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The Wrath of God

Macroeconomic Costs of Natural Disasters

Claudio Raddatz

The World Bank
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Abstract

The process of global climate change has been associated with an increase in the frequency of climatic disasters. Yet, there is still little systematic evidence on the macroeconomic costs of these episodes. This paper uses panel time-series techniques to estimate the short and long-run impact of climatic and other disasters on a country's GDP. The results indicate that a climate related disaster reduces real GDP per capita by at least 0.6 percent. Therefore, the increased incidence of these disasters during recent decades entails important macroeconomic costs. Among climatic disasters, droughts have the largest average impact, with cumulative losses of 1 percent of GDP per capita. Across groups of countries, small states are more vulnerable than other countries to windstorms, but exhibit a similar response to other types of disasters; and low-income countries responds more strongly to climatic disasters, mainly because of their higher response to droughts. However, a country's level of external debt has no relation to the output impact of any type of disaster. The evidence also indicates that, historically, aid flows have done little to attenuate the output consequences of climatic disasters.

This paper—a product of the Growth and the Macroeconomics Team, Development Research Group—is part of a larger effort in the department to understand the impact of external shocks and of the process of climate change. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The author may be contacted at craddatz@worldbank.org.

The Wrath of God: Macroeconomic Costs of Natural Disasters

Claudio Raddatz*

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1 Introduction

Shortly after hurricane Katrina hit the US Gulf Coast in August 2005, risk-modeling companies raised their estimation of the probability of a similar event from once every 40 years to once every 20 years, as a result of the warming of water temperatures in the North Atlantic Basin. This reassessment of the likelihood and severity of climatic disasters is not particular to the US and has taken place all over the world, as concerns about the consequences of global warming on world climate have increased in recent years.

Despite the increased interest in the consequences of climate change for the incidence of natural disasters, there is little systematic evidence on the macroeconomic consequences of these events that could provide a sense of the magnitude of the challenge. Existing evidence mainly consists of policy analyses based on simple correlations in a limited number of case studies (see for example Albala-Bertrand (1993), Otero and Marti (1995), Rasmussen (2004)) and on cross-country growth regressions (Skidmore and Toya (2002)). Although case studies can be insightful, they cannot isolate the impact of a disaster because they do not control for other simultaneous shocks. Also, the limited number of cases casts some doubts on the generality of the conclusions, and the selection of the cases, which is not random, is another source of concern. Cross-country growth regressions address some of these concerns but lack explicit dynamics, so their results are not informative of the short-run effect of disasters, and the methodology suffers from the standard criticisms associated with the possibility of omitted-variable bias, and additional problems resulting from the need to aggregate disasters across time. Outside academia, the proprietary models used by the insurance industry, while highly detailed, focus only on the insurance losses of specific events, mostly on developed countries.

This paper quantifies the macroeconomic consequences of climatic and other disasters in developing countries using a unified framework based on a vector auto-regression (VAR) model. Under the uncontroversial assumption that natural catastrophes are exogenous to a country's short-run performance, this approach provides estimates of the average impact on GDP of several types of disasters at various frequencies. Because of the short time-dimension of the series available, most of the analysis uses panel autoregressive distributed lags (PARDL) and panel vector autoregression (PVAR) models that restrict the response of various groups of developing countries to be identical.[1] This methodology provides an estimate of the output cost of a given type of disaster on a typical country within a group, which can be used as a starting point in the evaluation of the overall costs of an increased likelihood of these events, such as resulting, for instance, from climate change.

The analysis confirms that the incidence of climatic disasters has increased during the last four decades, and indicates that natural disasters, especially climatic ones, have a moderate but significant negative impact on real GDP per capita. A conservative estimate of their macroeconomic

[1] A similar approach has previously been used by Deaton and Miller (1995) to estimate the impact of commodity prices in African countries, Broda (2004) to estimate the impact of terms of trade socks in countries with different exchange regimes, and Ahmed (2003) to determine the effect of different sources of economic fluctuations in six Latin American countries.

cost is that a climatic disaster affecting at least half a percent of a country's population, which in the whole sample period occurs once every four years, reduces real GDP per capita in 0.6 percent. Therefore, the increase in the incidence of these disasters observed in the data can entail non-trivial macroeconomic costs. For instance, with the average incidence post-1990 of one climatic disaster every three years instead, these disasters would reduce GDP per-capita in 2 percent over a decade.

The findings also indicate that, historically, flows of official development assistance (ODA) do not importantly attenuate the output consequences of climatic disasters. Explicitly considering ODA in the model only reduces the output impact of climatic disasters from 0.77 to 0.63 percent of per capita GDP, and this reduction is not statistically significant.

Among climatic disasters, droughts have the largest average impact, with cumulative losses of 1 percent of GDP per capita. Extreme temperatures also have a large average impact of 5 percent of GDP per capita, but results for this type of climatic disaster are based only on a sample of 12 countries. Other types of climatic disasters, such as windstorms (e.g. hurricanes and cyclones) and floods do not have a significant impact when looking at the broad set of countries affected by any type of climatic disaster.

Across broad disaster's categories, small states are not significantly more affected than larger countries. However, wind storms have a larger estimated impact on small states than other countries. Among small states, windstorms typically result in a 3 percent decline in per capita GDP, while they have virtually no impact on larger states.

Output in low-income countries responds more strongly to climatic disasters. Among these countries, a climatic disaster results in a 1 percent decline in per-capita GDP that is also statistically significant at the 10 percent level during the initial years. In contrast, among middle and high-income countries, climatic disasters result in output losses of 0.5 and 0.25 percent, respectively. This larger response of low-income countries to climatic disasters is mainly due to the large output impact of droughts on this group, which reaches 2 percent of per capita GDP. In contrast, there is no significant response to any type of disaster (climatic and other) among middle and high income countries.

The level of external debt has no relation to the impact of any type of disasters. Output losses for climatic disasters are almost identical for countries with low, medium, and high initial levels of debt. Distinguishing among different types of climatic disasters (droughts, extreme temperatures, floods, and windstorms) does not change this conclusion; for no type of climatic (and non-climatic) disaster there is a clearly differential response among more indebted countries.

This paper contributes to a long literature that has aims to estimate the economic consequences of natural disasters. A large part of this literature relies on simple correlations arising from a limited number of case studies (see for example Albala-Bertrand (1993) and Otero and Marti (1995)). This approach permits focusing on the details of a particular event, but cannot isolate the impact of a disaster because, by construction, cannot control for other simultaneous shocks. For instance, disasters may be followed by aid flows that attenuate their macroeconomic consequences. Also, the limited number of cases typically analyzed (26 cases in Albala-Bertrand (1993)) also casts doubts on the generality and external validity of the conclusions. A different strand of this literature has started to use broad recently-available data sources to provide systematic evidence on the macroeconomic impact of disasters. Skidmore and Toya (2002) study the long-run growth consequences of natural disasters using data on the incidence of several types of disasters on a large sample of countries. They use cross-country regressions to determine the relation between the incidence of disasters (measured as the total number of disasters per land area) and growth, and find a positive effect of climatic disasters and a negative effect (although not always significant) of geological disasters. Although the paper controls for several country characteristics, the possibility of omitted variable bias and endogeneity cannot be ruled out in this setting.[2]

To overcome some of the problems associated with the cross-country approach, other papers have exploited the within country, time-series variation in the occurrence of disasters. Ramcharan (2007), and Noy (2009) use standard dynamic panel specifications to estimate the impact of disasters on various aspects of macroeconomic performance. Ramcharan (2007) estimates the differential impact of earthquakes and windstorms in 120 countries with fixed and flexible exchange rate regimes during the period 1961-2000 to test the hypothesis that a flexible exchange rate helps smoothing real shocks. Noy (2009) uses similar data to estimate the short run impact of disasters on growth controlling for the magnitude of a disaster and to relate the impact to structural characteristics such as the quality of institutions, financial development, and human capital. The close relation of these papers with the dynamic panel literature leads them, however, to not fully exploit the time variation of the data and to rely on restricted functional forms and identification assumptions. In particular, they impose the lag structure instead of deriving it from standard lag tests, assume first difference stationarity instead of testing for the stationarity of the variables, and rely on some controversial identification assumptions: exogeneity of exchange rate regimes in the case of Ramcharan (2007) and predeterminedness of variables (which is sensitive to the lag specification) in the case of Noy (2009). A recent paper by Raddatz (2007) addresses some of these problems using standard time-series techniques in a PVAR model, and relying on identification assumptions based mainly on the exogeneity of external shocks. However, this paper studies the impact of a broad set of external shocks and, therefore, treats natural disasters in a highly parsimonious manner that disregards part of the information contained in specific types of shocks and also group disaster prone countries with those that have never experience these types of episodes.

This paper contributes to this literature by providing systematic evidence on the output cost of natural disasters coming from a large and comprehensive set of different types of catastrophes on a large sample of countries and over an extensive period of time, applying standard time-series techniques that exploit mainly the within-country time series variation of the data and provide a natural manner of assessing the short and long run impact of disasters, and only relying on relatively uncontroversial assumptions about the exogeneity of disasters from within country output fluctuations.

[2] Although the occurrence of disasters is arguably exogenous, the criteria used to record events in the existing databases make disasters occurring in poor countries more likely to be recorded. Pure cross-country variation does not permit to control for this possibility.

This paper also relates to several recent articles that study how the impact of disasters vary with a country's structural characteristics or stage of development. Toya and Skidmore (2007) study the relation between various country characteristics besides income and the expected mortality and losses (as fraction of GDP) caused by natural disasters in a sample of 151 countries between 1960 and 2003, finding that higher educational attainment, greater openness, a strong financial sector, and smaller government were associated with a smaller cost of disasters. Benson et al. (2004) argue on theoretical grounds that the impact of disasters is the highest among middle income countries, where sectors are more interconnected than in poor countries but lack the coping mechanisms available in rich countries. These predictions are partially supported by evidence from Kellenberg and Mobarak (2008), who show that the relation between income and the deaths arising from floods and windstorms has an inverted U-shape. This paper contributes to this literature by providing complementary evidence on the costs of disasters across different groups of countries.

Finally, the paper also relates to the new empirical research on the macroeconomic consequences of climate change, in particular, to Dell et al. (2008), who estimate the impact of changes in temperature on growth at annual frequencies, and find that temperature increases have a significantly negative effect on growth in poor countries. The evidence on this paper complements Dell et al. (2008), by showing that droughts and extreme temperature episodes, those most likely related to rising temperatures indeed have a stronger impact on low income countries.

The rest of the paper is structured as follows. Section 2 describes the data sources, the main variables to use and presents summary statistics for the incidence of natural disasters around the world. Section 3 presents the empirical methodology used in the paper to estimate the output consequences of natural disasters. Section 4 presents in detail the main results of the paper. Section 5 concludes.

2 Data

Data for natural disasters were obtained from the Emergency Disasters Database (EM-DAT) maintained by the for Research on the Epidemiology of Disasters (2008) (CRED). This is a comprehensive database that includes data on the occurrence and effects of over 12,800 mass-disasters in the world since 1900, and is compiled from a diversity of sources. As a general principle, to enter into the database an event has to meet any of the following conditions: there are ten or more people reported killed; there are 100 or more people reported affected; a state of emergency is declared; or there is a call for international assistance.

The data contain information on various types of disasters that I classify in three broad categories. Geological disasters include earthquakes, landslides, volcano eruptions, and tidal waves. An important characteristic of this type of events is their unpredictability and relatively fast onset. The second category is climatic disasters. This category includes floods, droughts, extreme temperatures, and windstorms (e.g. hurricanes). Compared to the previous category, some of these disasters can be forecasted well in advance (so precautions can be undertaken) and have a relatively long onset.

Since these are the disasters whose incidence is most likely to be affected by the ongoing process of global climate change, I also consider them individually in the analysis. The final category is a residual group that includes famines, epidemics, insect plagues, wild fires, miscellaneous accidents, industrial accidents, and transport accidents.[3]

In each category, the incidence of disasters is measured by counting the annual number of events that classify as large disasters according to the following criteria established by the International Monetary Fund (see Fund (2003)): the event either affects at least half a percent of a country's population, or causes damages to the capital stock, housing, human lives, etc. of at least half a percent of national GDP, or results in more than one fatality for every 10,000 people.

Starting from this variable, I also construct a different measure that not only counts the number of disasters but also takes into account the month of the year when a disaster occurs, in a manner similar to Noy (2009). This allows disasters occurring early in the year to have a different contemporaneous impact that those that happen near the end of the year. This is basically a re-normalization of the incidence measure described above, since just counting the number of disasters yields an estimation of the output costs of a disaster occurring at the sample mean date during the year. Taking into account the date of occurrence, produces an estimate of the output cost of a disaster occurring January 1st.

Since the main goal of the paper is to estimate the impact of natural disasters related to the process of climate change, the analysis focuses on the set of countries that has experienced at least one large climatic disaster since 1950. This group of countries is shown in Figure 1, which maps the incidence of climatic disasters in the world (average number of disasters per year in each country, divided in four quartiles). It shows that these disasters occur across the world but tend to be more heavily concentrated in countries located around the Indian and Pacific oceans, probably related to the influence of El Niño. Figure 2 displays similar information as Figure 1, but separately for each type of climatic disasters (Panels A to D). Here the geographic clustering of various types of disasters is more evident. Wind storms tend to occur more frequently in the Caribbean, the Bay of Bengal, and around the East China Sea. Sub-Saharan Africa is mainly affected by droughts, and to a lesser extent, by floods, which are also frequent in Latin America. In contrast, extreme temperatures are concentrated in Europe, with some incidence also in Australia and South America.

There has recently been much discussion about the impact of the process of global warming on the incidence of natural disasters around the world. Figure 3 shows that the data indeed exhibits an increase in the incidence of climatic disasters during the last four decades. The average world incidence of climatic disasters (disasters per country) has increased from 10 percent in the early 1960s to about 30 percent in the late 1990s (Panel B). This is not the case for geological disasters that are not related to the global warming process (Panel A), so this trend is not purely caused by an increase in the frequency with which disasters are recorded in the database. For the residual

[3] Some of these events, such as famines, may be endogenous and related to the incidence of other truly exogenous disasters. Other, such as industrial accidents, are not natural disasters. They are included as a broad way of controlling for other episodes that may occur simultaneously to some of the disasters under analysis. The results are largely unchanged if this category is excluded or restricted to include only the most clearly exogenous events.

category that includes famines and wild fires (which are indirectly related to the climate) there is also an increasing, albeit less sharp trend. This increasing incidence of climatic disasters is not concentrated in a few countries but is a prevalent phenomenon. In fact, in almost all countries the average incidence (number of disasters per year) during 1985-2006 is larger in the period than during 1960-1984 (not reported).

Data on macroeconomic performance and other types of external shocks (used as controls in part of the analysis) come from various sources. Real GDP per-capita is measured in constant 2000 U.S. dollars and obtained from the Bank (2008) World Development Indicators (WDI). The terms-of-trade index is the ratio of export prices to import prices computed using the current and constant price values of exports and imports from the national accounts component of the Penn World Tables (version 6.1) and updated using the terms-of-trade data from WDI. Real per capita aid flows include the flows of official development assistance (ODA) and official aid in constant 2000 U.S. dollars, and was obtained from the WDI. Aid as a fraction of Gross National Income was also obtained from the WDI. Summary statistics for these variables for the sample of countries during the period of analysis are presented in Table 1. To have good coverage on all macroeconomic and disaster variables, the final sample used in the econometric analysis below is restricted to the post Bretton Woods, 1975-2006 period.

3 Methodology

The output impact of natural disasters across countries is estimated using a panel autoregressive distributed lags (PARDL) model that relates current output to its lagged values, and to contemporaneous and lagged indicators of the occurrence of various types of natural disasters. For a given country, the baseline specification of the model corresponds to

$$y_{i,t} = \sum_{j=1}^{q} \alpha_j y_{i,t-j} + \sum_{j=1}^{q} B_j D_{i,t-j} + \theta_i + \theta_t + \epsilon_{i,t}, \tag{1}$$

where $y_{i,t}$ is the (growth of) real GDP per capita (in constant 2000 US dollars) of country i at time t, and, in our baseline specification, $D'_{i,t} = (GEO_{i,,t}, CLIM_{i,t}, OTH_{i,t})'$ is a vector of variables capturing the occurrence of geological, climatic, or other disasters, as described in the previous section. However, the impact of different types of climatic disasters will also be separately estimated, in which case

$$D'_{i,t} = (GEO_{i,,t}, WIND_{i,t}, FLOOD_{i,t}, DROUGHT_{i,t}, TEMP_{i,t}, OTH_{i,t})',$$

where $WIND$, $FLOOD$, $DROUGHT$, and $TEMP$ are indicators of the incidence of wind storms, floods, droughts, and extreme temperatures, respectively. The parameters θ_i and θ_t are country and year fixed-effects that capture long run differences in growth across countries and the impact of global factors that are common to all countries in the sample and can be understood as the world business cycle. The residual term $\epsilon_{i,t}$ corresponds to an error term that is assumed i.i.d. The number of lags q is assumed to be equal in both summatories to ease comparison with the panel VAR described below. Relaxing this assumption does not importantly change the results.

In addition to the baseline specification described above, I also estimate models that control for the potential output impact of other external shocks. Since the specification described in equation (1) already controls for common global factors in a non-parametric way (through the time fixed-effect), these additional external shocks only include country-specific, time-varying variables. In particular, I estimate versions of the model above that control for the impact of terms-of-trade, aid flows, and real exchange rate shocks. Including these sources of fluctuations requires some non-trivial modifications to the empirical specification. The empirical specification corresponds in this case to a panel vector autoregression (PVAR) instead of a PARDL model, and is given by

$$A_0 x_{i,t} = \sum_{j=1}^{q} A_j x_{i,t-j} + \sum_{j=1}^{q} B_j D_{i,t-j} + \theta_i + \theta_t + \varepsilon_{it} \tag{2}$$

where $x_{i,t} = (TT_{i,t},\, y_{i,t})'$, $TT_{i,t}$ is the (growth of) a terms-of-trade index, and $y_{i,t} = (AID_{i,t},\, GDP_{i,t})'$ is now a vector of endogenous variables that includes the (growth of) real GDP per capita (in constant 2000 US dollars) (GDP), and the (growth of) real per capita aid flows (AID). Correspondingly, the parameters of the model are now matrices, denoted by A_j, instead of scalars, and the structural interpretation of the results depends on the identification of the parameters of the contemporaneous matrix A_0.

The main identification assumption of this empirical strategy is that the occurrence of natural disasters is exogenous. They are assumed to be acts of God that are unrelated to any present or past economic variable. Although the identification of the baseline model in equation (1) does not require further assumptions, identifying the impact of other shocks in model (2) require additional assumptions. Throughout the paper it is assumed that the terms-of-trade do not respond to the y variables at any lags but probably have a contemporaneous and lagged effect on them, which is equivalent to imposing a diagonal structure in all the A matrices. For the developing and small developed countries included in this study, these assumptions should be uncontroversial. The assumption is more debatable for the developed countries included, but the assumption is maintained to ease comparison across groups of countries and specifications.

The aid flows are included in the y vector because they are likely to respond to a country's economic performance, and are identified by assuming a contemporaneous causal order among the variables included that is given by their position in the vector. This means that the A_0matrix of contemporaneous relations among the y variables is assumed to be block triangular, which corresponds to assuming that output responds contemporaneously to changes in the aid flows, but the latter responds to changes in a country's economic conditions only after a year.[4]

The models described in equations (1) and (2) correspond to a PARDL and PVAR, respectively, because they assume that the dynamics, represented by the different parameters and matrices,

[4]For a discussion on the delays on aid allocation, see Odedokun (2003)

are common across the different cross-sectional units (countries) included in the estimation, which are indexed by i. This is a standard assumption in this literature (see Broda (2004); Ahmed (2003), Uribe and Yue (2006)) because, given the length of the time series dimension of the data (around 30 annual observations), it is not possible to estimate country-specific dynamics unless we reduce importantly the number of exogenous shocks under consideration, the number of lags, or both. However, as noticed by Robertson and Symons (1992), and Pesaran and Smith (1995), this assumption may lead to obtaining coefficients that underestimate (overestimate) the short (long) run impact of exogenous variables if the dynamics differ importantly across countries. For this reason, I also check some of the results using the Pesaran and Smith (1995) mean group (MG) estimator, which they show to estimate consistently the parameters of the model.

The baseline specification in equation (1) models the behavior of output growth (first differences of the log). There are several reasons for this modeling choice. First, standard tests suggest the presence of a unit root in the GDP series. The results of those tests are summarized in Table 2, which presents summary statistics for standard unit root tests performed on a country-by-country basis, as well as results from the Levin et al. (2002) panel unit root test. It is clear that the fraction of countries where the hypothesis of a unit root cannot be rejected is high for the levels of log GDP but negligible for its first difference. Also, the panel unit root test cannot reject the null hypothesis of a unit root for the series in levels but it clearly does for the series in differences. Second, previous empirical papers in this literature (e.g. Broda (2004), Ahmed (2003), Loayza and Raddatz (2007)) have estimated difference stationary models, so this specification has the advantage of being directly comparable with the existing results. Finally, on a more pragmatic note, the estimated impulse responses are better behaved in the model in differences than in alternative models specified in levels. Nevertheless, recognizing the low power of unit root tests I also present results for the model in levels as a robustness check.

Evidence on the order of integration of the other series included in the panel VAR version of the model is more ambiguous. Although in a majority of individual series the hypothesis of a unit root cannot be rejected, panel unit root tests are sensitive to the number of lags included. This sensitivity, however, largely disappears when testing for the presence of unit roots for the series in differences, case in which there is also a large fraction of countries where the hypothesis of a unit root can be rejected, reasons for preferring to model the series in differences.

Modeling the variables in first differences also requires testing for the possibility of cointegration, which is done using Pedroni (1999)'s test for cointegration in panels. The various statistics proposed by Pedroni (1999) yield somewhat ambiguous results, although in most cases the null hypothesis of no cointegration cannot be rejected (see Table 3). Moreover, Pedroni (2004) shows that for the sample characteristics that are closer to those used in this paper (N larger than T) the panel-rho test, which systematically cannot reject the null of no cointegration, has the best size and power properties. Therefore, standard tests of unit root and cointegration suggest that the models should be estimated a in differences and without cointegration relation. Nevertheless, because of the ambiguity of the tests, I also check the results after estimating the model in levels (which should yield a consistent albeit inefficient estimator under the null of cointegration). Results will prove to be similar in both cases.

Standard lag tests suggest estimating the model including two annual lags (Schwartz information criterion). Three annual lags are also considered for robustness.

The parameters of the two versions of the model, estimated in reduced form by OLS (eq. [1]) or SURE (eq. [2]) are used to recover the impulse-response functions (IRF) of per capita GDP to each of the structural shocks using the variance-covariance matrices of reduced form errors derived from these coefficients. The confidence bands for the IRF come from parametric bootstrapping on the model assuming normally distributed reduced form errors.[5]

4 Results

This section presents the results from the estimation of the panel ARDL and panel VAR models described above in the sample of countries that have experienced at least one large climatic disaster since the 1950s. It first describes the results on the sample as a whole and then presents results for sub-groups of the sample, split according to characteristics that have been mentioned to affect a country's vulnerability to disasters.

4.1 The output impact of natural disasters

The dynamic responses of output to the various types of natural disasters obtained from the estimation of the parameters of equation (1) are depicted in Figure 4. The different panels of this figure show the cumulative impulse-response functions (IRF) of (the growth of) real per capita GDP (GDP) to each type of natural disaster, under the benchmark identification assumptions. Since the model was estimated in growth rates, the cumulative IRF show the cumulative output effect of each of these shocks. The continuous line depicts the point estimate of the IRF, and the broken lines show the 90% confidence bands obtained from the empirical distribution.

Climatic disasters have, on average, a negative, statistically significant impact on per capita GDP (Panel A), which has a cumulative decline of 0.6 percent after a large climate related catastrophe. In other words, in the long run, per capita GDP is 0.6 percent lower as a result of a single climatic event. Most of the output cost (about 0.5 percent loss) occurs during the year of the disaster. In contrast, geological disasters do not have a statistically significant output impact, and a slightly positive long-run associated point estimate (Panel B). Other types of disasters (which include famines, epidemics, etc.) also negatively affect output, with an estimated cumulative output loss of about 2 percent (Panel C) that is larger that that of climatic disasters, but less statistically significant.

[5]The procedure corresponds to repeating 100 times the following set of steps: (i) the estimated variance-covariance matrix of the reduced form errors is used to simulate a random realization of the perturbations; (ii) the initial values of the different variables, the baseline coefficients, and the simulated perturbations are used to simulate a new set of observations for the variables in the VAR; (iii) a new set of coefficients is obtained from these fictitious observations. Each set of coefficients obtained from the bootstrapping procedure yields a different IRF; these IRFs are used to build the 90% confidence interval by computing the Euclidean distance between each simulated IRF and the baseline one and taking those IRFs whose distance falls between the 5th and 95th .percentile.

A direct criticism of the results presented above is that they may be attributing to natural disasters the impact of other external shocks that are excluded from the model. A commonly cited source of external shocks is the variation in a country's terms of trade. Another potential problem with the baseline results is that the actual impact of the disasters may be compounded with the response of the international community in the form of aid flows. Results presented in Figure 5, obtained from estimating the parameters of equation (2) that considers these two sources of external fluctuations, show that this is not the case. The dynamic responses show that terms-of-trade shocks have a positive and significant effect on per capita GDP; according to the estimates, a one standard deviation increase in terms of trade (corresponding to a 13 percent increase) results in a cumulative output effect of about 0.7 percent. Sudden increases in aid flows also positively impact output; in this case a one standard deviation increase in per capita aid flows (40 percent increase) induces a 0.4 percent increase in per capita GDP. Both results are in line with previous estimates obtained in the literature (see Raddatz (2007)). However, the figures also show that the impact of climatic and other disasters is qualitatively and quantitatively similar across specifications. The results from the estimation of equation (1) were not driven by a spurious correlation between terms of trade shocks and the occurrence of specific disasters, nor were attenuated importantly by the responses of the international community in terms of aid flows.[6]

All findings documented above are also robust to changes in the number of lags used in the estimation and to the estimation of the model in levels instead of differences. Panels A and B of Figure 6 show the dynamic responses obtained when using three lags in the estimation of the baseline model in differences and in levels, respectively. In the latter case, the output level is treated as stationary, although the persistence of the response to the shocks indicates that this assumption is probably incorrect. Nevertheless, the output costs of different shocks, which in this case are given by the area under the dynamic response curves, are similar to those obtained in the baseline estimation (not reported).

As mentioned in section 3, despite its advantages in terms of increased degrees of freedom and power, pooled estimators may suffer from important biases in presence of significant parameter heterogeneity across cross-sectional units. Pesaran and Smith (1995) pointed out this problem and suggested using a mean group estimator to obtain consistent estimates of the model's parameters. Their approach requires separately estimating the model's parameters for each cross sectional unit and averaging the estimated parameters, so it can only be implemented in the simplest version of equation (1) which includes only three groups of disasters. Adding more variables or lags yields individual models with too few degrees of freedom. Also, Pesaran and Smith (1995)'s approach relies on having a large number of cross sectional units, so it can only be feasibly applied to the whole sample of countries instead of the smaller groups considered later on. With these caveats, the results obtained from applying this approach, summarized in the dynamic responses depicted in Figure 7 show that the qualitative nature of the results is not affected by the pooling across large

[6] The estimation of equation (1) in the sample of countries with terms of trade data also yield similar results as above. The separate consideration of terms of trade and aid flows to the model described in equation (2) also yields similar results (both non reported).

groups of countries. Quantitatively, however, most disasters have a higher impact according to this estimator, which indicates that the pooled estimator may suffer from attenuation. The estimated cumulative output loss is in this case 1 percent of GDP for Climatic disasters and 5 percent of GDP for Other Disasters (residual category). If these results offer some indication of the magnitude of potential biases, they suggest that pooled estimators result in an attenuation of about 40 percent. Therefore, while qualitatively correct, results from pooled VARs should probably be considered as conservative estimates of the impact of natural disasters.

The results reported in Figure 4 quantify the impact of a general climatic disaster. However, this category embeds different types of disasters that can arguably have different output consequences. The dynamic responses of GDP per capita to various types of climatic disasters obtained from estimating the extended version of equation (1) and depicted in Figure 8 check for this possibility. The results show some interesting variation across disaster's types. Droughts and extreme temperatures are those with the largest average impact, reaching cumulative losses of 1 and 5 percent of GDP respectively, both statistically significant at the 10 percent level. Results for extreme temperatures, however have to be taken with caution because of the small set of countries affected by this type of disaster (only 12). When looking across the baseline sample of all countries affected by some type of climatic disaster, windstorms and floods do not seem to have a significant output impact. It is possible, however, that these types of disasters affect specific groups of countries. The results in the following sections come back to this issue.

The dynamic responses reported so far depict the output effect of a unique disaster occurring at time zero. This approach implicitly treats disasters as independent events across time, whose occurrence can be modeled as Bernoulli events. Because of the nature of catastrophes this is a reasonable assumption. However, in the case of climatic disasters it is possible to argue for some serial correlation in the incidence of disasters arising from climate cycles such as those associated with El Niño. In fact, the data show some statistically significant serial correlation among Climatic disasters that is largely absent among other types of catastrophes (Table 4). No significant serial correlation among other types of disasters or cross-correlations across disasters is found in the data. Because of the serial correlation of climatic disasters, an alternative exercise is to model the expected dynamic response of output to a climatic event taking into consideration that the event itself affects the probability of another event occurring in the future. Results allowing for serial correlation are much like those reported in the baseline case, although climatic and other disasters have slightly larger estimated output costs corresponding to 0.8 and 2.5 percent of per capita GDP, respectively (not reported).

All results above use a measure of the incidence based on the number of disasters occurring in a given year, regardless of the moment of the year the disaster takes place. In that sense, the output effects documented correspond to those of a disaster occurring at the sample average day of the year (i.e. the average of the day of the year when the different events included in the sample occurred). However, it might be argued that disasters occurring very late in a year may have little contemporaneous output effect and instead impact next year's reported GDP. Results reported in

Figure 9 consider this possibility by using the weighted incidence measure described in section 3. This figure, therefore, shows the dynamic responses of output to a disaster occurring on January 1st. It can be seen that the timing of the disaster makes a difference: disasters occurring earlier in the year have a larger annual impact on the year of the incident. For instance, compared to a disaster occurring at the sample average day with a per-capita output loss of 0.6 percent, a climatic disaster occurring on January 1st induces a loss of about 1 percent. This timing effect should be kept in mind during the rest of the paper that follows the convention of reporting results for disasters occurring at the sample average day.

4.2 Are small states special?

It is often claimed that small states have a harder time dealing with natural disasters because of their inability to diversify geographically. If this is the case we would expect disasters to have a larger output impact in small states. This section tests this hypothesis comparing the dynamic responses of output to natural disasters in small states (those with population smaller than one million people) with that of larger countries. The results are depicted in Figures 10.

When looking at broad disaster's categories, small states do not seem to be significantly more affected by disasters than larger countries (rows 1 to 3).[7] In fact, there is no type of natural disaster with significant impact among small states. In contrast, climatic disasters and those in the residual category have a sizable negative significant effect in the rest of the world, both with a cumulative loss of about 0.5 percent. However, because of the broad confidence intervals reported for small states, none of the differences in responses between small states and the rest of the world is statistically significant.

The previous finding is not driven by potential biases in the pooled estimator, although the magnitude of the response partly does. When estimating the impact of disasters using the MG estimator there is a negative, but insignificant response of small states' output to climatic disasters, but the magnitude of this response is similar to the (significant) response observed among other countries (not reported). The evidence, therefore, indicates that small states do not respond more than other countries to a general type of climatic disaster.

While not significantly more sensitive to broad categories of disasters, the differences documented above on the differential impact of various types of climatic disasters suggest the possibility that small might be more sensitive to the impact of specific types of climatic disasters. This possibility is checked by opening the climatic disaster category into its components, and estimating the response of small states to these different climatic disasters. The results indicate that small states do have a stronger response to wind storms than other states (row 4). The difference between the response of small and other states to this type of catastrophes is also statistically significant.[8] Small states also exhibit a positive and significant response to floods (not reported), but this last result has to

[7]Within a row, figures are reported on the same scale to ease comparison.

[8]The significance is based on the empirical distribution of the differential response, estimated in a nested version of the model.

be taken with caution because only 7 of the 16 small states in the sample experienced one flood in the sample period. The identification of this result, therefore, relies on very little information. In contrast, 15 of the 16 small states experienced windstorms, and typically several of them during the period. The composition of the countervailing response of small states to windstorms and floods explains the lack of differential response documented in the aggregate. Among small states, a wind storm typically results in a cumulative output loss of 2 percent of GDP, while the same figure among larger states is an insignificant increase of 0.3 percent. On the other hand, droughts and extreme temperature events have a higher impact among larger countries (more on this below). Considering wind storms in isolation in the sub-sample of countries affected by this type of disasters yields similar results (not reported). [9]

4.3 Does the level of development matter?

Less developed countries are also frequently considered as having more difficulty in dealing with natural disasters because of budgetary restrictions. A government that is cash strapped can hardly gather the resources to respond to natural catastrophes. To explore the validity of these claims, results in this section present the dynamic response of output to various types of disasters for countries at different levels of income.

The results clearly show that low-income countries respond more strongly to climatic disasters (Figure 11, columns 1 to 3). Among these countries, a climatic disaster results in a cumulative per-capita output loss of about 1 percent, which is also statistically significant at the 10 percent level during the initial years. For middle and high-income countries, climatic disasters result in cumulative losses of 0.5 and 0.25 percent respectively, the former also being statistically significant at the 10 percent level. This difference is also statistically significant at 10 percent level.

Separately estimating the impact of different types of climatic disasters across income groups shows that the largest response of low-income countries to climatic disasters is mainly due to the large output impact that droughts have on this group (Column 4). A drought results in a cumulative output loss of 2 percent of GDP in low-income countries. The difference is significant only at 15 percent level, however. Poor countries also seem to respond much more strongly to episodes of extreme temperatures (not reported), but this result is based only on one episode, so it is not a robust pattern of the data. In contrast, there is no significant response to any type of disaster among middle and high-income countries, although the impact of windstorms in middle-income countries is nearly significant (not reported).[10]

The stronger response of low-income countries to climatic disasters is not only driven by a higher share of agriculture in these countries GDP. While the share of agriculture is indeed larger in low-income countries (38 percent versus 11 percent in the rest of the world), the response of low income

[9] Results for mean group estimations within the group of small countries cannot be relied on because, by opening climatic disasters into its components, the underlying equation cannot be estimated on a country-by-country basis without running out of degrees of freedom.

[10] The response becomes significant if, instead of building the confidence bands based on the Euclidean distance among IRFs, one uses the empirical distribution of the responses at each point in time.

countries to climatic disasters is larger even after controlling for the agriculture share of GDP. This is shown in Figure 12 that compares the cumulative output effect of climatic disasters among low and high-income countries with low and high shares of agriculture in GDP (above and below the sample median). While the impact of these disasters is clearly lower among countries with a small agricultural share, the output consequences are are always larger for low-income countries. Also, despite the wide confidence intervals obtained for high (non low) income countries, the one sided test that the response is larger for low income countries cannot reject the null at the 10 percent level of significance.

4.4 Does indebtedness matter?

A country's level of indebtedness is also frequently mentioned as a limit to its capacity to respond to disasters and, therefore, to the impact that catastrophes may have on output. Countries that have to service large amounts of debt have little fiscal space to quickly react to catastrophes and provide relief and reconstruction. Results comparing the dynamic responses of output to disasters for countries with different initial ratios of external debt to GDP (measured by the average ratio of external debt to GDP during the period 1975-1980) show that this is not the case. [11]

The results show no correlation between the level of initial indebtedness and the impact of various types of disasters (Figure 13). The cumulative output loss of climatic disasters is almost identical for countries with initial debts below and above the median level of 30 percent of GDP. In contrast to previous results, in this case opening for type of climatic disasters indicates does not change the qualitative conclusion (not reported). For no type of climatic disasters there is a clearly differential response among more indebted countries.

It may be the case that only extreme debt levels amplify the impact of disasters. To check for this possibility, instead of comparing countries above and below the median level of indebtedness, the sample is divided in three groups of initial indebtedness defined by the 33rd and 66th percentiles of this variable. The results are largely unchanged (not reported), most indebted countries do not seem to exhibit a stronger output response to climatic disasters than countries with intermediate or low levels of debt.

5 Final Remarks

There is nowadays increasing concern about the consequences of the process of global warming on various aspects of economic performance such as a country's productive structure, environmental costs, costs of reducing emissions, and exposure to natural disasters. Disasters typically have devastating effects on physical and human capital, with losses as a percentage of GDP that easily reach

[11] I use initial ratios to address potential endogeneity concerns on the relation between the incidence of disasters and indebtedness over the sample period. Ideally one would like to use ratios from before the sample period but this is inconvenient for two reasons. First, the sample of countries with debt information is already smaller than the overall sample, going further back in time reduces the sample even more. Second, in addition to the lack of data, many countries in the sample obtained their independence during the 1960s, it is unclear how these post-independence debt ratios have to be interpreted.

two digits. However, from a welfare point of view it is especially relevant to assess the cost of catastrophes in terms of forgone output and consumption, more than determining their impact on the stocks.

This paper uses a broad set of data to quantify the cost of natural disasters, especially those related to climatic events, in terms of GDP per capita. The results indicate that disasters have modest but economically meaningful output consequences, resulting on a decline in output per capita of about 1 percent. To fix ideas, this is larger than the typical impact of terms-of-trade shocks, which are frequently considered as important sources of fluctuations. The paper also shows an increase in incidence of these disasters of about 30 percent in the last decades, which implies an increased expected output cost of about 0.3 percent of per capita GDP.

It is important to highlight in these final remarks that these estimates come from a semi-structural model that does not cover all the potentially relevant macroeconomic variables. This means that the estimated output responses are conditional on the endogenous responses taken to alleviate their consequences. Although the paper shows that the most obvious of these responses in terms of foreign aid flows reduces only marginally the impact of the shocks, it is not possible to extrapolate these results to other palliative measures coming, for instance, from local government spending. The estimates are therefore an accurate description of the reduced form cost of disasters but probably a conservative estimate of the cost that would be observed in the absence of any mitigation effort.

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Figure 1: Incidence of Climatic Disasters Around the World

The figure displays the average incidence (number of disasters per year) of climatic disasters (windstorms, floods, droughts, and extreme temperatures) around the world. Different shades indicate thata c ountry belongs to different quartiles of the distribution of incidence. Darker shades indicate a higher incidence as detailed in the enclosed desciprion in the figure.

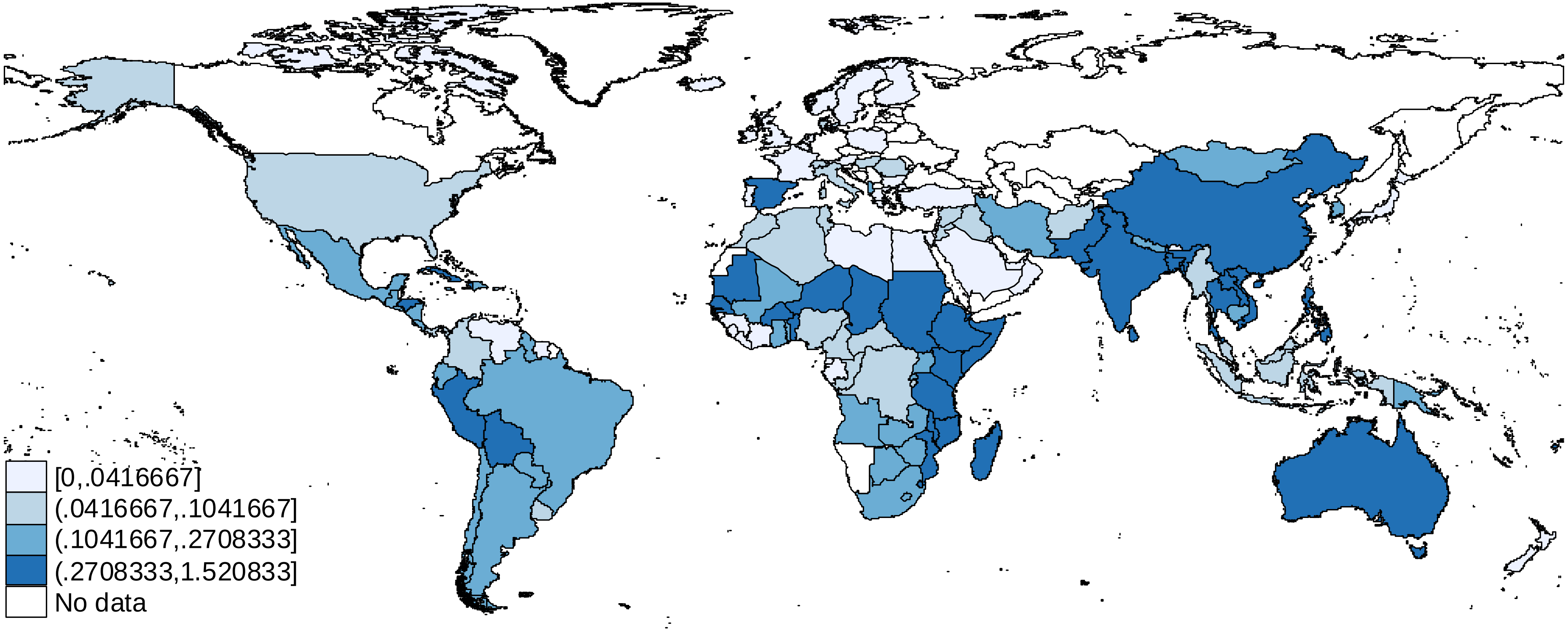


Figure 2. Incidence of Various Types of Climatic Disasters Across the World

Each panel displays the average incidence (number of disasters per year) of a different type of climatic disaster (windstorms, floods, droughts, and extreme temperatures) around the world. Different shades indicate thata c ountry belongs to different quartiles of the distribution of incidence. Darker shades indicate a higher incidence as detailed in the enclosed desciprion in the figure.

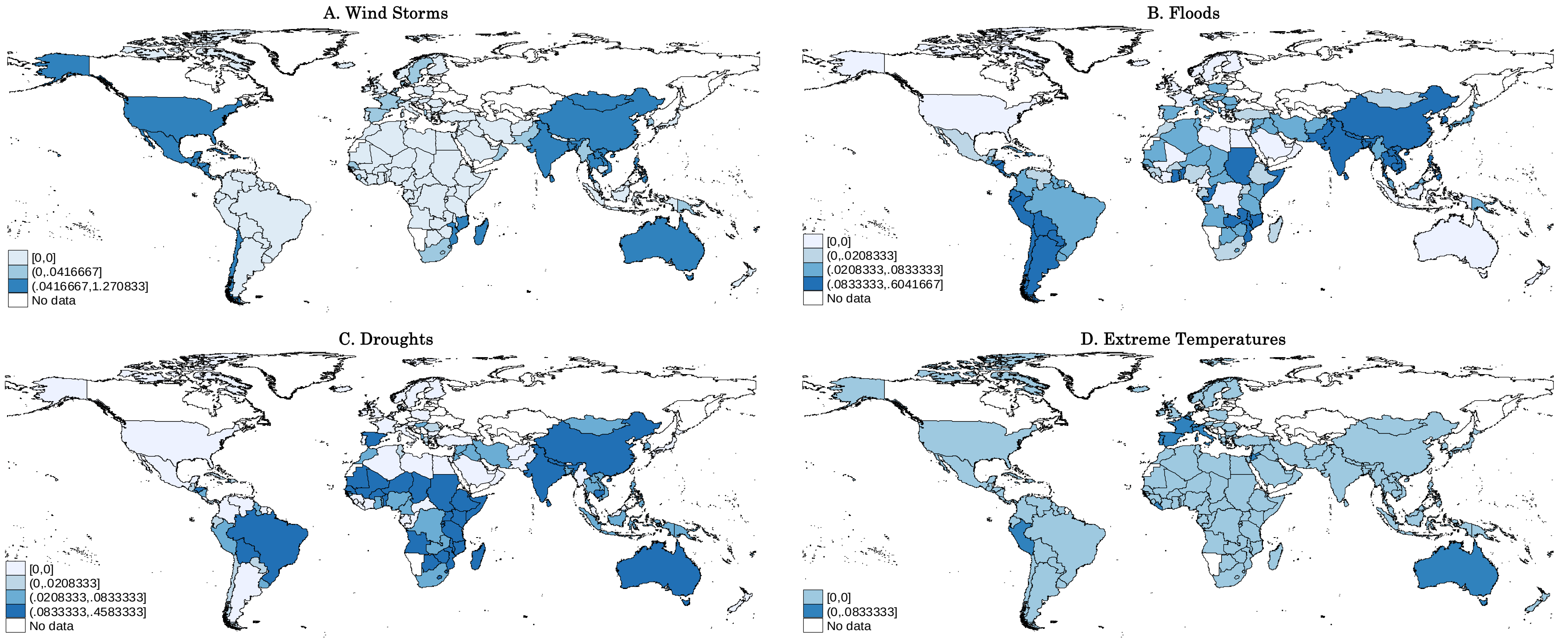
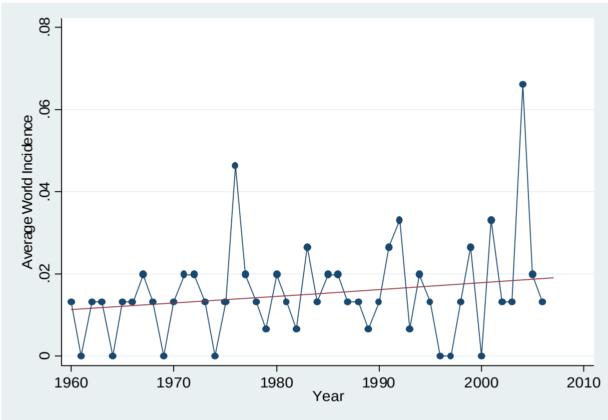


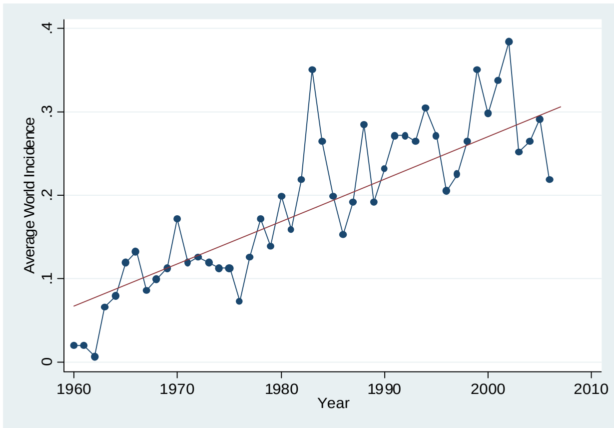
Figure 3. Evolution of the Average World Incidence of Various Disasters

The different panels of the figure display the evolution of the average world incidence of disasters, corresponding to the total number of disasters of a given type in a year divided by the total number of countries in the sample, during the 1960-2006 period, as well as a fitted trend line showing the evolution of each series

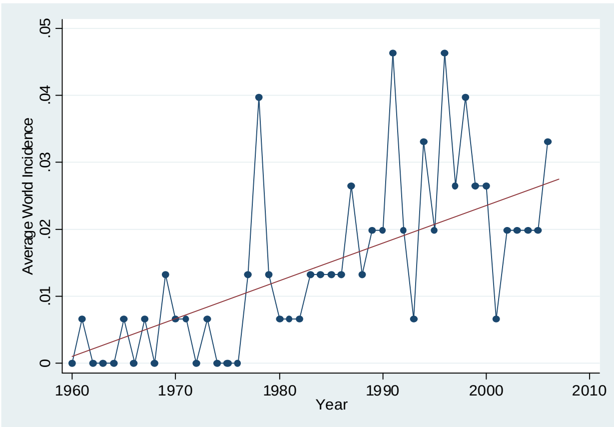
A. Geological Disasters



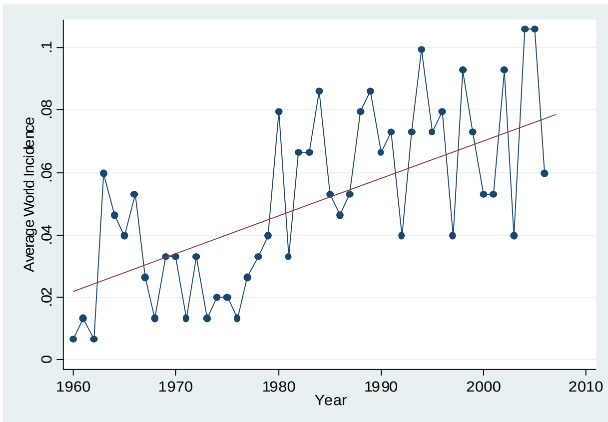
B. Climatic Disasters



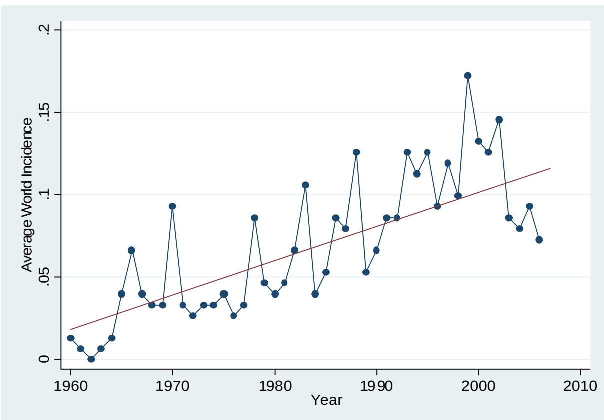
C. Other Disasters



D. Windstorms



E. Floods



F. Droughts

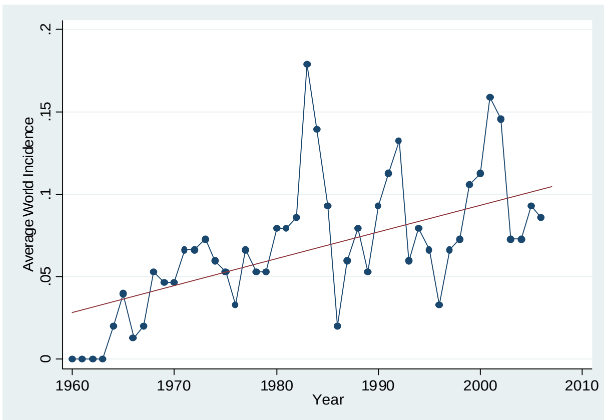


Figure 4. Output Effect of Natural Disasters, 1975-2006.

The different figures show the estimated response of per-capita GDP to the ocurrence at time zero of various types of natural disasters, indicated at the top of each figures, (solid lines) and its 90 percent confidence interval (broken lines). Time horizon is in years.

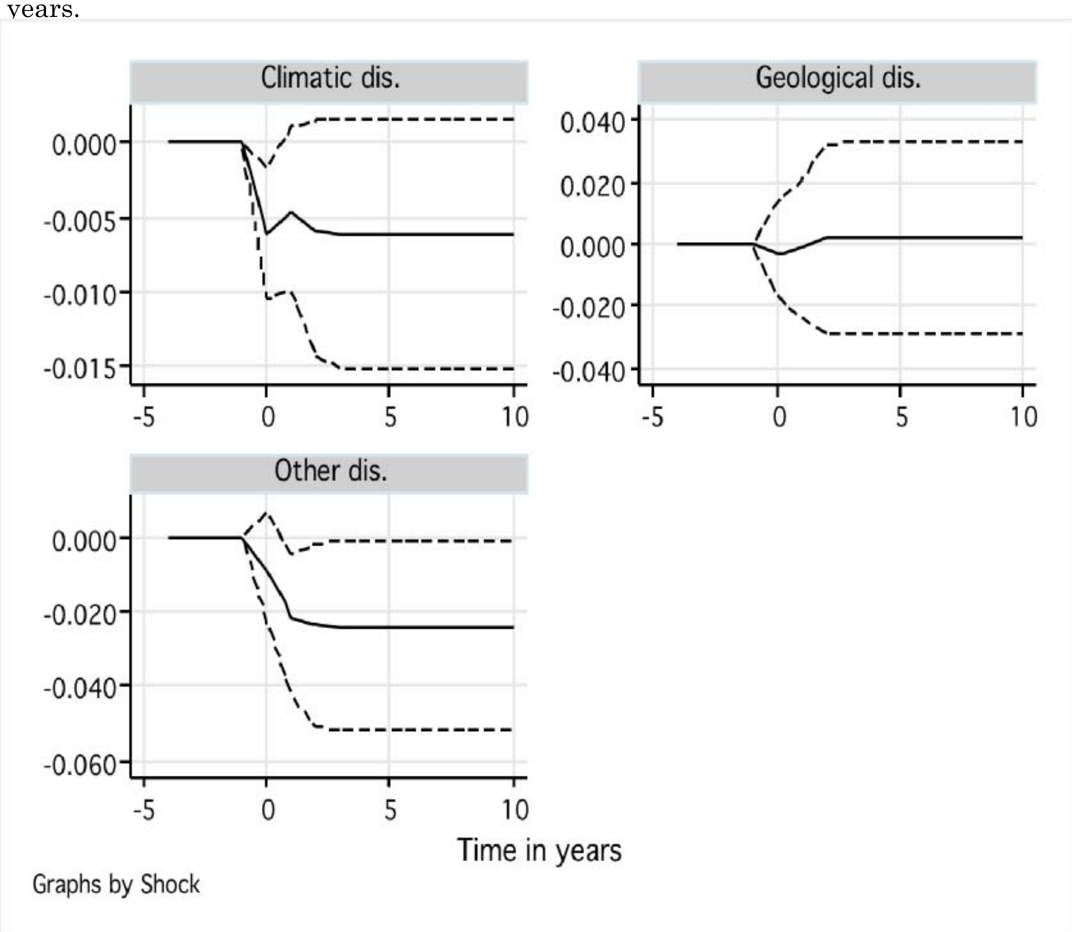


Figure 5. Cumulative Output Effect of Disasters Controlling for Terms of Trade and Aid Shocks

The different figures show the estimated cumulative (per capita) output effect of a time zero, one standard deviation orthogonal shock to the variable indicated at the top of the figure (solid lines) and its 90 percent confidence interval (broken lines), except for the cases of Climatic, Geological, and Other disasters, which report the cumulative impulse response to the occurrence of one of these events. The time horizon is in years.

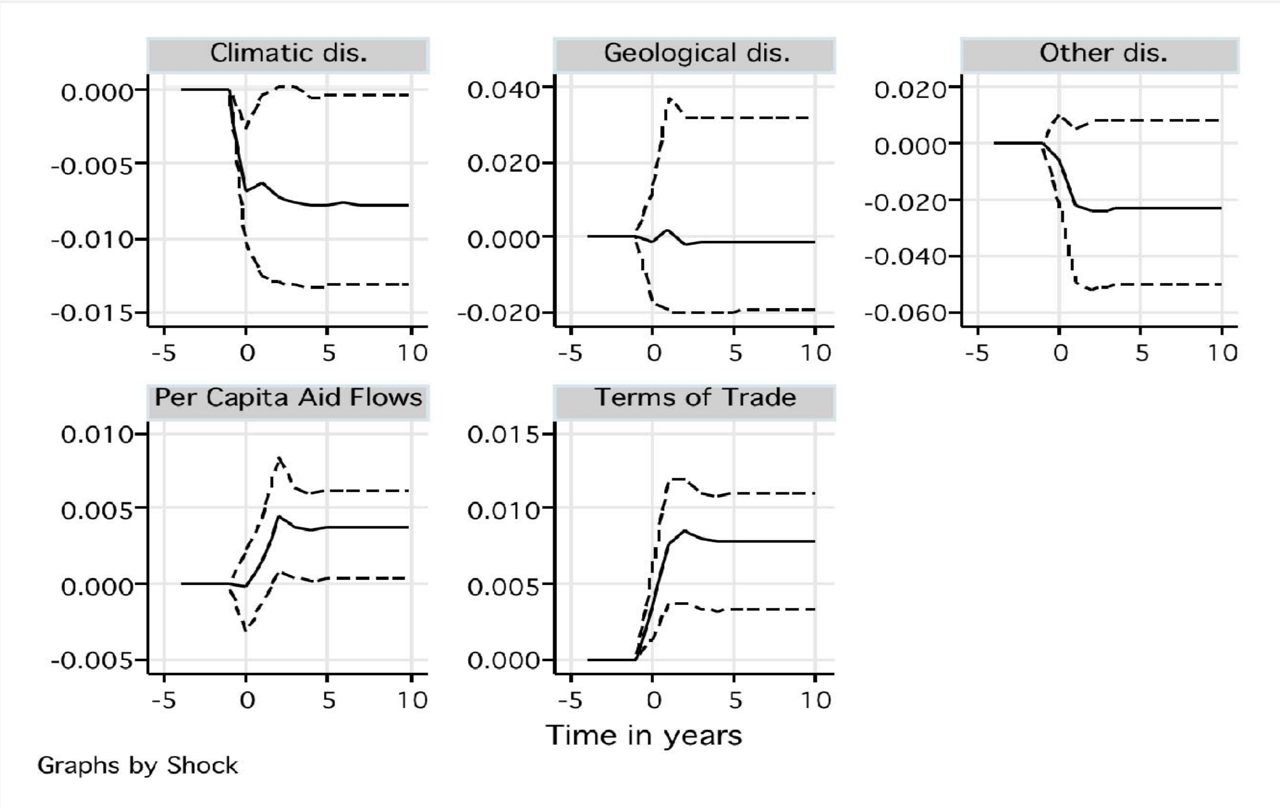


Figure 6. Output Effect of Natural Disasters Under Alternative Model Specifications.

In Panel A, the different figures show the response of per-capita GDP to the ocurrence of various types of natural disasters (indicated at the top of each figures) at time zero (solid lines) and its 90 percent confidence interval (broken lines) for the panel ARDL model estimated in differences and including three lags of each variable. Figures in Panel B instead exhibit the response of per capita GDP to similar shocks, coming from a model estimated in levels and including three lags of each variable. In both cases the time horizon is in years.

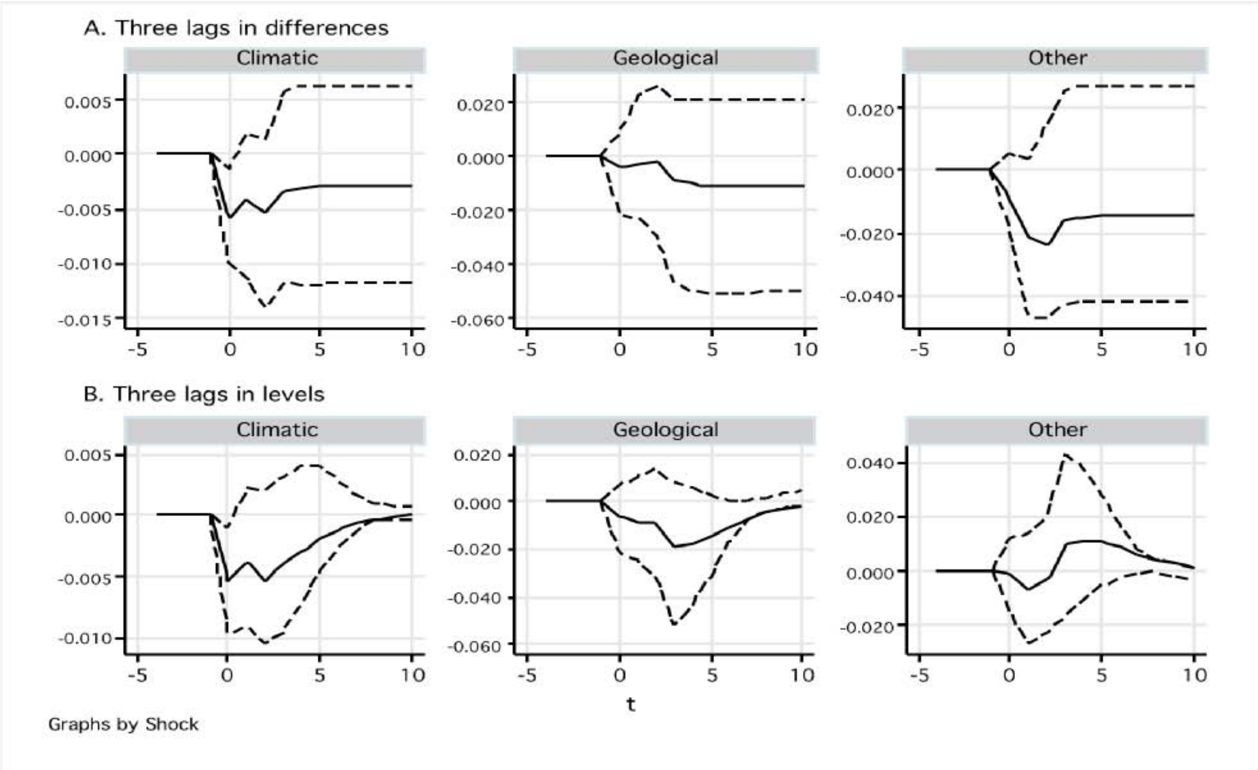


Figure 7. Output Effect of Natural Disasters, 1975-2006. Mean Group Estimates.

The different figures show the effect on per-capita GDP of various types of natural disasters (indicated at the top of each figures) at time zero (solid lines) and its 90 percent confidence interval (broken lines) estimated using Pesaran and Smith (1995) Mean Group (MG) estimator. Time horizon is in years.

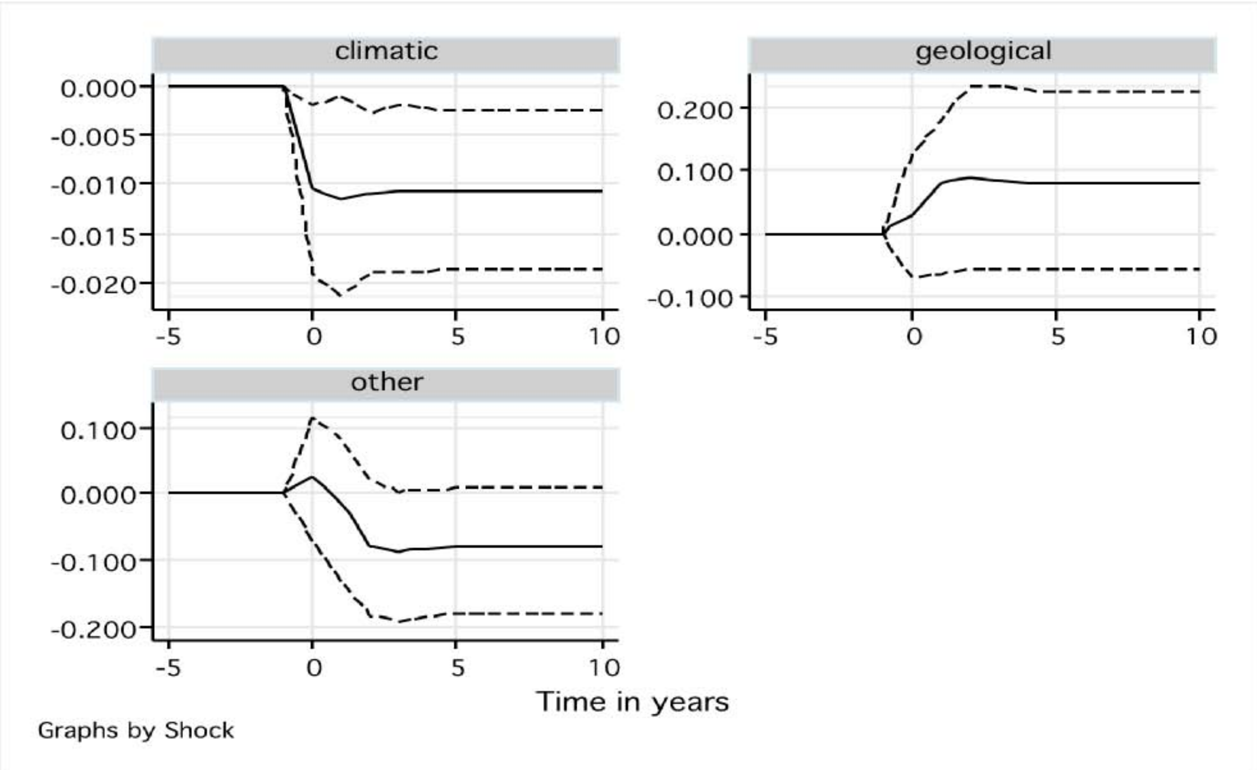


Figure 8. Output Effect of Different Climatic Disasters and other Types of Catastrophes, 1975-2006.

The different figures show the estimated response of per-capita GDP to the ocurrence at time zero of various types of natural disasters, indicated at the top of each figure, (solid lines) and its 90 percent confidence interval (broken lines). Time horizon is in years.

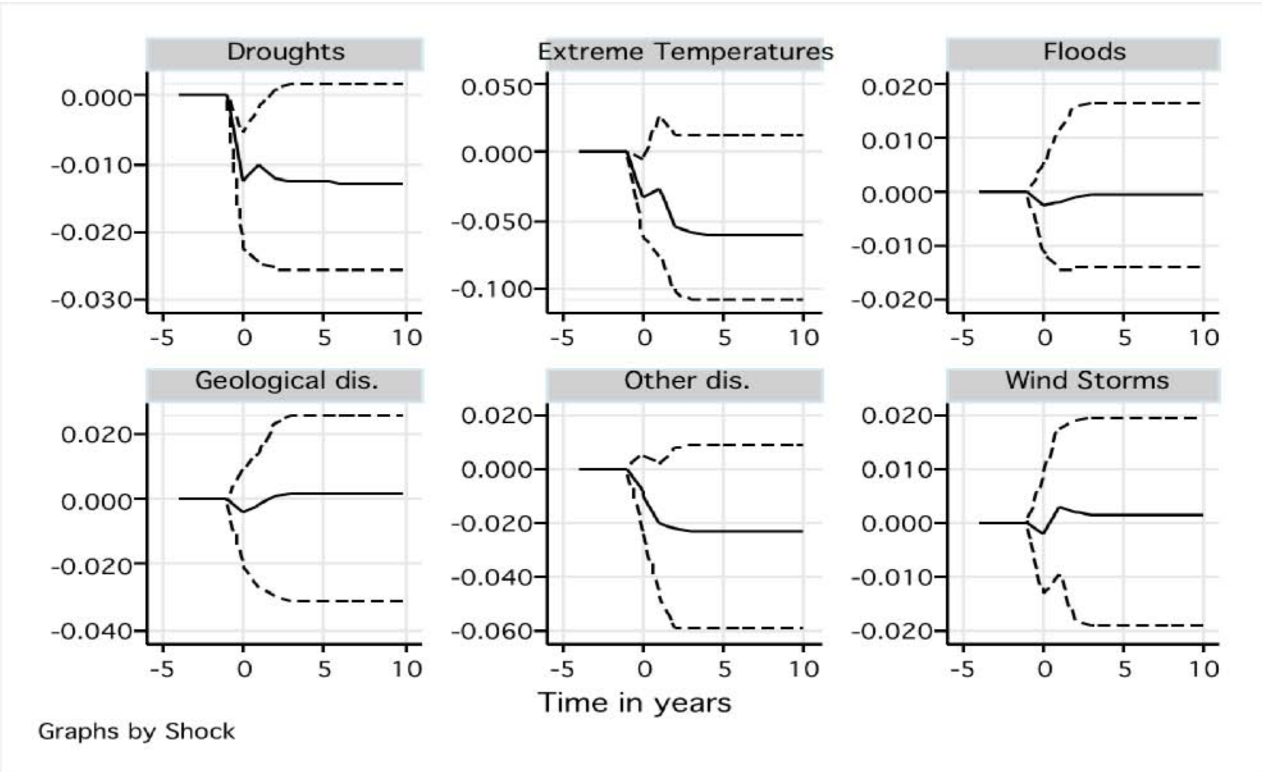


Figure 9. Output Effect of Natural Disasters. Considering within Year Timing

The different figures show the estimated response of per-capita GDP to the ocurrence of various types of natural disasters, indicated at the top of each figures, at the first day of the year indicated as time zero (solid lines) and its 90 percent confidence interval (broken lines). Time horizon is in years.

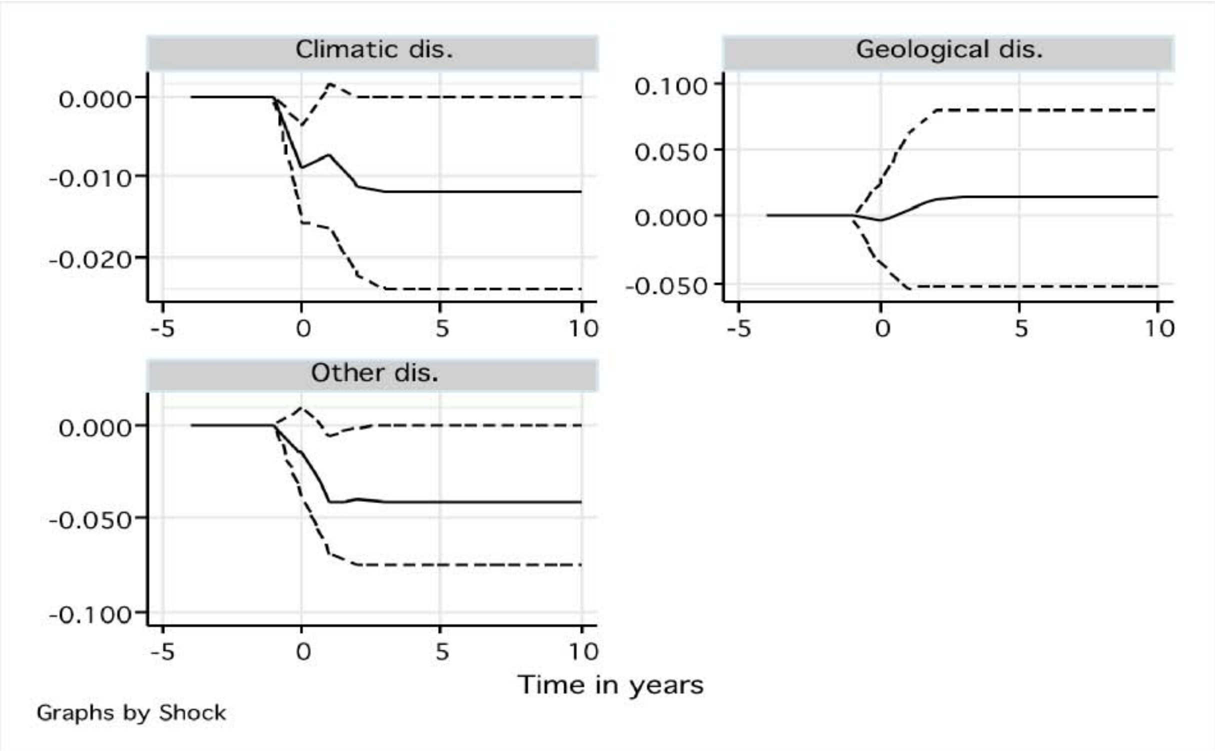


Figure 10. Output Effect of Natural Disasters, 1975-2006. Small States and Rest of the World

The various figures exhibit the estimated response of per-capita GDP to the ocurrence at time zero of various types of natural disasters, indicated at the top of each figure, (solid lines) and its 90 percent confidence interval (broken lines). Windstorms are a sub-category of Climatic Disasters. Other sub-categories (not reported) include Droughts, Floods, and Extreme Temperatures. Panel A presents results for small states (countries with average population during 1975-2006 smaller than one million people), and Panel B shows similar results for the rest of the world (countries with average population above one million people). In both panels time horizon is in years.

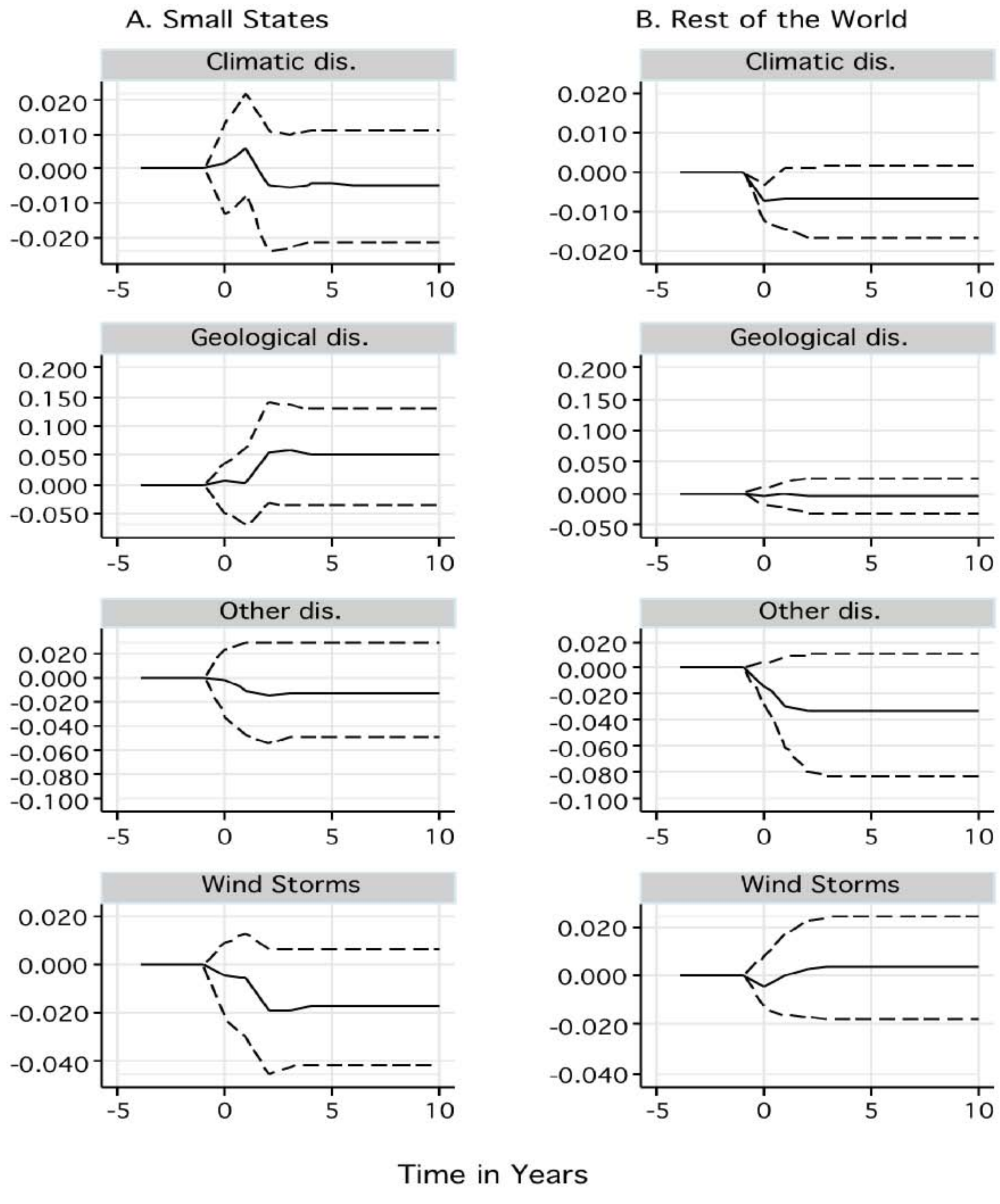


Figure 11. Cumulative Output Effect of Broad Classes of Natural Disasters by Income Level

The different figures show the estimated response of per-capita GDP to the ocurrence at time zero of various types of natural disasters, indicated at the top of each figures, (solid lines) and its 90 percent confidence interval (broken lines). Time horizon is in years. Droughts are a sub-category of Climatic Disasters. Other sub-categories (not reported) include Windstorms, Floods, and Extreme Temperatures. Panels A to C show results for low, middle, and high income countries, respectively. Countries are separated in income bins according to the classification of the World Bank (2008) World Development Indicators.

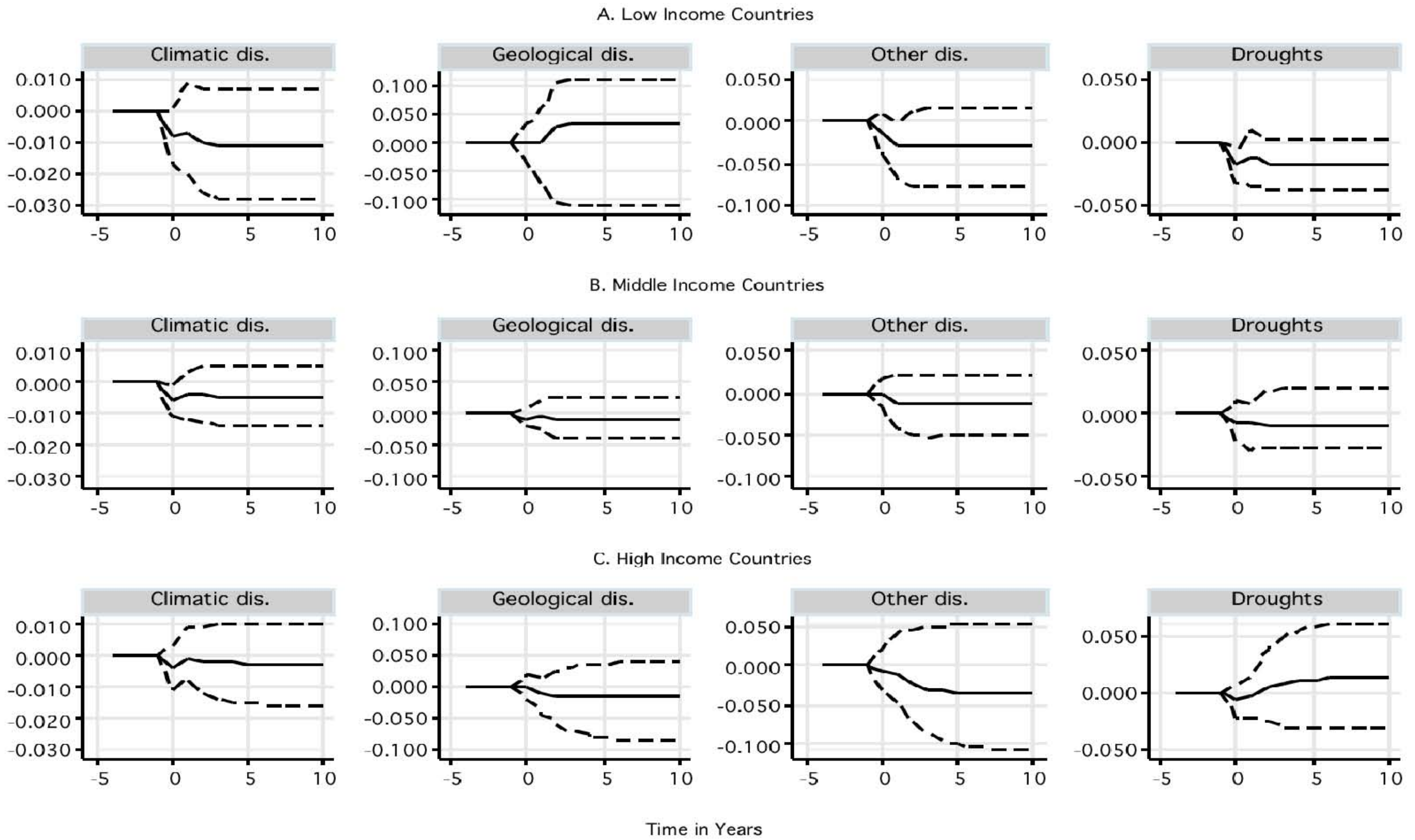
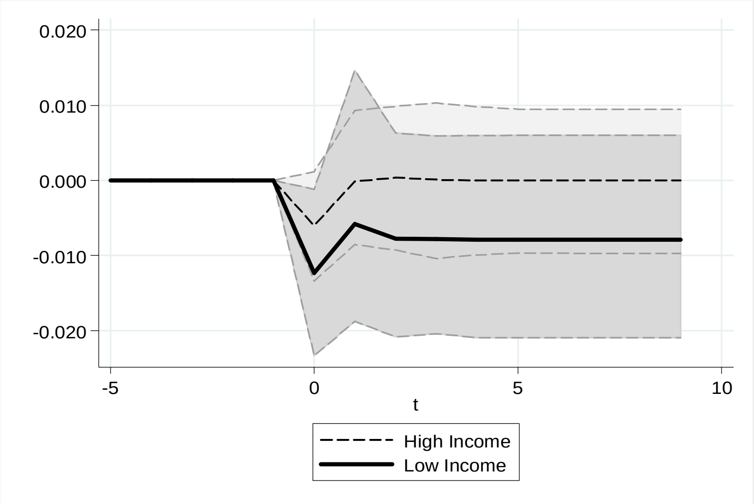


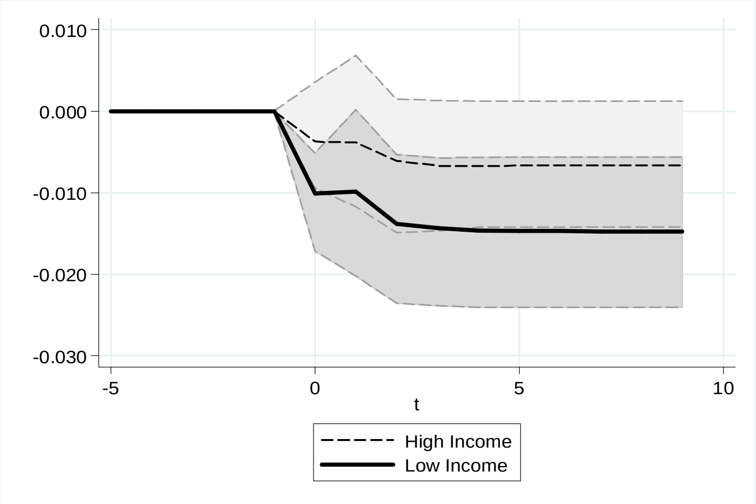
Figure 12. Output Effect of Climatic Disasters by Income Level and Agricultural Share of GDP.

The different figures show the effect on per-capita GDP of a climatic disaster at time zero on low-income and high- and middle-income countries controlling for the importance of agriculture as a share of GDP. Panel A compares the response of low and high income countries with agricultural shares of GDP below the cross country median (20%). Panel B presents the same comparison for countries with agricultural share of GDP above the cross-country median.

A. Low Agriculture Share of GDP



B. High Agriculture Share of GDP



<u>Figure 13. Cumulative Output Impact of Broad Categories of Disasters by Initial Indebtedness</u>

The various figures exhibit the response of per-capita GDP to the ocurrence at time zero of various types of natural disasters, indicated at the top of each figure, (solid lines) and its 90 percent confidence interval (broken lines). Panel A presents results for countries with average levels of external debt to GDP during 1975-1980 below 30 percent and Panel B shows similar results for countries with average initial debt above 30 percent of GDP. In both panels time horizon is in years.

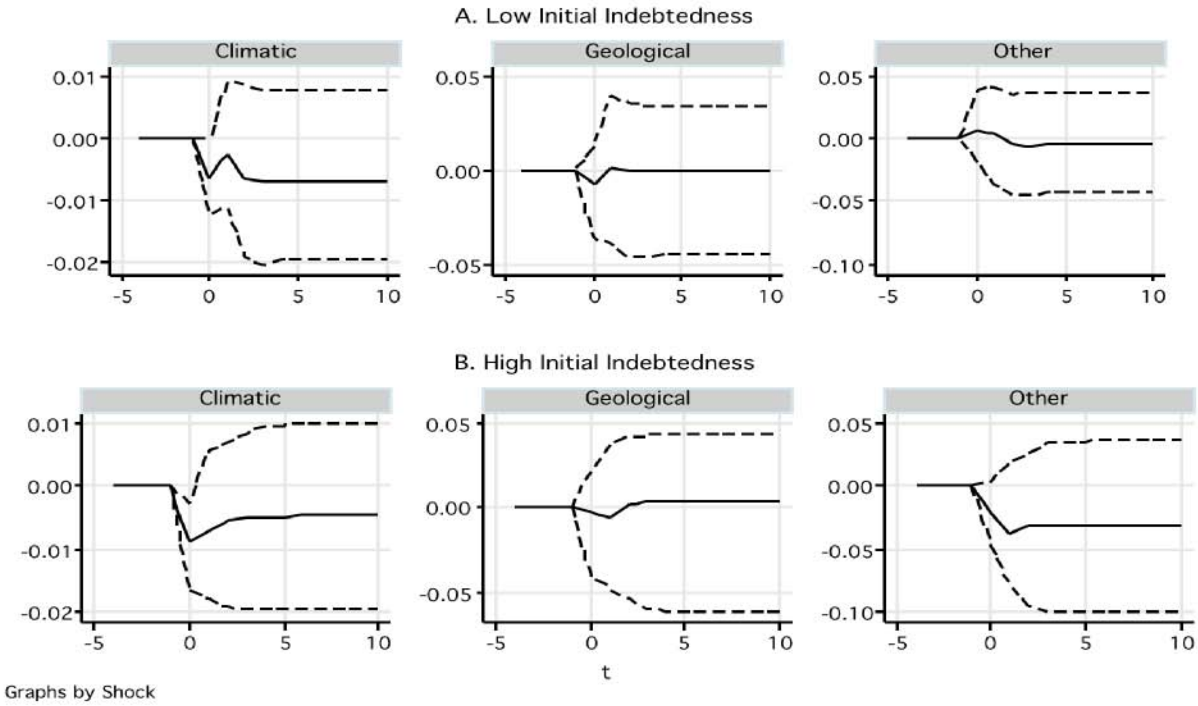


Table 1. Summary Statistics for the Sample of Countries

Country	Average growth rate	Avg growth terms of trade	Average aid/gni	Avg. real exch. rate appreciation	Incidence Geological Disasters	Incidence Climatic Disasters	Incidence Other Disasters	Incidence Windstorms	Incidence Extreme Temp.	Incidence Droughts	Incidence Floods
Albania	0.0155	0.0782	10.88		0	0.21875	0	0.0625	0	0.09375	0.0625
Algeria	0.0089	0.0118	0.47	-0.0432	0.0625	0.03125	0.03125	0	0	0	0.03125
Argentina	0.0066	0.0018	0.07		0	0.28125	0	0	0	0	0.28125
Australia	0.0187	0.0060		-0.0025	0	0.5	0	0.1875	0.125	0.1875	0
Austria	0.0209	-0.0027		0.0045	0	0.03125	0	0	0	0	0.03125
Bangladesh	0.0222	0.0098	4.78		0.03125	1.125	0.0625	0.34375	0	0.0625	0.71875
Belgium	0.0193	-0.0006		-0.0001	0	0.03125	0	0	0.03125	0	0
Benin	0.0051	-0.0157	10.10		0	0.40625	0	0	0	0.125	0.28125
Bhutan	0.0553		16.68		0	0.0625	0.03125	0.03125	0	0	0.03125
Bolivia	0.0000	0.0031	7.14	-0.0237	0.0625	0.53125	0	0	0	0.15625	0.375
Botswana	0.0543	-0.0186	5.38		0	0.28125	0.0625	0	0	0.21875	0.0625
Brazil	0.0108	-0.0104	0.05		0	0.3125	0	0	0	0.1875	0.125
Bulgaria	0.0201	-0.0050	1.88	0.0668	0	0.0625	0	0	0	0	0.0625
Burkina Faso	0.0176	0.0098	13.25		0	0.375	0.09375	0	0	0.34375	0.03125
Burundi	-0.0065	-0.0175	20.37	-0.0171	0	0.15625	0.0625	0	0	0.15625	0
Cameroon	0.0047	0.0094	4.54	-0.0078	0.03125	0.0625	0	0	0	0.0625	0
Cape Verde	0.0321		24.66		0.03125	0.125	0.0625	0.0625	0	0.0625	0
Central African Republic	-0.0141	-0.0051	12.10	-0.0100	0	0.0625	0	0	0	0	0.0625
Chad	0.0082	-0.0134	11.98	0.0206	0	0.34375	0.03125	0	0	0.21875	0.125
Chile	0.0365	0.0166	0.18	-0.0183	0.0625	0.28125	0	0.0625	0	0.03125	0.1875
China	0.0773	-0.0120	0.31	-0.0430	0.03125	1.6875	0	0.5	0	0.375	0.8125
Colombia	0.0163	0.0130	0.32	-0.0145	0.09375	0.09375	0	0	0	0	0.09375
Comoros	-0.0025	-0.0222	22.12		0.0625	0.125	0.09375	0.125	0	0	0
Congo, Dem. Rep.	-0.0402	0.0062	9.88	-0.0716	0	0.09375	0.03125	0	0	0.09375	0
Congo, Rep.	0.0079	0.0086	8.30		0	0.15625	0	0	0	0	0.15625
Costa Rica	0.0171	-0.0056	1.76	-0.0181	0.0625	0.25	0	0.125	0	0	0.125
Cyprus	0.0428	-0.0016	1.51	-0.0033	0	0	0	0	0	0	0
Denmark	0.0201	0.0036		0.0042	0	0.09375	0	0.0625	0	0.03125	0
Dominica	0.0334		12.77	-0.0011	0	0.1875	0.03125	0.1875	0	0	0
Dominican Republic	0.0238	-0.0200	1.15	-0.0116	0	0.21875	0	0.125	0	0	0.09375
Ecuador	0.0094	-0.0063	1.15	-0.0184	0.125	0.1875	0.03125	0	0	0	0.1875
El Salvador	0.0022	-0.0002	4.37		0.125	0.1875	0.0625	0.0625	0	0.0625	0.0625
Ethiopia	0.0057	-0.0087	9.97	-0.0039	0	0.59375	0.03125	0	0	0.5625	0.03125
Fiji	0.0107	0.0005	2.84	-0.0150	0	0.59375	0	0.5	0	0.0625	0.03125
France	0.0178	-0.0023		-0.0007	0	0.0625	0	0.03125	0.03125	0	0
Gabon	-0.0136	-0.0037	1.82	-0.0314	0	0.03125	0	0	0	0	0.03125
Gambia, The	0.0018	-0.0285	21.46	-0.0384	0	0.28125	0.0625	0.03125	0	0.21875	0.03125
Ghana	0.0060	-0.0185	8.20	-0.0756	0	0.21875	0	0	0	0.09375	0.125
Greece	0.0177	0.0059		0.0132	0.125	0.03125	0	0	0	0.03125	0
Grenada	0.0323		5.86	0.0056	0	0.15625	0.03125	0.15625	0	0	0
Guatemala	0.0063	0.0011	1.48		0.03125	0.15625	0	0.0625	0	0.03125	0.0625
Guinea	0.0069	-0.0503	9.78		0	0.03125	0	0	0	0	0.03125
Guinea-Bissau	-0.0104	-0.0072	44.52		0	0.0625	0.21875	0	0	0.0625	0
Guyana	0.0056	-0.0157	16.31	-0.0612	0	0.15625	0.09375	0	0	0.0625	0.09375
Haiti	-0.0164	0.0089	9.00		0	0.375	0.0625	0.1875	0	0.0625	0.125
Honduras	0.0108	0.0043	7.87		0	0.59375	0	0.15625	0	0.1875	0.25
Hungary	0.0215	-0.0060	0.49	0.0193	0	0.09375	0	0	0	0.0625	0.03125
India	0.0341	-0.0073	0.66		0.0625	1.15625	0	0.15625	0	0.21875	0.78125
Indonesia	0.0380	0.0136	1.13		0.0625	0.03125	0.09375	0	0	0.03125	0
Iran, Islamic Rep.	-0.0002	0.0102	0.09	-0.0011	0.15625	0.21875	0	0	0	0.09375	0.125
Israel	0.0170	0.0006	3.19	-0.0060	0	0.03125	0	0	0.03125	0	0
Italy	0.0196	0.0025		0.0019	0.0625	0.09375	0	0	0.03125	0	0.0625
Jamaica	0.0038	-0.0017	3.21		0	0.34375	0	0.15625	0	0	0.1875
Japan	0.0219	-0.0096		-0.0065	0.09375	0	0.03125	0	0	0	0
Jordan	0.0214	0.0075	13.14		0	0.125	0	0	0.03125	0.0625	0.03125
Kenya	0.0042	-0.0009	6.68		0.03125	0.5	0.0625	0	0	0.4375	0.0625
Korea, Rep.	0.0554	-0.0089	0.12		0	0.125	0	0.0625	0	0	0.0625
Lesotho	0.0293	-0.0184	10.15	0.0087	0	0.28125	0	0	0	0.21875	0.0625
Liberia	-0.0569		18.41		0	0.03125	0.0625	0	0.03125	0	0
Luxembourg	0.0339	0.0011		-0.0005	0	0.15625	0	0.125	0.03125	0	0
Madagascar	-0.0140	-0.0043	10.41		0	0.875	0	0.53125	0	0.3125	0.03125
Malawi	-0.0011	0.0018	20.00	-0.0290	0.03125	0.5	0	0	0	0.3125	0.1875
Malaysia	0.0384	0.0046	0.40	-0.0146	0	0	0	0	0	0	0
Mali	0.0083	-0.0008	16.74		0	0.28125	0.0625	0	0	0.28125	0
Mauritania	0.0017	0.0074	22.57		0	0.5625	0	0	0	0.46875	0.09375
Mauritius	0.0406	-0.0225	1.91		0	0.25	0.03125	0.21875	0	0.03125	0
Mexico	0.0139	-0.0015	0.06		0.03125	0.1875	0.03125	0.15625	0	0	0.03125
Mongolia	0.0166		10.70		0	0.28125	0.0625	0.1875	0	0.09375	0
Morocco	0.0199	0.0082	2.76	-0.0114	0.03125	0.09375	0	0	0	0.09375	0
Mozambique	0.0169	-0.0475	29.45		0	0.96875	0.03125	0.125	0	0.5	0.34375
Nepal	0.0178	-0.0002	8.18		0.125	0.25	0	0	0	0.09375	0.15625
Netherlands	0.0184	-0.0010		0.0008	0	0.03125	0	0.03125	0	0	0
Nicaragua	-0.0163	-0.0070	16.91	-0.2354	0.0625	0.34375	0.0625	0.125	0	0.09375	0.125
Niger	-0.0113	0.0203	13.93		0	0.46875	0.09375	0	0	0.40625	0.0625
Nigeria	0.0012	0.0177	1.08	-0.0440	0	0.125	0	0	0	0.09375	0.03125
Oman	0.0263		1.22		0	0.03125	0	0.03125	0	0	0
Pakistan	0.0258	-0.0216	2.62	-0.0256	0.0625	0.375	0	0	0	0	0.375
Panama	0.0144	-0.0008	0.89		0.03125	0.09375	0	0.03125	0	0.03125	0.03125
Papua New Guinea	-0.0008	-0.0049	10.64	-0.0161	0.09375	0.25	0	0.03125	0	0.125	0.09375
Paraguay	0.0105	0.0171	1.22	-0.0279	0	0.28125	0.03125	0	0	0.03125	0.25
Peru	0.0033	0.0114	1.11		0.03125	0.34375	0.0625	0	0.0625	0.0625	0.21875

Country	Average growth rate	Avg growth terms of trade	Average aid/gni	Avg. real exch. rate appreciation	Incidence Geological Disasters	Incidence Climatic Disasters	Incidence Other Disasters	Incidence Windstorms	Incidence Extreme Temp.	Incidence Droughts	Incidence Floods
Philippines	0.0101	0.0023	1.37	-0.0122	0.09375	1.90625	0	1.59375	0	0.125	0.1875
Portugal	0.0243	0.0048		-0.0012	0	0.03125	0.0625	0	0.03125	0	0
Romania	0.0107	-0.0116	0.93	0.0050	0.03125	0.125	0	0	0	0.03125	0.09375
Rwanda	0.0081	0.0018	19.62		0	0.375	0	0	0	0.375	0
Samoa	0.0165		19.45	-0.0047	0	0.15625	0.03125	0.125	0	0	0.03125
Senegal	0.0001	-0.0087	10.58		0	0.40625	0.03125	0.03125	0	0.3125	0.0625
Seychelles	0.0239	0.0284	8.14		0.03125	0.0625	0.03125	0.03125	0	0	0.03125
Sierra Leone	-0.0076	0.0163	16.85	-0.0291	0	0.0625	0	0.03125	0	0	0.03125
Solomon Islands	0.0164		26.02	-0.0195	0.0625	0.125	0.03125	0.125	0	0	0
South Africa	0.0023	0.0003	0.33	-0.0089	0	0.1875	0	0.03125	0	0.125	0.03125
Spain	0.0207	0.0051		0.0121	0	0.375	0.03125	0.03125	0.03125	0.25	0.0625
Sri Lanka	0.0339	0.0154	6.06		0.03125	1.125	0	0.0625	0	0.25	0.8125
St. Lucia	0.0314		4.42	-0.0095	0	0.125	0	0.125	0	0	0
Vincent and the Grenadines	0.0373		7.84	-0.0095	0.03125	0.15625	0	0.125	0	0	0.03125
Sudan	0.0174	0.0008	6.36		0	0.5	0.03125	0	0	0.3125	0.1875
Suriname	0.0032		7.16		0	0.03125	0.03125	0	0	0	0.03125
Swaziland	0.0112	-0.0125	4.77		0	0.4375	0	0.0625	0	0.34375	0.03125
Sweden	0.0171	-0.0086		-0.0041	0	0.03125	0	0.03125	0	0	0
Switzerland	0.0108	0.0098		0.0045	0	0.09375	0	0.03125	0.03125	0	0.03125
Syrian Arab Republic	0.0112	-0.0010	4.26		0	0.0625	0	0	0	0.0625	0
Thailand	0.0472	-0.0156	0.69		0.03125	0.8125	0	0.09375	0	0.09375	0.625
Togo	-0.0084	0.0098	9.77	-0.0169	0	0.15625	0.03125	0	0	0.03125	0.125
Trinidad and Tobago	0.0232	0.0094	0.18	0.0045	0	0	0	0	0	0	0
Tunisia	0.0258	-0.0076	2.33	-0.0247	0	0.09375	0	0	0	0.03125	0.0625
Turkey	0.0209	0.0033	0.34		0.25	0.03125	0	0	0	0	0.03125
Uganda	0.0187	-0.0125	10.52	-0.1014	0.03125	0.34375	0	0	0	0.3125	0.03125
United States	0.0208	-0.0047		-0.0078	0	0.09375	0	0.09375	0	0	0
Uruguay	0.0152	-0.0023	0.26	-0.0060	0	0.09375	0	0	0	0.0625	0.03125
Venezuela, RB	-0.0038	0.0466	0.04	-0.0105	0	0.03125	0	0	0	0	0.03125
Zambia	-0.0115	-0.0171	17.07	0.0178	0	0.28125	0	0	0	0.125	0.15625
Zimbabwe	-0.0144	-0.0104	3.88		0	0.40625	0.03125	0	0	0.34375	0.0625
Mean	0.013671867	-0.00092461	7.90	-0.0158	0.022321429	0.271484375	0.020089286	0.068359375	0.004464286	0.099888393	0.098772321
Median	0.01536535	-0.0007737	5.86	-0.0095	0	0.15625	0	0	0	0.046875	0.03125
Stdev	0.018528551	0.015686309	8.16	0.0368	0.041191385	0.318136976	0.03325683	0.176304823	0.015614942	0.133365834	0.165016122
P25	0.0036895	-0.0086944	1.15	-0.0195	0	0.0625	0	0	0	0	0
P75	0.021575075	0.006474525	10.88	-0.0005	0.03125	0.34375	0.03125	0.0625	0	0.1328125	0.125

Table 2. Unit Root Tests

The table shows the results of country-by-country and panel unit root tests performed for the main series used in the paper. The first and second halves of the table (Panels A and B) show the tests for the series in levels and differences, respectively. In each panel, sections I and II report the fraction of countries inthe sample in which a standard, country-by-country augmented Dickey Fuller and Phillips-Perron tests could not reject the null hypothesis of a unit root selecting the optimal number of lags on a country by country basis, or using the optimal number of 2 lags for the system as a whole. Section III shows the p-values of the Levin-Lin-Chu (2002) panel unit root test obtained for each variable. All the tests allow for a country-specific intercept and trend, and use the Newey-West bandwith selection with the Bartlett kernel for the estimation of the long run variance of the series.

Groups	GDP per capita	Terms of Trade	Real Exchange Rate
	(1)	(2)	(3)
A. Tests for Series in levels			
I. Fraction of countries that cannot reject UR in ADF test			
Automatic lag selection	85	73	69
All countries with 2 lags	88	90	88
II. Fraction of countries that cannot reject UR in PP test			
Automatic lag selection	96.00	77.00	66.00
III. P-values of Levin-Lin-Chu test			
Automatic lag selection	0.27	0	0
All countries with 2 lags	0.99	0.99	0.96
B. Tests for Series in Differences			
I. Fraction of countries that cannot reject UR in ADF test			
Automatic lag selection	14	1	4
All countries with 2 lags	44	23	28
II. Fraction of countries that cannot reject UR in PP test			
Automatic lag selection	12.00	1.00	2.00
III. P-values of Levin-Lin-Chu test			
Automatic lag selection	0	0	0
All countries with 2 lags	0	0.01	0.21

Table 3. Panel cointegration tests

The table reports the statistic and associated p-value of the different variants of Pedroni's (1999) panel cointegration test. The null hypothesis in each case is no cointegration.

	VAR including GDP and TT		VAR including GDP, TT, and AID	
Alternative hypothesis: common AR coefs.				
	Statistic	Prob.	Statistic	Prob.
Panel v-Statistic	6.12	0.00	3.31	0.00
Panel rho-Statistic	5.38	1.00	10.38	1.00
Panel PP-Statistic	0.61	0.73	1.73	0.96
Panel ADF-Statistic	-1.48	0.07	1.46	0.93
Alternative hypothesis: individual AR coefs.				
	Statistic	Prob.	Statistic	Prob.
Group rho-Statistic	6.83	1.00	12.64	1.00
Group PP-Statistic	0.71	0.76	0.91	0.82
Group ADF-Statistic	-2.7	0.00	-1.19	0.12

Table 4. Cross and Serial Correlation of Disaster Measures

Panel A reports the results of regressions of each disaster incidence measure (at the top of the column) on the other two broad measures and a set of country fixed effects. Panel B runs similar regressions of each disaster incidence measure on two of its lags and a set of country fixed effects. *, **, and *** denote significance at the 10, 5, and 1 percent, respectively.

	(1) Geological	(2) Climatic	(3) Other
A. Cross correlation of the incidence of disasters within countries			
Climatic	0.00456		0.00428
	(0.00506)		(0.00459)
Other	-0.00583	0.0532	
	(0.0142)	(0.0575)	
Geological		0.0501	-0.00516
		(0.0553)	(0.0125)
Country FE	Yes	Yes	Yes
N	3584	3584	3584
B. Serial correlation of the incidence of disasters within countries			
L.Geological	-0.0166		
	(0.0313)		
L2.Geological	-0.0424		
	(0.0298)		
L.Climatic		0.149***	
		(0.0295)	
L2.Climatic		0.0792**	
		(0.0280)	
L.Other			0.0342
			(0.0347)
L2.Other			0.00892
			(0.0354)
Country FE	Yes	Yes	Yes
N	1260	3360	1320