients correspond to the change in the odds ratio $p/(1-p)$ due to a unit increase in the explanatory variable.

[10] Fixed effects are used to control for land area, for example, so that together with lnPOP they account for population density.

The failure to report an observed disaster to international agencies, on the other hand, may cause systematic bias and affect the results in unpredictable ways. One can conceive a number of reasons for some regimes to hide the extent of disasters, or to exaggerate it; and the correlation of these incentives with our macroeconomic variables is not at all clear. In this aspect, the variety of sources of the EM-DAT database is an advantage, as it minimizes the chances that a given event goes completely unrecorded, even if no official report is filed by the affected country. Partly as a result of this possibility, I believe that any measurement error problem is likely to be less severe for the variable *disd* than it is for the other three measures.[11]

A third data concern includes endogeneity and timing. I partially address both issues by concentrating on events that are clearly exogenous (natural disasters) and punctual in time, i.e. they last a short time (less than a month) and give only short warning. Nevertheless, this does not completely deal with either issue, as (i) the measured impact of a given disaster is likely to vary with the economic characteristics of the country itself, and (ii) the consequences of a disaster need not be punctual or immediate, even if the disaster itself is. Insofar as this is the case, the disaster counter variable *disd* is arguably the least affected by this endogeneity.

This point about the way a LND affects economic activity is complicated by the differences in the time aggregation of the macroeconomic and disaster time series. Suppose for instance that there is some delay in part of the impact of earthquakes. If an earthquake happens in May, its negative impact will be recorded in this year's national accounts. If it happens in November, most of that impact will show in next year's macroeconomic data. Suppose instead that the reconstruction activity after the earthquake occurs over a long period of time. In this case, it is the spurt of investment activity that may be recorded (positively) in different years depending on the exact month of occurrence. Of course, this pattern of impact is likely to vary by disaster and by country.

[11] Nevertheless, I do exclude from the panel the former communist countries that remain after merging the PWT and EM-DAT, as their incentives for reporting seem particularly dubious. They are Hungary, Romania, Poland and China.

While the time pattern of the economic reaction to disasters is precisely what I want to inspect, this particular aggregation issue is an undesired source of error. For events that occur randomly throughout the year (like earthquakes), this error is most likely white noise and causes attenuation bias in some controls of the estimation. In contrast, events that occur consistently in a given moment of the year (like hurricanes) will bias the results in a systematic but unpredictable manner.

Finally, even after narrowing the set of events, one might wonder what exactly is exogenous about them. A country like Colombia, for instance, may not know when an earthquake will happen, but it certainly knows that it is prone to such disasters. Its infrastructure is likely to be built using anti-seismic technology, and the actual physical damages of the eventual earthquake will be smaller. Thus, it is the actual timing of the disaster that is exogenous, rather than the extent of destruction it causes. Again, this lends more credibility to the event count variable *disd*, and it calls for fixed country effects in the estimation.

4. Estimation

I carry out estimates of two types. First, a naïve cross-section regression of GDP level in 1996 on its 1960 level and the number of disasters in the 36 years in between. In the second estimation I use a reduced-form panel data specification where I regress the dependent variable on measures of disaster severity, both instantaneous and cumulative, and on lags of the instantaneous measures.

4.1 Cross-Section Specification

For a cross section of 104 countries, I regress the level of per capita GDP observed in 1996 on its initial 1960 level and measures of the disasters in the period. To the extent discussed, the disaster measures are not caused by GDP growth. However, there are exogenous features of the countries that may cause both higher absolute number of disasters and growth. Thus I control for the country area (larger countries may have more disasters ceteris paribus) and population growth (or, equivalently, population density). The regression is then

$$\ln GDP1996_i = a_0 \ln GDP1960_i + a_1 X_i + a_2 \ln POPgrowth_i + a_2 \ln AREA_i + \varepsilon_i$$

where the X_i are the cumulative disaster measures in 1996.

I estimate this specification for all countries together, and for two partitions of the sample: low, medium and high-income countries; and small, medium and large-population countries.[12] Also, I estimate the effects of each type of disaster separately on each subsample.

Cross-country regression results are reported in Table 5. The dependent variable is the log of per-capita GDP in 1996 of a cross section of 102 countries, all those for which GDP, area and population data is available for both 1960 and 1996. The first dependent variable is the natural logarithm of per-capita GDP in 1960. The population growth over the period is given as a percentage change. The disaster measures are the aggregates of all types of disasters. The estimation is performed by OLS. Columns (1-3) are displayed for comparison.

In the estimates in column (3), a disaster is related to 0.6% higher per-capita GDP at the end of the period, significant at the 1% level.[13] How large are these effects in practice?

Table 6 below reports the implied change in the 1996 level of GDP if a country increased its disaster measure by a standard deviation in the corresponding regressions of Table 5. For instance, the effect of having a standard deviation more disasters would have meant 19.81% higher per capita GDP in 1996.

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[12] The income subsamples are determined according to the countries' per capita GDP level in 1960. Similarly, the population subsamples depend on their 1960 population. The countries in each subsample are listed in the Appendix C.

[13] It is possible that the effects of disasters over a long period of time have a non-linear component, either because of cumulative aspects of events over several years, or because multiple catastrophic events in a given year are compounded in a non-linear fashion.

The usual precaution regarding unobserved variables is required in this analysis. The assumption that the changes in population and the initial GDP are uncorrelated with the error terms is precarious at best. Even if population growth is viewed as truly exogenous, the initial GDP is most certainly correlated with unobserved idiosyncratic country features, fixed and otherwise. We address this problem in detail later. Still, for the time being a relationship between LNDs and growth seems likely.

Table 7 is analogous to column (4) in Table 6 and reports implied level effects for each subsample of countries, using the cross-country specification. Some of the level effects are large: a 20% increase in the 1996 GDP level corresponds to a yearly increase in growth rates from 2.0% to 2.3% for 36 years[14].

Finally, Table 8 reports similar calculations for each type of disaster and each country subsample.

4.2 Panel Data Specification

In the panel-data specification, I include country fixed effects on the right hand side to control for land area and other unchanging, unobservable features of the countries. Year-fixed effects account for worldwide phenomena that affect all countries in any given year. Foreign aid as a fraction of GDP is also an explanatory variable, implicitly assuming that

[14] This is a table of equivalent annualized growth rates.

I f the world GDP per capita grew annually	0.0%	0.5%	1.0%	1.5%	2.0%	2.5%	3.0%
And you added extra	**After 36 years, you'd get a level of GDP that was higher by**						
0.10%	3.7%	4.4%	5.2%	6.2%	7.3%	8.7%	10.3%
0.20%	7.5%	8.9%	10.6%	12.6%	14.9%	17.7%	21.0%
0.30%	11.4%	13.6%	16.1%	19.2%	22.7%	27.0%	32.0%
0.40%	15.5%	18.4%	21.9%	26.0%	30.9%	36.6%	43.4%
0.50%	19.7%	23.4%	27.8%	33.1%	39.3%	46.6%	55.2%
0.60%	24.0%	28.6%	34.0%	40.4%	48.0%	56.9%	67.4%
0.70%	28.5%	34.0%	40.4%	48.0%	56.9%	67.5%	80.0%
0.80%	33.2%	39.5%	47.0%	55.8%	66.3%	78.6%	93.1%
0.90%	38.1%	45.3%	53.8%	63.9%	75.9%	90.0%	106.6%
1.00%	43.1%	51.2%	60.9%	72.3%	85.8%	101.8%	120.6%

Between 1960 and 1996, the world's per capita GDP grew at an annualized rate of 2%.

this reaction of the rest of the world to a LND is exogenous to the affected country's GDP growth. Finally, I include an interaction between this aid variable and a dummy indicating a disaster ($disaster_{it}$), to test if the effect of foreign aid is different on disaster years:

$$d\ln GDP_{it} = a_0 + a_1 X_{it} + a_2 X_{it}^{cum} + a_3 * \left(\frac{AID_{it}}{Y_{it}}\right) + a_4 * disaster_{it} * \left(\frac{AID_{it}}{Y_{it}}\right)$$
$$+ v_i + \tau_t + \eta_{it}$$

Here, X_{it} includes contemporary and one-period-lagged measures of disaster, and X_{it}^{cum} are cumulative measures. The coefficients on the disaster measures reflect short and long-term effects: if $a_1 = 0$, disasters have no temporary effects on GDP growth; if $a_2 = 0$ they have no persistent effects.

Table 9 shows the results of regressions according to this specification. Column (1) includes only current measures of disaster magnitude.[15] Column (2) adds and one-period-lagged and column (3) cumulative measures of disasters. Columns (4) and (5) include controls for openness (one-period-lagged) and the foreign aid received as percentage of the country's GDP. Finally, column (6) includes the interaction term: this is the specification used hereafter. Openness seems a relevant control, but it does not change the coefficients on the disaster measures. Neither foreign aid nor the interaction between foreign aid and *disaster* have statistically significant coefficients.[16]

The cumulative casualties are negatively correlated with GDP growth: an increase in 1% in this measure yields 4% lower growth. The cumulative fraction of people affected, on the other hand, has a positive correlation: 1% higher measure yields 0.022% higher growth in the long run. Damages and the number of disasters have short-term effects, both positive, which may be due to the national accounts' failure to consider capital losses.

[15] We include all measures of disaster simultaneously to capture as much of the disaster effect. However, the estimated coefficients do not change if we run regressions one type of measure at the time.
[16] Neither does the interaction between openness and event in regressions not reported here.

The regression specification in column (6) of Table 9 is carried out for each country subsample in Table 10. The impact pattern varies depending on country population and income level. Small and medium-population countries (columns 1 and 2) seem affected by the fraction of people killed, although only medium-population countries show a long-term impact (negative). For countries with large populations (column 3), on the other hand, the fraction of people affected is relevant both in the short and long term, and the long-term effect is positive.

The picture changes if the countries are grouped according to per capita income. Countries in the bottom third (column 4) show no statistically significant correlation between the disaster measures and GDP growth. Medium and high-income countries, in columns 5 and 6, show short-term effects. High-income countries also show a persistent effect corresponding to roughly 0.5% higher growth by 1996 for the average country in the group.[17]

The final set of regressions, in Table 11, examines the effect of each type of disaster on GDP growth using a panel specification. In each column, the sample includes all available countries. For instance, the capital losses due to earthquakes (EQ) have a negative short-term effect on growth. However, the impact on labor (deaths and affected) has persistent growth effects, positive in the case of affected and negative for casualties.

Given the prior evidence and their economic meaning, the most interesting results are the coefficients for long-term effects. Floods (FL) have no statistically significant long-term relationship with growth. The damages due to slides (SL), on the other hand, do decrease the growth rate. deaths due to wind storms (WS) and wild fires (WF) are correlated with higher and extreme temperatures (XT) with lower growth. Extreme temperatures also decrease growth through the fraction of people affected. Finally, the numbers of tsunamis (WA) and extreme temperatures are correlated with higher persistent growth, while that of wild fires is correlated with lower growth.

[17] The average country in the high-income group has 40 disasters at the end of the period. The country with the most disasters has 272.

While the directions of the effects are interesting, their economic relevance depends on their actual magnitudes and their ability to explain the observed variation in GDP growth rates. These depend in turn on the values of the variables by the year 1996 and the sample variation in those values. Table 12 shows the change in the long-term growth rate of a country if the value of the cumulative disaster measures increased by one standard deviation (of the 1996 levels). The estimated effects are not negligible: they range between a decrease of 0.9% (casualties due to earthquakes) and an increase of 0.6% (affected population, also due to earthquakes).

A word of caution regarding these long-term effects of LNDs. As mentioned in the discussion of the data, a country that suffers regularly from earthquakes is likely to build its infrastructure accordingly. This awareness of the likelihood of suffering a disaster is thus a fixed country effect. The disaster measures do not capture it. Rather, they capture the effect having the disaster in one year and not another; and it is well so, for it is the timing of the earthquakes that is really exogenous in the econometric sense.

The same argument applies to some extent to all disasters. However, this interpretation of the measures poses some difficulties for the long-term effects identified in the estimation. How can the timing of the disasters affect the long-term growth? Is it perhaps related to the institutional ability of the country to cope with the disasters –as suggested by the case studies and the microeconomic literature? The answer to this question is beyond the scope of this paper.

5. Concluding remarks

This paper attempts to determine if there are short and long-term effects of large natural disasters (LNDs) on GDP growth in a large panel of countries. The disasters examined are earthquakes, floods, slides, volcano eruptions, tsunamis, wind storms, wild fires and extreme temperatures. The paper uses original panel data on recorded disaster events from EM-DAT: The OFDA/CRED International Disaster Database and macroeconomic variables of 113 countries from the Penn World Tables 6.0. The data covers the period between 1960 and 1996.

As a first approximation, I examine the relationship between the disasters that occurred in the period 1960–1996 and the countries' per capita GDP level in 1996. The cross-section regression results show large and mostly positive level effects. However, these effects are associated with the number of LNDs, rather than with the measures of their impact on the population or capital stock.

Then, using a panel data regression with fixed country effects and year-dummies, and controlling for trade openness and foreign aid, I test for the effect of a disaster on current and next-year GDP growth (short-run effects) and for cumulative effects of disasters (long-run effects). The results suggest a heterogeneous pattern of short and long-term impact of LNDs, depending on the per capita GDP, the size of the countries studied and the type of LND. Overall, and contrary to previous research, LNDs appear to have persistent effects on the rate of GDP growth in the period between 1960 and 1996. These effects range from a decrease of 0.9% to an increase of 0.6%, depending on the type of disaster.

Several features of the data advise caution in the interpretation of these results. First, national accounts usually fail to include capital losses due to disasters, but they do include the additional investment activity in the disaster's aftermath. Also, this investment to rebuild capital may span several years, depending on the type of disaster and the exact month of the year the disaster happens.

A second concern is that there is an increase in the yearly number of countries reporting disasters and in the yearly number of disasters reported in the 36-year period. This may signal institutional development in the countries, population growth, or simply more economic activity. Thus, the disaster measures may be endogenous to some extent.

In addition, the impact of those disasters, as measured by the peopled affected, people killed and damages, changes substantially. Again, this may be due to development. However, these changes seem to be related to increases in foreign aid flows. One possible interpretation is then strategic reporting of disasters by the national governments.

A final issue is what the exogenous measures of disaster actually capture. I argue that they capture whether a disaster happens in one year or the next: they do not capture the fact that disasters of a certain type tend to occur in a given country, which fixed country effects. Thus, the source of identification of disaster impact is the timing of the events. It is not clear how this timing may affect long-term growth.

An important clarification is necessary about the interpretation of the results. Even when the estimated effects are possitive, by no means do they mean that the overall welfare effects of LNDs are positive. The analysis focuses on variables that are only imperfectly correlated with welfare.

Ultimately, this paper suggests that, for the economist, natural disasters are perhaps natural macroeconomic experiments that may help to further understand the determinants of growth. The insights from the large literature on disasters and development should guide macroeconomic modelling in this context. The role of institutions in the affected country needs to be accounted for explicitly. The different build-up times and aftermaths of the disasters may imply differences in their overall impact. The reaction of consumption and investment patterns after a disaster may be a determinant of its long-term effect on growth. In the area of investment, the differential effects on the types of physical capital are of interest. Is it the case that reconstruction after a disaster concentrates in different economic activities from those before? How do human capital investment and –more controversial perhaps– social networks affect the effects of LNDs? These are possible avenues for future research.

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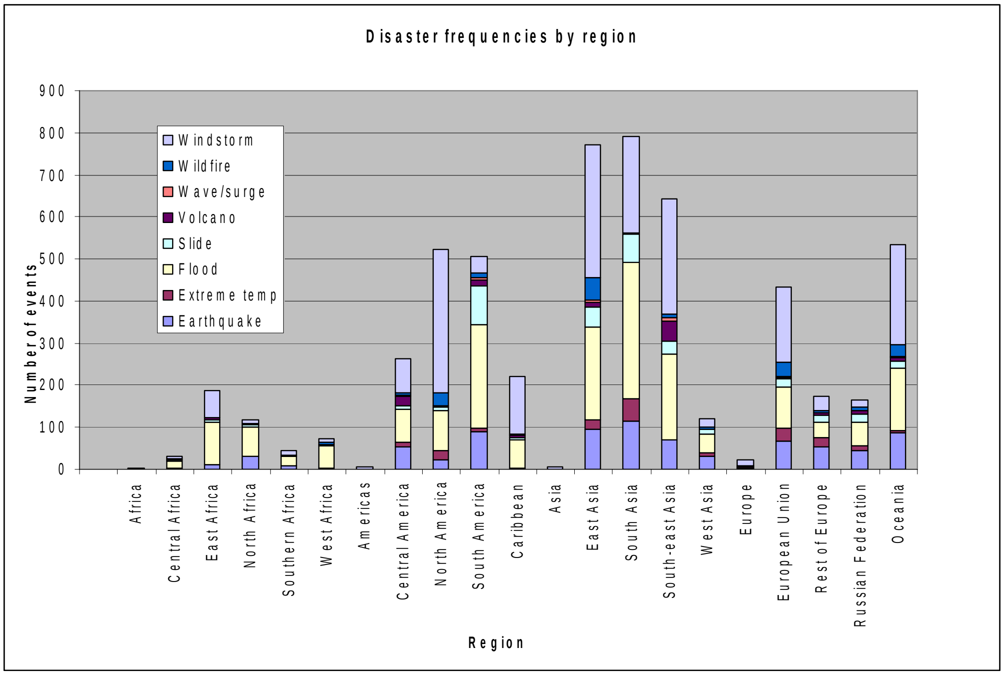
Figures and Tables

Table 1 : Disaster types

NATURAL	TECHNOLOGICAL	CONFLICT
Drought	Industrial accident	Civil disturbance
Earthquake (460)	Miscellaneous accident	Civil strife
Epidemic	Transport accident	Displaced
Extreme temperature (141)		International conflict
Famine		
Insect infestation		
Flood (1285)		
Slide (241)		
Volcano (115)		
Wave/surge (20)		
Wild fire (160)		
Wind storm (1271)		

These are the types of disaster for which events are recorded in EM-DAT. Those shaded are the ones used, and the figure in parenthesis is the number of events reported in the period 1960-1998 for the countries in our sample.

Figure 1: Frequency of events by type and region



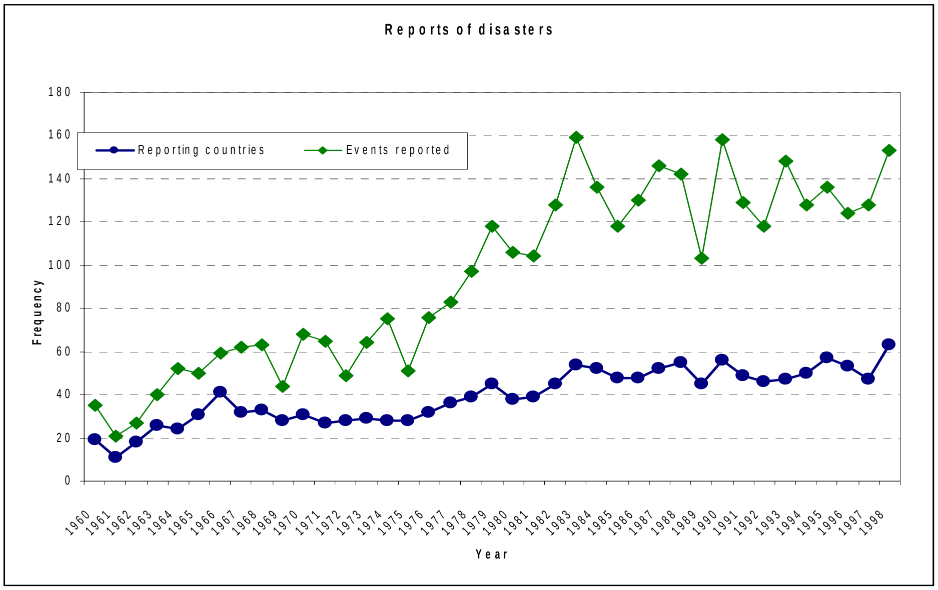
These are the events used in the regressions.

Table 2: Correlation among aggregate disaster measures

	dama	*kill*	*taff*	*disd*
dama	1			
kill	0.2215*	1		
taff	0.3388*	0.3478*	1	
disd	0.0622*	0.0558*	0.1652*	1

(*) significant at the 5% level.

Figure 2: Reported events by year



These are only the types of events used in the regressions, and only for the countries included in the sample.

Figure 3: GDP per capita vs. number of reported disaster events

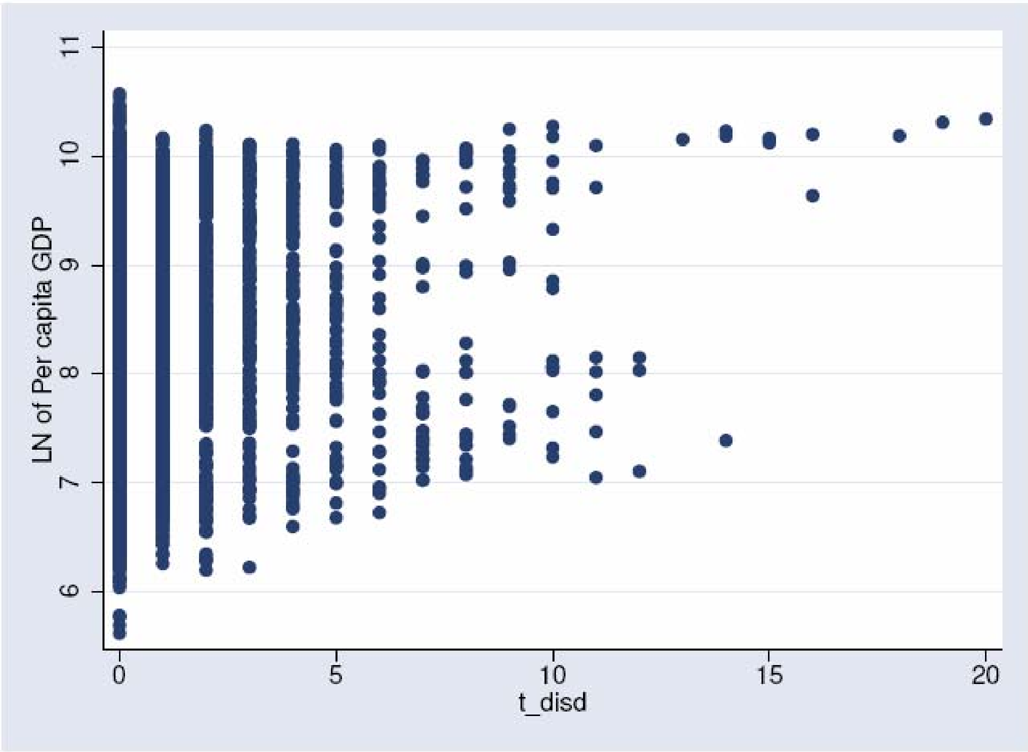


Figure 4 : Number of reported disasters by type

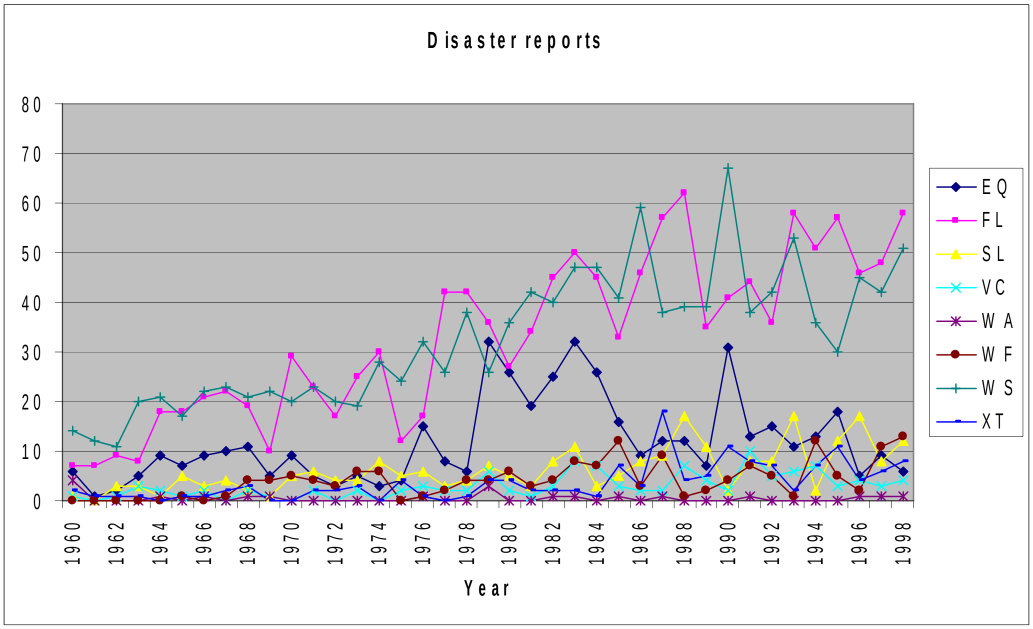
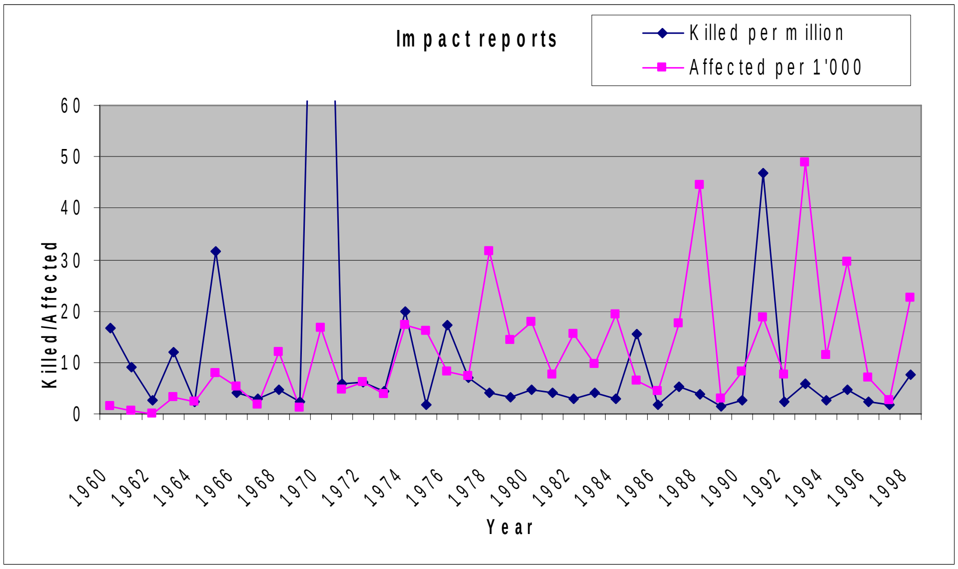
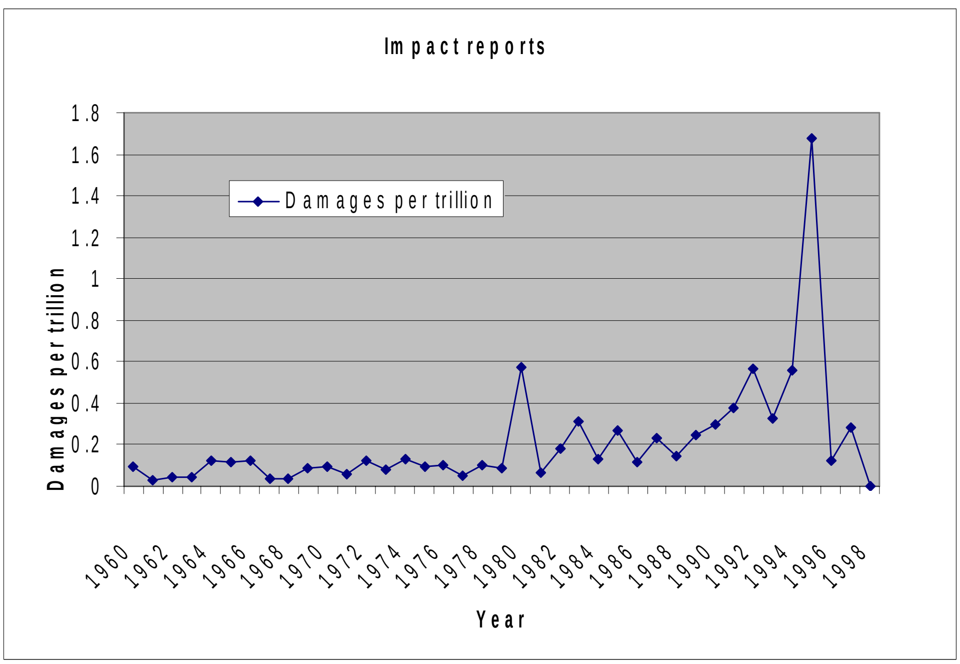


Figure 5: **Reported impact of disasters**





Upper panel: Fraction of the population affected and killed. Lower panel: Damages as a fraction of GDP.

Table 3: Probability of a country reporting at least a disaster.

DEPVAR: 1 if country reported a disaster	(1)	(2)	(3)	(4)	(5)	(6)	(7)
lnPOP		2.530	2.405	1.537	1.569	-0.602	-0.838
		(12.16)**	(9.65)**	(5.41)**	(5.24)**	(1.30)	(1.75)
lnYpc		0.304	0.314	-0.041	-0.064	-0.684	-0.873
		(1.85)	(1.77)	(0.23)	(0.33)	(3.15)**	(3.89)**
lag of own AID			3.154		-1.302	-2.953	-2.594
			(0.83)		(0.32)	(0.73)	(0.65)
lag of world AID				631.788	639.547	286.681	33.650
				(5.20)**	(5.13)**	(2.08)*	(0.21)
trend	0.063					0.077	0.163
	(16.15)**					(6.09)**	(5.53)**
trend^2							-0.002
							(3.27)**
Observations	4134	4027	3921	3929	3921	3921	3921
Number of isogrp	106	106	106	106	106	106	106
R-squared							

Absolute value of z statistics in parentheses

* significant at 5%; ** significant at 1%

Panel data logit model with country FE. I report the odds ratios (change in p/1-p). The data includes years 1960-1996.

Table 4: Number of reported events by year

DEPVAR: number of disasters reported by a country	(1)	(2)	(3)	(4)
lnPOP	0.283	0.303	0.312	0.312
	(2.96)**	(3.11)**	(3.26)**	(3.24)**
lnYpc	-0.436	-0.433	-0.444	-0.429
	(5.05)**	(4.63)**	(5.01)**	(4.59)**
lag of own AID		1.550		1.178
		(0.60)		(0.45)
lag of world AID			88.012	85.128
			(1.30)	(1.25)
trend	0.103	0.105	0.095	0.094
	(11.08)**	(10.52)**	(7.10)**	(7.03)**
trend^2	-0.001	-0.001	-0.001	-0.001
	(7.58)**	(7.44)**	(5.45)**	(5.42)**
Observations	4105	3997	4005	3997
Number of isogrp	108	108	108	108
R-squared				
Absolute value of z statistics in parentheses				
* significant at 5%; ** significant at 1%				
Model	Neg Bin	Neg Bin	Neg Bin	Neg Bin
Country fixed effects	Yes	Yes	Yes	Yes

The model estimates the expected number of events reported by a negative binomial regression. The coefficients are incidence rate ratios, interpreted as the change in the expected number of events due to a unit increase in the regressor.

Table 5: **Cross-country regression of GDP level in 1996.**

	(1)	(2)	(3)	(4)
	lnGDP1996	lnGDP1996	lnGDP1996	lnGDP1996
lnGDP1960	0.992	1.006	1.009	0.967
	[12.45]***	[11.22]***	[11.47]***	[12.39]***
lnPOPgrowth	-0.269	-0.324	-0.318	-0.256
	[2.35]**	[2.61]**	[2.57]**	[2.33]**
lnAREA	-0.103	-0.070	-0.069	-0.118
	[3.14]***	[1.97]*	[1.97]*	[3.55]***
Number of disasters	0.004			0.006
	[3.79]***			[4.32]***
Cumul. fraction affected		-0.026		-0.296
		[0.41]		[2.15]**
Cumul. fraction killed			-21.809	3.986
			[0.78]	[0.09]
Constant	2.075	1.773	1.744	2.464
	[2.83]***	[2.21]**	[2.24]**	[3.28]***
Observations	102	102	102	102
R-squared	0.76	0.73	0.73	0.77

Robust t statistics in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

The sample includes all countries.

Table 6: **Effect of the disaster measures on the level of GDP in 1996.**

	Implied impact on 1996 GDP level			
	(1)	(2)	(3)	(4)
Number of disasters	**19.81%**			**29.72%**
	[3.79]***			[4.32]***
Cumul. fraction affected		**-1.22%**		**-13.93%**
		[0.41]		[2.15]**
Cumul. fraction killed			**-2.47%**	**0.45%**
			[0.78]	[0.09]

Robust t statistics in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

The results that are statistically significant at the 10% level or better are highlighted. The percentage is the implied impact of an increase in the explanatory variable by one standard deviation.

Table 7: Effect of the disaster measures on the level of GDP in 1996, by country subsample.

Implied impact on GDP level	(1)	(2)	(3)	(4)	(5)	(6)
Number of disasters	**0.00%**	**18.90%**	**13.55%**	**39.93%**	**38.55%**	**11.14%**
	[0.03]	[2.15]**	[1.48]	[2.51]**	[3.54]***	[1.90]*
Cumul. fraction affected	**-5.05%**	**-15.31%**	**-16.00%**	**-60.01%**	**-25.93%**	**-0.26%**
	[0.60]	[0.94]	[1.64]	[1.45]	[1.80]*	[0.05]
Cumul. fraction killed	**-12.43%**	**11.67%**	**2.57%**	**37.73%**	**-3.21%**	**-3.37%**
	[1.85]*	[1.07]	[0.37]	[1.07]	[0.40]	[0.65]
Robust t statistics in brackets						
Countries in sample	Small pop	Medium pop	Large pop	Low income	Medium income	High income

The results that are statistically significant at least at the 10% level are highlighted. The percentage is the implied impact of an increase in the explanatory variable by one standard deviation.

Table 8: Effect of the disaster measures on the level of GDP in 1996, by country subsample and type of disaster.

		Countries in sample						
Type of disaster	**Measure of disaster**	**All**	**Small pop.**	**Medium pop.**	**Large pop.**	**Low income**	**Medium income**	**High income**
Earthquake EQ	Number of disasters	**19.24%**	**-8.45%**	**8.78%**	**17.18%**	**25.44%**	**20.20%**	**10.36%**
		[4.98]***	[1.06]	[2.79]***	[2.23]**	[3.68]***	[2.27]**	[1.77]*
	Cumulative fraction affected	**1.35%**	**171.08%**	**11.78%**	**-32.95%**	**2.25%**	**13.86%**	**21.36%**
		[0.37]	[0.86]	[0.93]	[3.16]***	[0.49]	[1.75]*	[1.11]
	Cumulative fraction killed	**-6.60%**	**-151.82%**	**-10.05%**	**24.61%**	**9.89%**	**-25.10%**	**-22.75%**
		[1.63]	[0.94]	[1.18]	[2.67]**	[2.86]***	[2.19]**	[1.23]
Flood FL	Number of disasters	**25.15%**	**-2.43%**	**20.75%**	**16.47%**	**34.22%**	**37.58%**	**3.86%**
		[4.03]***	[0.51]	[1.36]	[1.11]	[2.06]**	[4.20]***	[0.56]
	Cumulative fraction affected	**-8.81%**	**3.42%**	**-5.71%**	**-13.86%**	**-23.12%**	**-1.53%**	**-6.29%**
		[1.58]	[0.36]	[0.34]	[0.93]	[1.42]	[0.13]	[3.45]***
	Cumulative fraction killed	**1.25%**	**-8.78%**	**-4.26%**	**0.49%**	**6.83%**	**-20.32%**	**-4.75%**
		[0.21]	[0.65]	[0.55]	[0.04]	[0.59]	[1.84]*	[1.24]
Slide SL	Number of disasters	**18.72%**	**16.96%**	**19.66%**	**11.46%**	**48.52%**	**27.65%**	**8.21%**
		[3.44]***	[2.12]**	[0.49]	[1.09]	[2.57]**	[3.32]***	[1.38]
	Cumulative fraction affected	**-0.31%**	**-10.37%**	**1.05%**	**-1.59%**	**-35.09%**	**13.64%**	**-6.89%**
		[0.09]	[1.35]	[0.16]	[0.29]	[2.44]**	[2.31]**	[5.80]***
	Cumulative fraction killed	**-2.44%**	**-3.94%**	**-5.59%**	**-5.94%**	**7.97%**	**-1.88%**	**0.45%**
		[1.06]	[1.10]	[0.33]	[1.55]	[1.64]	[0.45]	[0.52]
Volcano VC	Number of disasters	**16.25%**	**24.73%**	**-6.75%**	**11.07%**	**18.25%**	**11.55%**	**12.26%**
		[5.54]***	[2.79]***	[2.00]*	[1.76]*	[3.37]***	[1.78]*	[2.38]**
	Cumulative fraction affected	**-29.85%**	**-39.85%**	**18.11%**	**-2.67%**	**0.12%**	**-33.43%**	**-3.38%**
		[5.85]***	[5.27]***	[4.73]***	[0.63]	[0.02]	[5.46]***	[0.60]
	Cumulative fraction killed	**1.40%**	**-2.21%**	**0.58%**	**2.48%**	**0.00%**	**6.01%**	**-1.01%**
		[1.38]	[0.90]	[0.62]	[3.12]***	[.]	[3.09]***	[0.30]
Wave/surge WA	Number of disasters	**11.03%**	**0.00%**	**-12.95%**	**23.38%**	**18.26%**	**-6.73%**	**14.67%**
		[1.67]*	[.]	[4.63]***	[1.61]	[4.01]***	[0.80]	[2.53]**
	Cumulative fraction affected	**-3.72%**	**0.00%**	**-2.76%**	**-16.20%**	**0.00%**	**-8.26%**	**-5.09%**
		[0.69]	[.]	[1.29]	[1.08]	[.]	[1.64]	[2.34]**
	Cumulative fraction killed	**-1.38%**	**0.00%**	**20.99%**	**-1.28%**	**0.00%**	**14.59%**	**-6.15%**
		[0.30]	[.]	[16.22]***	[0.23]	[.]	[2.45]**	[2.31]**
Wildfire WF	Number of disasters	**14.97%**	**-3.23%**	**11.13%**	**-1.31%**	**7.61%**	**17.06%**	**13.34%**
		[6.60]***	[0.35]	[1.48]	[0.10]	[0.68]	[2.30]**	[1.73]*
	Cumulative fraction affected	**5.49%**	**-15.14%**	**27.21%**	**3.52%**	**6.78%**	**21.38%**	**-6.33%**
		[0.80]	[2.94]***	[4.39]***	[0.54]	[0.65]	[3.91]***	[2.68]**
	Cumulative fraction killed	**-2.33%**	**-3.06%**	**-17.24%**	**0.49%**	**-2.46%**	**5.87%**	**-1.43%**
		[1.59]	[1.03]	[6.40]***	[0.09]	[1.51]	[2.83]***	[0.38]
Windstorm WS	Number of disasters	**17.47%**	**7.24%**	**10.58%**	**7.92%**	**29.47%**	**32.58%**	**10.10%**
		[2.44]**	[0.25]	[1.54]	[0.90]	[1.56]	[2.67]**	[1.64]
	Cumulative fraction affected	**-15.53%**	**-11.99%**	**-33.62%**	**-2.37%**	**-28.80%**	**-31.80%**	**3.39%**
		[2.22]**	[0.48]	[3.72]***	[0.40]	[2.51]**	[1.76]*	[0.99]
	Cumulative fraction killed	**-2.41%**	**-3.63%**	**61.76%**	**-6.61%**	**-2.48%**	**2.38%**	**-3.94%**
		[1.55]	[0.72]	[3.75]***	[2.81]***	[0.28]	[0.61]	[0.74]
Extreme temp. XT	Number of disasters	**14.09%**	**53.99%**	**9.39%**	**-4.15%**	**4.62%**	**23.85%**	**6.68%**
		[2.55]**	[0.99]	[1.16]	[0.61]	[0.35]	[4.39]***	[1.78]*
	Cumulative fraction affected	**2.06%**	**-22.40%**	**10.44%**	**3.07%**	**8.26%**	**3.41%**	**3.32%**
		[1.72]*	[0.61]	[4.00]***	[1.16]	[0.98]	[0.41]	[2.55]**
	Cumulative fraction killed	**1.40%**	**-13.08%**	**0.00%**	**-1.26%**	**0.84%**	**7.29%**	**-0.31%**
		[2.14]**	[0.57]	[.]	[0.75]	[0.09]	[1.74]*	[0.23]

The results that are statistically significant at the 10% level or better are highlighted. The percentage is the implied impact of an increase in the explanatory variable by one standard deviation.

Table 9: **Panel regression of GDP growth on disasters.**

Dep var: Growth in per capita GDP

	(1)	(2)	(3)	(4)	(5)	(6)
cum_disd			**-0.000**	**-0.000**	**-0.000**	**-0.000**
			[0.000]	[0.000]	[0.000]	[0.000]
cum_dama			**-33.583**	**-27.624**	**-26.995**	**-24.845**
			[43.646]	[44.090]	[44.017]	[44.657]
cum_kill			**-4.932**	**-4.082**	**-4.100**	**-4.000**
			[2.161]**	[2.194]*	[2.197]*	[2.207]*
cum_taff			**0.023**	**0.022**	**0.022**	**0.022**
			[0.007]***	[0.007]***	[0.007]***	[0.007]***
disd	**0.002**	**0.001**	**0.001**	**0.001**	**0.001**	**0.001**
	[0.001]***	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]*
dama	**89.775**	**100.192**	**134.498**	**133.769**	**133.903**	**136.501**
	[108.768]	[108.503]	[116.273]	[120.571]	[120.664]	[119.477]
kill	**-1.090**	**-0.840**	**2.078**	**1.435**	**1.461**	**1.203**
	[4.092]	[4.331]	[4.863]	[4.811]	[4.798]	[4.862]
taff	**0.009**	**0.010**	**-0.008**	**-0.011**	**-0.011**	**-0.009**
	[0.027]	[0.027]	[0.029]	[0.030]	[0.030]	[0.030]
disd [t-1]		**0.002**	**0.002**	**0.002**	**0.002**	**0.002**
		[0.001]***	[0.001]***	[0.001]***	[0.001]***	[0.001]***
dama [t-1]		**91.741**	**123.042**	**127.843**	**127.952**	**126.276**
		[61.393]	[71.709]*	[73.222]*	[73.182]*	[73.809]*
kill [t-1]		**1.900**	**4.897**	**4.210**	**4.242**	**4.140**
		[5.834]	[5.558]	[5.585]	[5.592]	[5.577]
taff [t-1]		**-0.001**	**-0.019**	**-0.022**	**-0.022**	**-0.021**
		[0.024]	[0.025]	[0.025]	[0.025]	[0.025]
open [t-1]				**0.000**	**0.000**	**0.000**
				[0.000]***	[0.000]***	[0.000]***
aid					**0.035**	**0.049**
					[0.091]	[0.092]
aid*disaster						**-0.088**
						[0.167]
Observations	4168	4168	4168	4168	4168	4168
Number of isogrp	113	113	113	113	113	113
R-squared	0.05	0.05	0.05	0.06	0.06	0.06

Robust standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

All regressions have country and year fixed effects. [t-1] indicates the one-period lag of the variable.

Table 10: Panel regression of GDP growth on disasters, by groups of countries.

Dep var: Growth in per capita GDP

Countries in sample	**(1)** Small pop	**(2)** Medium pop	**(3)** Large pop	**(4)** Low income	**(5)** Medium income	**(6)** High income
cum_disd	**0.00041**	**-0.00026**	**-0.00003**	**0.00002**	**-0.00010**	**-0.00012**
	[0.00032]	[0.00019]	[0.00007]	[0.00012]	[0.00011]	[0.00006]**
cum_dama	**0.462**	**54.482**	**-110.146**	**130.159**	**-75.675**	**209.962**
	[139.213]	[142.716]	[208.580]	[120.318]	[98.844]	[167.004]
cum_kill	**-2.489**	**-12.237**	**-5.144**	**-2.818**	**-1.259**	**-1.394**
	[5.447]	[6.321]*	[3.407]	[4.987]	[2.750]	[38.330]
cum_taff	**0.014**	**0.046**	**0.028**	**0.012**	**0.013**	**0.013**
	[0.020]	[0.035]	[0.008]***	[0.013]	[0.014]	[0.022]
disd	**0.001**	**-0.000**	**0.001**	**0.003**	**0.002**	**0.001**
	[0.003]	[0.002]	[0.001]	[0.002]	[0.001]	[0.001]
dama	**16.102**	**-440.710**	**-672.279**	**-486.086**	**151.013**	**-561.659**
	[212.179]	[301.510]	[465.889]	[528.947]	[231.836]	[263.266]**
kill	**-17.262**	**23.644**	**5.318**	**5.844**	**-0.146**	**-79.817**
	[6.454]***	[14.294]*	[4.115]	[6.720]	[6.032]	[77.120]
taff	**0.054**	**-0.044**	**0.062**	**0.059**	**-0.037**	**0.100**
	[0.035]	[0.067]	[0.048]	[0.049]	[0.036]	[0.031]***
disd [t-1]	**0.002**	**0.004**	**0.001**	**0.003**	**0.002**	**0.001**
	[0.003]	[0.002]**	[0.001]	[0.002]	[0.001]*	[0.001]*
dama [t-1]	**-79.633**	**-424.976**	**362.993**	**-53.090**	**476.749**	**-142.237**
	[295.184]	[411.124]	[631.440]	[808.257]	[255.625]*	[229.612]
kill [t-1]	**4.870**	**25.313**	**0.153**	**3.562**	**1.882**	**6.467**
	[8.288]	[25.100]	[6.987]	[15.466]	[5.268]	[27.598]
taff [t-1]	**0.030**	**-0.031**	**-0.049**	**-0.040**	**-0.055**	**0.040**
	[0.041]	[0.135]	[0.028]*	[0.035]	[0.050]	[0.050]
open [t-1]	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**
	[0.000]***	[0.000]	[0.000]	[0.000]	[0.000]*	[0.000]***
aid	**0.196**	**0.054**	**-1.005**	**-0.095**	**0.234**	**-0.523**
	[0.128]	[0.175]	[0.467]**	[0.155]	[0.146]	[0.410]
aid*disaster	**-0.514**	**0.485**	**0.322**	**-0.154**	**-0.204**	**1.106**
	[0.247]**	[0.218]**	[0.603]	[0.261]	[0.207]	[0.502]**
Observations	1321	1321	1329	1329	1322	1289
Number of isogrp	35	35	35	35	35	34
R-squared	0.09	0.08	0.11	0.06	0.08	0.17

Robust standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

All regressions have country and year fixed effects. [t-1] indicates the one-period lag of the variable.

Table 11: Panel regression of GDP growth on disasters, by type of disaster.

Dep var: Growth in per capita GDP

	(1) EQ	(2) FL	(3) SL	(4) VC	(5) WA	(6) WS	(7) WF	(8) XT
cum_disd	**-0.000**	**0.000**	**0.000**	**-0.000**	**0.008**	**-0.000**	**-0.001**	**0.001**
	[0.000]	[0.000]	[0.001]	[0.001]	[0.004]*	[0.000]	[0.000]*	[0.001]***
cum_dama	**97.699**	**152.222**	**-2,315.337**	**97.119**	**-877,287.511**	**-74.044**	**-518.302**	**-714.685**
	[165.020]	[232.298]	[958.243]**	[192.295]	[733,248.454]	[62.754]	[1,199.007]	[658.527]
cum_kill	**-11.876**	**67.492**	**7.327**	**2.635**	**-181.984**	**4.417**	**1,991.177**	**-174.182**
	[4.267]***	[46.485]	[8.449]	[13.739]	[113.565]	[2.086]**	[1,165.592]*	[79.193]**
cum_taff	**0.058**	**0.009**	**0.657**	**-0.066**	**1.266**	**0.018**	**0.126**	**-0.046**
	[0.025]**	[0.008]	[0.436]	[0.163]	[18.674]	[0.014]	[1.888]	[0.026]*
disd	**0.005**	**0.001**	**0.003**	**0.001**	**0.000**	**0.002**	**-0.001**	**-0.004**
	[0.002]***	[0.002]	[0.003]	[0.004]	[0.010]	[0.001]	[0.003]	[0.004]
dama	**-697.719**	**-1,364.951**	**1,424.942**	**284.050**	**377,733.873**	**266.009**	**1,177.754**	**5,034.503**
	[248.025]***	[547.936]**	[1,871.188]	[310.068]	[904,575.871]	[109.830]**	[1,467.356]	[600.221]***
kill	**0.509**	**152.992**	**11.461**	**25.431**	**194.925**	**-3.451**	**-4,598.006**	**-199.716**
	[4.721]	[109.993]	[14.414]	[59.525]	[147.341]	[7.297]	[9,126.668]	[81.367]**
taff	**0.079**	**0.028**	**-0.527**	**0.097**	**-21.550**	**-0.036**	**2.774**	**0.277**
	[0.043]*	[0.031]	[0.515]	[0.096]	[30.843]	[0.037]	[2.085]	[0.049]***
disd [t-1]	**0.002**	**0.003**	**0.005**	**0.003**	**-0.009**	**0.002**	**0.003**	**0.002**
	[0.002]	[0.001]**	[0.003]*	[0.005]	[0.011]	[0.001]*	[0.003]	[0.003]
dama [t-1]	**259.877**	**729.963**	**2,585.924**	**-376.040**	**565,978.829**	**157.245**	**-3,023.566**	**1,124.962**
	[283.961]	[585.457]	[1,381.494]*	[370.269]	[132,276.453]*	[94.446]*	[3,168.671]	[572.793]**
kill [t-1]	**12.532**	**33.695**	**-38.009**	**3.455**	**198.702**	**-12.581**	**4,878.326**	**186.601**
	[8.447]	[67.184]	[18.174]**	[19.240]	[114.108]*	[6.610]*	[1,868.334]***	[85.669]**
taff [t-1]	**-0.049**	**-0.087**	**-0.235**	**-0.083**	**-19.888**	**-0.002**	**-1.228**	**0.211**
	[0.052]	[0.036]**	[0.409]	[0.131]	[26.504]	[0.036]	[2.155]	[0.067]***
open [t-1]	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***
aid	**0.028**	**0.048**	**0.035**	**0.026**	**0.025**	**0.037**	**0.019**	**0.038**
	[0.092]	[0.092]	[0.092]	[0.091]	[0.091]	[0.091]	[0.091]	[0.091]
aid*disaster	**-0.040**	**-0.094**	**-0.047**	**-0.040**	**-0.040**	**-0.065**	**-0.038**	**-0.050**
	[0.162]	[0.165]	[0.161]	[0.163]	[0.160]	[0.164]	[0.159]	[0.161]
Observations	4168	4168	4168	4168	4168	4168	4168	4168
Number of isogrp	113	113	113	113	113	113	113	113
R-squared	0.06	0.06	0.06	0.05	0.05	0.06	0.06	0.06

Robust standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

All regressions have country and year fixed effects. [t-1] indicates the one-period lag of the variable. EQ: earthquake; FL. flood; SL: slide; VC: volcano; WA: wave/surge; WS: wind storm; WF: wildfire; XT: extreme temperature.

Table 12 : Effect on (long-term) growth rates of having, in the year 1996, a cumulative measure of disaster that is higher by one standard deviation

	EQ	FL	SL	VC	WA	WS	WF	XT
cum_disd	0.000	0.000	0.000	0.000	0.005	0.000	-0.005	0.003
cum_dama	0.001	0.001	-0.003	0.001	-0.010	-0.004	-0.001	-0.002
cum_kill	-0.009	0.005	0.001	0.000	-0.003	0.003	0.002	-0.002
cum_taff	0.006	0.003	0.003	-0.002	0.000	0.005	0.000	-0.001

Each column corresponds to a type of disaster. The values that are highlighted correspond to estimated coefficients that are statistically significant at the 10% level or better.

Appendix A: Disaster Data

The format of a disaster event entry in EM-DAT is exemplified by Table 1. The data it may contain depends on availability:[18]

DisNo	19670020
Country	Colombia
ISOCode	COL
Region	South America
Continent	Americas
DisGroup	Natural
DisType	Earthquake
DisSubset	Earthquake
DisName	
Year	1967
Month	2
Day	9
Killed	61
Injured	200
Homeless	
Affected	40000
TotAff	40200
DamageUS(000s)	600
DamageEuros(000s)	
DamageLocal(000s)	
Local Currency	Colombia, Peso (COP)
Location	Huila Dep. Coordinates for Neiva.
Latitude	2.58N
Longitude	75.15W
DisScaleVal	
DisScale	Richter
TimeLocal	
TimeGMT	
PrimarySource	US Gov:OFDA
AddSource1	UN:OCHA
AddSource2	Priv:RFF
AddSource3	UN
AddSource4	
AddSource5	
AddSource6	
OFDAresp	TRUE
Reason	Kill
LastMod	7/25/1999
Comments	US GOV:OFDA: + UN:OCHA:b: Huila Dept, Neiva; Nbr Kill and Homel UN:OCHA:b: Feb 1967 US GOV:OFDA: Nbr Affect, Inj; K,Dam: 600 PRIV:RFF: Feb 1967; Rep Deaths: Max: 1 UN: Min: 61

Typical entry in EM-DAT

18 This variable description is quoted directly from the webpage of the EM-DAT Guidelines at http://www.cred.be/emdat/intro.htm

The following is a short explanation for each of these variables, quoted from the EM-DAT Guidelines:

- Country: Country in which the disaster has occurred (see Country list). If a disaster has affected more than one country, there is one entry for each country. If the quantitative data (killed, injured, homeless, affected, estimation of damage) are not given by country, they will be entered under the NA-related region/continent and an entry will be made for each country without data.
- ISO Code: Automatically linked to the country (see ISO Code list). The International Organization for Standardization has attributed a 3-letter code to each country. CRED is using the ISO 3166.
- Region: Automatically linked to the country (see Region list).
- Continent: Africa, Americas, Asia, Europe and Oceania are the five continents. This field is automatically linked to the country.
- Disaster group: Three groups of disasters are distinguished in EM-DAT: natural disasters, technological disasters and conflict. This field is automatically linked to the disaster type.
- Disaster type: Description of the disaster according to a pre-define classification scheme scheme (See Disaster type list). Two or more disasters may be related, i.e. a disaster may occur as a consequence of a primary event. For example, a cyclone may generate a flood or a landslide; or an earthquake may cause a gas line to rupture, causing an ecological disaster. The primary disaster type is recorded first, followed in the comments field by a related disaster description.
- Disaster subset: Specific information related to the disaster type (see Dissubset list).
- Date: When the disaster occurred. The date is entered as follow: Year/Month/Day. This date is easily defined for all sudden disasters, but for disaster situations developing gradually over a longer time period, only month and/or year are recorded. The data available for long-term disaster are divided by the number of affected years (in the chronological table of the profiles, and in the raw data). The totals of people reported killed or affected or estimated damage are only used in the TOP 10 tables in the disaster profiles.

- Killed: Persons confirmed as dead and persons missing and presumed dead (official figures when available).
- Injured: The number of injured is entered when the term "injured" is written in the source. Injured people are always part of the affected population. Any related word like "hospitalized" is considered as injured. If there is no precise number like "hundreds of injured", 200 injured will be entered (although it is probably underestimated). Any other specification will be written in the comments field.
- Homeless: They are always part of the affected population. Reporting from the field should give the number of individuals that are homeless; if only the number of families or houses is reported, the figure is multiplied by the average family size for the affected area (x5 for the developing countries, x3 for the industrialised countries, according to UNDP country list). Any other specification will be written in the comments field. Specific examples: Number of houses destroyed = 50 x 5 = 250 homeless (although it is probably underestimated) If the value ranging from a minimum to a maximum: take the average Thousands of homeless = 2000 homeless (although it is probably underestimated) Affected: People requiring immediate assistance during a period of emergency; it can also be displaced or evacuated people. Any other specification will be written in the comments field.
- Total affected: Sum of injured, homeless, and affected.
- Estimated Damage: Although several institutions have developed methodologies to quantify these losses in their specific domain, no standard procedure to determine a global figure for the economic impact exists up to now. Estimated damage are (if available) given in 3 different currencies (in thousand):
- Dam US Dam Euros DamLocal: the local currency field is automatically linked to the country. If cost damage is given in the local currency, it will be directly converted in US and in EURO for European countries. For each disaster, the registered figure corresponds to the damage value at the moment of the event, i.e. the figures are shown true to the year of the event
- Primary source: Primary source of disaster information. A priority list as been established (see Source list). In some specific case, a secondary source can become

a primary one according to the relevance of the data given by the source or the updating of a report.

- Additional source: All other data sources.
- Reason: Reason for taking into account the disaster
    - Code Reason Kill 10 or more people killed
    - Affected 100 or more people affected/injured/homeless
    - SigDis Significant disaster (e.g. second worst)
    - SigDam Significant damage
    - Decla/int Declaration of a state of emergency or/and appeal for an international assistance
    - Regional Disaster entered at the country level without data, because it has affected several countries/regions.
    - Unknown Reason not known (old entries)

Appendix B: Foreign Aid Data

I use three data series from the DAC/GEO database of Geographic Distribution of Financial Flows to Aid Recipients, 1960-1998, included in the OECD publication International Development Statistics (IDS), edition 2000. I reproduce here the database descriptions of this series.

Total Official Net Flows The sum of Official Development Assistance (ODA) and Other Official Flows (OOF) represents the total net disbursements by the official sector at large to the recipient country.

Official Development Assistance (ODA) Includes grants or loans to countries and territories on Part I of the DAC List of Aid Recipients (developing countries) which are a) undertaken by the official sector; b) with promotion of economic development and welfare as the main objective, and c) at concessional financial terms (if a loan, have a grant element of at least 25 per cent).
In addition to financial flows, Technical Co-operation is included in official aid. Grants, loans and credits for military purposes are excluded.

Other Official Flows (OOF) Transactions by the official sector whose main objective is other than development motivated, or, if development motivated, whose grant element is below the 25% threshold which would make them eligible to be recorded as ODA. The main classes of transactions included here are official export credits, official sector equity and portfolio investment, and debt reorganisation undertaken by the official sector at non-concessional terms (irrespective of the nature or the identity of the original creditor).

Appendix C: Countries in the sample

According to their population in 1960, the countries in the sample are:

Small		Medium		Large		Not included	
barbados	4	angola	1	algeria	30	antigua and	5
benin	9	austria	20	argentina	47	dominica	8
botswana	3	bolivia	22	australia	169	grenada	4
cape verde	4	burkina faso	4	bangladesh	136	saint kitts	5
central afri	4	burundi	1	belgium	20	saint vincen	9
comoros	6	cameroon	5	brazil	84	sao tome and	0
congo	1	chad	6	canada	53	sierra leone	3
costa rica	31	chile	44	colombia	80	tunisia	11
cyprus	4	cote d'ivoir	2	egypt	15		
equatorial g	0	denmark	9	france	66		
fiji	30	dominican re	20	greece	44		
gabon	1	ecuador	52	india	236		
gambia	2	el salvador	12	indonesia	153		
guinea-bissa	2	finland	1	italy	65		
guyana	3	ghana	5	japan	132		
honduras	25	guatemala	20	kenya	7		
iceland	10	guinea	3	korea, repub	44		
israel	7	haiti	28	mexico	92		
jamaica	17	hong kong	184	morocco	18		
jordan	9	ireland	6	nepal	41		
lesotho	6	madagascar	21	netherlands	11		
luxembourg	3	malawi	8	nigeria	6		
mauritania	3	malaysia	16	pakistan	58		
mauritius	18	mali	2	peru	68		
namibia	0	mozambique	15	philippines	215		
new zealand	66	niger	3	south africa	29		
nicaragua	20	norway	5	spain	40		
panama	13	senegal	7	sri lanka	32		
papua new gu	33	sweden	7	taiwan, prov	31		
paraguay	11	switzerland	25	tanzania, un	16		
seychelles	0	syrian arab	3	thailand	36		
singapore	0	uganda	5	turkey	50		
togo	3	venezuela	13	united kingd	31		
trinidad and	9	zambia	2	united state	272		
uruguay	4	zimbabwe	2	zaire	0		
TOTAL	361		579		2427		45

Countries in the sample by 1960 population
The countries are classified according to their 1960 population. Those under “Not Included” are in the sample but there was no population data for that year. The number in front of the country is the number of disasters it had in the period of analysis.

According to their per capita GDP in 1960, the countries in the sample are:

Poor		Medium		Rich		Not included	
bangladesh	136	algeria	30	argentina	47	antigua and	5
benin	9	angola	1	australia	169	dominica	8
botswana	3	bolivia	22	austria	20	grenada	4
burkina faso	4	brazil	84	barbados	4	haiti	28
burundi	1	cameroon	5	belgium	20	saint kitts	5
cape verde	4	central afri	4	canada	53	saint vincen	9
chad	6	colombia	80	chile	44	sao tome and	0
congo	1	comoros	6	costa rica	31	sierra leone	3
dominican re	20	cote d'ivoir	2	denmark	9	tunisia	11
egypt	15	cyprus	4	el salvador	12		
gambia	2	ecuador	52	finland	1		
ghana	5	equatorial g	0	france	66		
guinea-bissa	2	fiji	30	greece	44		
india	236	gabon	1	iceland	10		
indonesia	153	guatemala	20	ireland	6		
kenya	7	guinea	3	israel	7		
korea, repub	44	guyana	3	italy	65		
lesotho	6	honduras	25	japan	132		
madagascar	21	hong kong	184	luxembourg	3		
malawi	8	jamaica	17	mauritius	18		
mali	2	jordan	9	mexico	92		
mauritania	3	malaysia	16	namibia	0		
morocco	18	mozambique	15	netherlands	11		
nepal	41	nicaragua	20	new zealand	66		
niger	3	panama	13	norway	5		
nigeria	6	papua new gu	33	south africa	29		
pakistan	58	paraguay	11	spain	40		
sri lanka	32	peru	68	sweden	7		
syrian arab	3	philippines	215	switzerland	25		
taiwan, prov	31	senegal	7	trinidad and	9		
tanzania, un	16	seychelles	0	united kingd	31		
thailand	36	singapore	0	united state	272		
togo	3	turkey	50	uruguay	4		
uganda	5	zambia	2	venezuela	13		
zaire	0	zimbabwe	2				
TOTAL	940		1034		1365		73

Countries in the sample by per capita GDP level

The countries are classified according to their 1960 per capita GDP. Those under “Not Included” are in the sample but there was no GDP data for that year. The number in front of the country is the number of disasters it had in the period of analysis.