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Assessing the Macroeconomic Impacts of Natural Disasters

Are there Any?

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Abstract

There is an ongoing debate on whether disasters cause significant macroeconomic impacts and are truly a potential impediment to economic development. This paper aims to assess whether and by what mechanisms disasters have the potential to cause significant GDP impacts. The analysis first studies the counterfactual versus the observed gross domestic product. Second, the analysis assesses disaster impacts as a function of hazard, exposure of assets, and, importantly, vulnerability. In a medium-term analysis (up to 5 years after the disaster event), comparing counterfactual with observed gross domestic product, the authors find that natural disasters on average can lead to negative consequences. Although the negative effects may be small, they can become more pronounced depending mainly on the size of the shock. Furthermore, the authors test a large number of vulnerability predictors and find that greater aid and inflows of remittances reduce adverse macroeconomic consequences, and that direct losses appear most critical.

This paper—a product of the Global Facility for Disaster Reduction and Recovery Unit, Sustainable Development Network Vice Presidency—is part of a larger effort in the Network to disseminate the emerging findings of the forthcoming joint World Bank-United Nations' Assessment of the Economics of Disaster Risk Reduction.. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The authors may be contacted at hochrain@iiasa.ac.at. We are grateful to Apurva Sanghi, Reinhard Mechler and participants of the seminar at the World Bank held on this topic for their suggestions and constructive comments.

ASSESSING THE MACROECONOMIC IMPACTS OF NATURAL DISASTERS: ARE THERE ANY?

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1 INTRODUCTION

A small, but growing literature has emerged over the last few years on the macroeconomic and development impacts of natural disasters. Interestingly, there is as yet no agreement on whether disasters are important from a macroeconomic perspective, and two positions can be identified. The first considers natural disasters a setback for economic growth and is well represented by the following citation:

> It has been argued that although individuals are risk-averse [to natural disasters risk], governments should take a risk-neutral stance. The reality of developing countries suggests otherwise. Government decisions should be based on the opportunity costs to society of the resources invested in the project and on the loss of economic assets, functions and products. In view of the responsibility vested in the public sector for the administration of scarce resources, and considering issues such as fiscal debt, trade balances, income distribution, and a wide range of other economic and social, and political concerns, governments should not act risk-neutral (OAS, 1991).

The other position sees disasters as entailing little growth implications and consider disasters and their reduction a problem *of*, but not *for* development (e.g. Albala-Bertrand, 1993, 2006; Caselli and Malhotra, 2004). These authors find natural disasters do not negatively affect GDP and “if anything, GDP growth is improved” (Albala-Bertrand, 1993: 207). This paper can be understood as an attempt at reconciling this body of literature. There are two entry points for the analysis. The first is to look at counterfactual vs. observed GDP, the second entry point is to assess disaster impacts as a function of hazard, exposure of assets (human, produced, intangible), and, importantly vulnerability.

Overall, the evidence reveals adverse macroeconomic consequences of disasters on GDP. In a medium-term analysis, natural disasters on average seem to lead to negative effects on GDP. The negative effects may be small, yet they can become more pronounced depending on the size of the shock. We tested a large number of vulnerability predictors and found that higher aid rates as well as higher remittances lessen the adverse macroeconomic consequences, while capital stock loss is the most important predictor for the negative consequences.

The paper is organized as follows. Section 2 reviews the literature on the macroeconomic impacts of disasters and locates the proposed analysis within the disaster risk management paradigm. In section 3, we present the data and methodology used for projecting the economic impacts for a medium term horizon (up to 5 years after an event), as well as the regression analysis used for identifying predictor variables explaining potential impacts. Section 4 ends with a discussion of possible implications of our analysis.

2 LITERATURE REVIEW

The literature on the macroeconomic effects of disasters can be divided into studies looking into the short-to-medium term (1-5 years in economic analysis) and the longer term (beyond 5 years), with almost all studies taking a shorter-term perspective. A key response variable analyzed in this line of work is GDP. In principle, after a disaster event the following trajectories may be distinguished (see figure 1) leading to no, positive or negative follow-on effects.

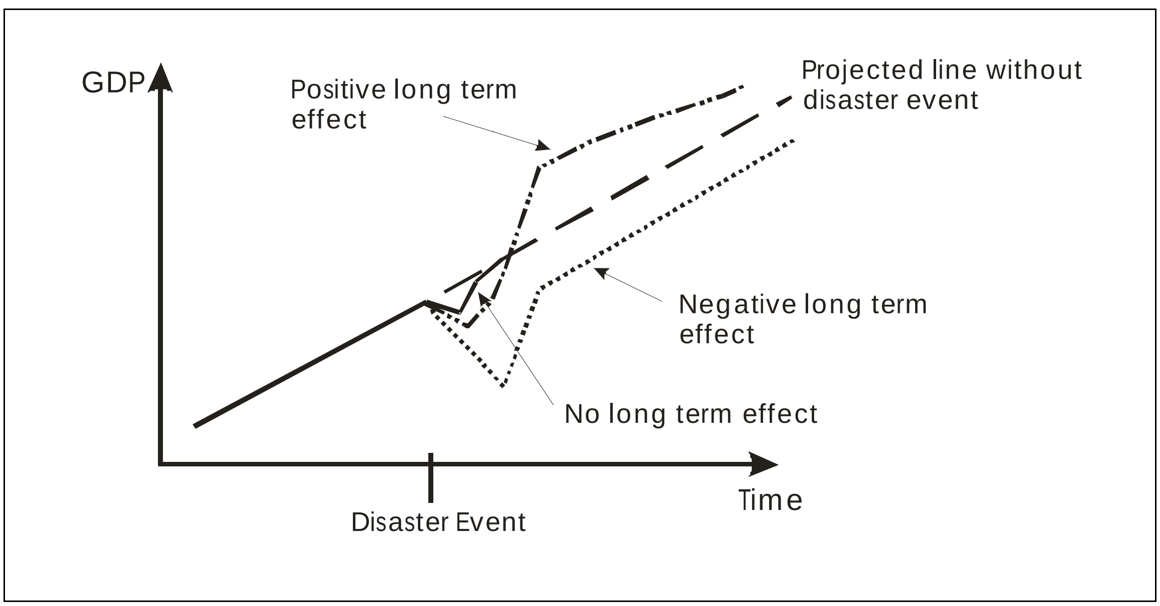

Fig. 1: Possible trajectories of GDP after a disaster. Source: Hochrainer, 2006

Two positions can be distinguished as shown in table 1. Position 1 broadly suggests the post-disaster trajectory will fall short of the planned trajectory, while position 2 contends that there is no negative effect beyond the first year and the planned GPD path can be achieved or even surpassed.

Table 1: Synopsis of macroeconomic perspectives on natural disasters

Position 1 **"Natural disasters are setbacks for economic growth"**	**Position 2** **"Disasters have no effects on economic growth"**
Methodologies involving • Supply side focus • Model projections • Neoclassical intuition • Empirical evidence	Methodologies involving • Supply side and demand side • Empirical evidence
Studies by Benson (various); ECLAC (various); Otero and Marti, 1995; Crowards, 2000; Charveriat, 2000; Murlidharan and Shah, 2001; Freeman et al., 2002; Mechler, 2004; Cuaresma, Hlouskova, and Obersteiner, 2004; Hochrainer, 2006; Noy, 2009; Okuyama, 2009	Studies by Albala-Bertrand, 1993, 2006; Skidmore and Toya, 2002; Caselli and Malhotra, 2004.

Source: Adapted from Zenklusen, 2007

The body of research subscribing to position 1 generally finds significant short-to-medium-term macroeconomic effects (Otero and Marti, 1995; Benson, 1997a,b,c; Benson, 1998; Benson and Clay, 1998, 2000, 2001; ECLAC 1982, 1985, 1988, 1999, 2002; Murlidharan and Shah, 2001; Crowards, 2000; Charveriat, 2000; Mechler, 2004; Hochrainer, 2006; Noy, 2009) and considers natural disasters *a barrier for development* in disaster-vulnerable developing countries.

ECLAC (various studies) has been conducting numerous case studies on disaster impacts in Latin American countries since 1972. Otero and Marti (1995) summarized the results and generally found serious shorter-term impacts as national income decreases, an increase in the fiscal deficit as tax revenue falls, and an increase in the trade deficit as exports fall and imports increase. Substantial longer term impacts on development prospects, perpetual external and fiscal imbalances due to increased debt service payments post-disaster and spending requirements, and negative effects on income distribution were also found (ECLAC and IDB, 2000; Otero and Marti, 1995). They generally hold that the significance of the impact depends on the size of the disasters, the size of the economy and the prevailing economic conditions (Otero and Marti, 1995). Benson (1997a,b,c) and Benson and Clay (1998, 2000, 2001) produced a number of case studies on Fiji, Vietnam, the Philippines, and Dominica. The timeframe of this analysis was mainly short-term, i.e. the period up to one year after a disaster. They detected severe negative economic impacts, with agriculture being hit most strongly, an exacerbation of inequalities, and reinforcement of poverty, however also finding it difficult to isolate disaster impacts on economic variables from other impacts. Murlidharan and Shah (2001) by means of a regression analysis analyzed a large data set of 52 catastrophes in 32 developed and developing countries with a the short-term focus (year before event compared to year of event). They found catastrophes for all country income groups to affect short-term growth very significantly. In the medium-term (average of two preceding years compared to average of event and two following years), the effect on growth was still significant. Over time, they detected impact on economic growth to subside. They also discovered associations between disasters and the growth of external debt, the budget deficit and inflation. Crowards (1999 discussed in Charveriat, 2000) examined the impacts of 22 hurricane events in borrowing member countries of the Caribbean Development Bank and found that GDP growth slowed by 3% points on average post-event, but rebounded due to the increase in investment the following year. He also detected large variations around averages.[2] Charveriat (2000) for most cases in her disaster sample identified a typical pattern of GDP with a decrease in the year of an event and a recuperation of the growth rate in the following two years due to high investment into fixed capital. She detected the scale of short-term impacts to depend on the loss-to-GDP-ratio and whether the event was localized or country-wide. For high-

[2] This study could not be obtained and we rely on Charveriat (2000) as a secondary source.

loss-to-GDP ratios and country-wide events she found larger impacts. She found the following crucial variables affecting the scale of aggregate effects: structure of the economy and general conditions prevailing, the size of economy, the degree of diversification and the speed of assistance of the international community. Another study, Rasmussen (2004), is in accordance with above studies and for a cross-country sample identified a median reduction of the growth rate by 2.2% points in the year of the event. Raddatz (2007) generally assessed the role of external shocks (such as commodity price fluctuations, natural catastrophe, and adverse influences from an international economic environment) on output volatility of low-income countries. While he found external shocks to explain a fraction of output variance, their contribution to output fluctuations was dwarfed by more important contributors from internal sources such as level of inflation, a possible overvaluation of the real exchange rate and large public deficits. Noy (2009) took a look at the reduction of GDP growth rates for a large sample of disaster events, for which while using a linear regression modeling approach he concluded that the ability to mobilize resources for reconstruction as well as the financial condition of the country are important predictors of GDP growth effects. As one of the few longer term studies, Cuaresma et al. (2004) concluded that the degree of catastrophic risk has a negative effect on knowledge spillovers between industrialized and developing countries. Further, they suggested that only countries with relatively high levels of development may benefit from capital upgrading through trade after a natural catastrophe.

There are only a few studies adopting position 2 and the key papers here are Albala-Bertrand (1993) and to a lesser extent Caselli and Malhotra (2004). In (partial) contrast to the above studies, Albala-Bertrand (1993) came to different conclusions and finds himself partially in opposition to accepted views when analyzing impacts mainly on developing countries. He first statistically analyzed part of the ECLAC data set discussed above and found that natural disasters do not negatively affect GDP, public deficit and inflation in the short to medium term. His findings on the trade deficit are in accordance with ECLAC and other research. These findings he explains with a sharp increase in capital inflows and transfers (private and public donations). He holds that natural disasters do not lower GDP growth rates and "if anything, they might improve them" (1993: 207). Albala-Bertrand also examined longer-term effects for a number of developed and developing countries and found no significant long-term effects in developed countries; he came to the conclusion that in developing countries aggregate effects fade away after two years, but that some negative effects on income distribution and equality persist. Overall, Albala-Bertrand considered disasters "a problem *of* development, but essentially not a problem *for* development." (Albala-Bertrand 1993). According to his analysis, while the number of deaths and people affected and the extent of monetary losses are determined by the current state of a country's development, disasters do not normally hinder long-term development, with the sole exception being widespread droughts.[3] Further, Caselli and Malhotra (2004) based their analysis on neoclassical growth theory and analyzed the losses in relation to country growth rates after disaster events using a dataset of 172 countries for events between 1975 and 1996. They concluded that their hypothesis that losses of labor and capital stock have no effect on short-term economic growth could not be rejected. Finally, Skidmore and Toya (2002) discovered a robust positive correlation between the frequency of natural disasters and long-run economic growth after conditioning for other determinants, which they explain by some type of Schumpeterian creative destruction.

Overall, while the balance of evidence and studies seems to imply that there are adverse economic disaster effects in terms of the “negative” trajectory stylized above, there are important “outliers” that merit more investigation. Another observation is that the studies generally have a short-term focus, and in their analyses often do not go beyond the year following an event. Finally, analyses generally compare key indicators of interest after the fact to their pre-disaster states, rather than comparing the counterfactual, i.e. the system without a shock, to the observed. The latter point seems important, as important opportunity costs, e.g. in terms of economic growth foregone, are consequently often not accounted for in analyses on the macro effects of disasters.

[3] Albala-Bertrand (1993) started fruitful discussions about some assumptions and estimating issues in the literature, and his findings were discussed and replicated by various other authors including Mechler (2004) and Hochrainer (2006). For example, Hochrainer (2006) extended Albala-Bertrand’s sample to 85 disaster events in 45 countries and found GDP growth (on average) negatively affected in the disaster year and no significant increases in growth for the subsequent post-disaster years, which implies that, due to a lack of recovery, a net loss of GDP.

2.1 Economic effects and vulnerability

In order to set the stage for the analyses, we hold it important to locate the discussion within the disaster risk management framework. The standard approach here is to understand natural disaster risk as a function of hazard, exposure and (physical) vulnerability (see figure 2). *Hazard* analysis entails determining the type of hazards affecting a certain area with specific intensity and recurrence. Assessing *exposure* involves analyzing the relevant elements (population, assets) exposed to relevant hazards in a given area. *Vulnerability* is a multidimensional concept encompassing a large number of factors that can be grouped into physical, economic, social and environmental factors as outlined on the figure. We refer mostly to physical vulnerability as the susceptibility to incurring harm of people and engineered structures leading to direct risk in terms of people affected and, important from the perspective taken in this paper, capital stock destroyed. As a consequence of such direct impacts, follow-on effects may materialize leading to indirect potential and actual impacts. Economic vulnerability may refer to the economic or financial capacity to absorb disaster events, e.g. the ability to refinance asset losses and to recover quickly to a previously planned economic growth path. It may relate to private households and businesses as well as governments, the latter often bearing a large share of a country's risk and losses. Based on assessments of disaster risks and its determinants, risk management measures may be systematically planned for risk reduction and risk transfer.

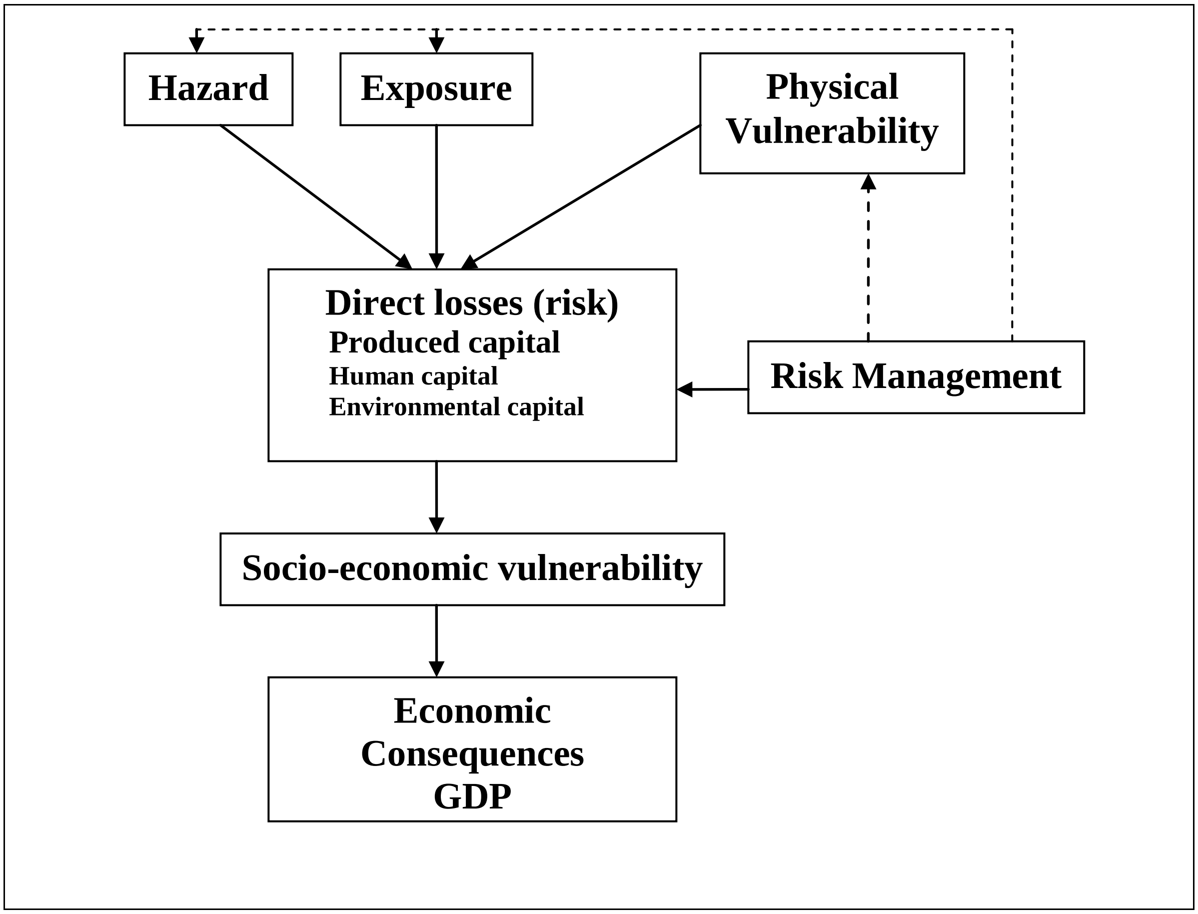

Fig. 2: Conceptual framework used in this study for explaining economic risk due to natural disasters

The literature on the economic impacts discussed above can be related to this framework, and table 2 lists the key studies and general factors contributing to a discussion of (macro) economic risk. Determinants of impacts and risk can be distinguished according to (i) the type of natural hazard (hazard variable), (ii) geographical area and spatial scale of impact (exposure), (iii) the overall structure of the economy, (iv) the stage of development of the country, (v) prevailing socio-economic conditions, and (vi) the availability of formal and informal mechanisms to share risks (the latter four variables related to economic vulnerability).[4]

[4] It should be mentioned that in the studies discussed and our analysis, observed losses are used for examining future economic consequences. However, when it comes to risk management, losses should be based on probabilities and the discussion framed in terms of risk in order the incorporate the full possible range of potential losses (and its probabilities) in the analysis.

Table 2: Studies assessing macroeconomic consequences and economic vulnerability to natural hazards.

Study	**Vulnerability variables for predicting economic impacts and risk**	**Response variables**
Charveriat, 2000	• Size of the economy, degree of diversification and size of the informal and agricultural sectors.	• GDP
ECLAC and IDB, 2000; Freeman et al. 2002; Mechler,2004; Hochrainer, 2006	• Ability to refinance losses and provide relief to the affected population (financial vulnerability) • Availability of implicit (aid) and explicit (insurance) risk sharing arrangements	• GDP, fiscal variables
Burton et al.,1993; Kahn, 2005.	• Income	• Deaths due to natural disasters
Benson and Clay, 2004	• Structure of the economy • Size • Income level and stage of development • Prevailing socioeconomic conditions	• Total GDP annual change • Agricultural GDP annual change • Non-Agric. GDP annual change
Toya and Skidmore, 2007	• Educational attainment in population aged 15 and over • Economic openness (exports+imports)/GDP • Financial sector level of development (M3/GDP) • Government consumption • Additional variables that determine the deaths caused by disasters (population, land area, disaster type).	• Disaster-related deaths • Damages/GDP
Noy, 2009	• Literacy rate • Quality of institutions • Per capita income • Openness to trade • Levels of government spending • Foreign exchange reserves • Levels of domestic credit • Openness of capital accounts	• GDP
Raschky, 2008	• Availability of financial risk sharing institutions	• GDP

Source: extended from Barrito, 2008.

All of the indicators used for explaining the response variables mentioned above are valid candidates as proxies for hazard, exposure and vulnerability and most of them will be used in the analysis in the next section.

3 ASSESSING ECONOMIC DISASTER CONSEQUENCES AND RISK

In order to identify the macroeconomic effects of disasters, we suggest comparing a counterfactual situation ex-post to the observed state of the system ex-post. This involves assessing the potential trajectory (projected unaffected economy without disaster) versus the observed state of the economy. This contrasts with observing economic performance post-event and actual performance pre-event, as usually done in similar analysis. Our analysis requires projecting economic development into a future without an event. The approach is illustrated via the case of Honduras, which was heavily hit by Hurricane Mitch at the end of 1998. In figure 3 absolute GDP with the event and projected GDP without an event were estimated. The chart exhibits GDP growth to become negative in the year after, then rebound later; yet, overall the net effect would seem to be a loss.

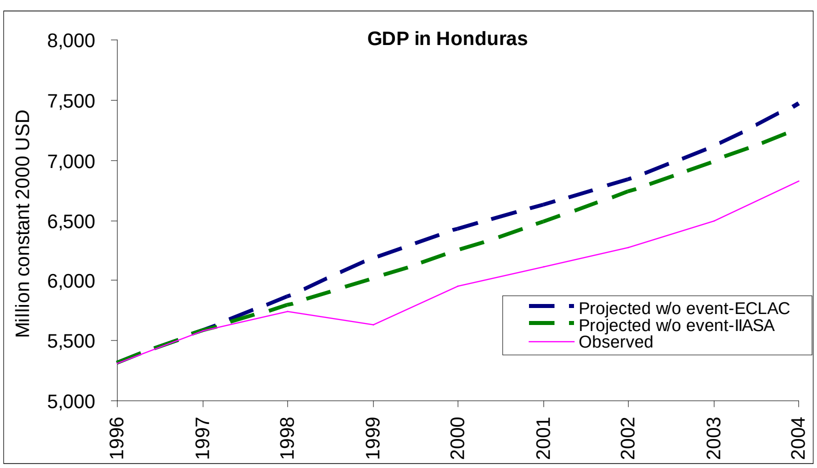

Fig. 3: Observed GDP in Honduras with events vs. projected growth without events. Source: Zapata, 2008; World Bank, 2007; own calculations

Note: Zapata (2008) uses a model based projection, IIASA projects growth statistically based on pre-disaster observed GDP.

Using this approach for Honduras, a “GDP gap” as a follow-on consequence after the hurricane can be identified. For example, in 2004, about 6 years after the event, this gap can be considered to have, *ceteris paribus*, amounted to about 6% of potential GDP given extrapolation of pre-disaster GDP with a 4-year average growth rate, and to 8.6% percent based on the ECLAC projection.

In the following, similarly we compare GDP effects in terms of counterfactual vs. observed trajectories by projecting absolute GDP into the future under the assumption of a no disaster event scenario and comparing it with observed GDP values. A 5 year time horizon is chosen as it is the minimum data requirement for estimating time series projections into the future and reflects the trade-off between data requirements and number of samples (the larger the sample the lower the time horizon). There are two avenues for deriving the counterfactual: (i) running a (statistical or behavioral) economic model without a disaster event, for which a large number of models calibrated to the respective countries would be necessary; (2) using time series models. We adopt the second option to eliminate as much possible business cycles in the dataset. We use econometric models which seem to be able to handle empirically observed patterns, which is important as a large number of the countries examined are of developing nature and exhibit strong growth volatility.

3.1 Estimation methodology

We use autoregressive integrated moving average models, also called ARIMA(p,d,q) (Box and Jenkins, 1976) for forecasting GDP into the future after the disaster event. ARIMA modeling approaches are chosen because they are sufficiently general to handle virtually all empirically observed patterns and often used for GDP forecasting (see for example Abeysinghe and Rajaguru, 2004). While such a type of modeling may be criticized for its black box approach (Makridakis and Wheelwright, 1989), it here serves well due to the large number of projections to be made and the difficulty identifying suitable economic model approaches, such as input-output models for all the different countries within the sample and over a time period starting from 1965.

The ARIMA process

Recall, an autoregressive process of order AR(p) can be defined as

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + \ldots + \phi_p x_{t-p} + \varepsilon_t$$

A moving-average process of order MA(q) may be written as

$$x_t = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q}$$

and an ARMA(p,q) process, with p autoregressive and q moving average terms can be defined to be

$$x_t = \phi_1 x_{t-1} + \ldots + \phi_p x_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q}$$

where ϕ and θ are parameters to be estimated and ε are white noise stochastic error terms. Now, let y_t be a non-stationary series and define the first order regular difference of y_t as

$$\Delta y_t = y_t - y_{t-1}$$

or more generally using a back-shift operator denoted as $B^k z_t = z_{t-k}$

$$\Delta^d y_t = (1-B)^d y_t$$

An ARIMA(p,d,q) model can then be expressed as

$$\phi_p(B)(1-B)^d y_t = \theta_q(B)\varepsilon_t$$

with

$$\phi_p(B) = 1 - \phi_1 B - \ldots - \phi_p B^p$$

and

$$\theta_q(B) = 1 - \theta_1 B - \ldots - \theta_q B^q$$

The Box-Jenkins methodology (Box and Jenkins, 1976) is applied for determining the components of the ARIMA process; i.e. we test different ARIMA(p,d,q) models with p and q to be smaller or equal 4 (due to the limited amount of data) and estimate ϕ and θ using Maximum likelihood techniques and the Akaike Information Criterion (AIC) as well as diagnostic checks to detect a suitable model. The data requirements were set thus that at least 5 observed data points are needed for projections into the future. This is the smallest number of observations which are needed to estimate ARIMA(4,1,4) models (however, the majority of the sample (greater 90 percent) has at least 10 data points). Furthermore, all models are tested to be stationary (usually d=1 suffices to assure a stationary process) and all series are demeaned. To include uncertainty in the projections, also 95 percent confidence forecasts were calculated and analyzed.

Forecasts into the future are performed with the selected models and then compared to the observed variables. Increases or decreases of GDP in future years are measured as a percentage increase or decrease to baseline GDP (i.e., baseline =100) which is defined to be GDP a year before the disaster event. [5] Furthermore, the differences between observed values and projected ones are calculated and called Diff(t), which indicates the percentage difference between the observed and projected value of GDP in year t. We focus on projections with a medium term perspective (up to 5 years into the future). This limitation is due to important data constraints for the ARIMA models within the sample and increasingly large uncertainties beyond the medium-term time horizon.

3.2 Data used

Our sample consists of 225 large natural disaster events during 1960-2005. The sample is based on information from two databases and was compiled by Okuyama (2009) with the threshold for a large event defined arbitrarily to a loss exceeding 1 percent of GDP.[6] One database is the open-source EMDAT disaster database (CRED, 2008) maintained by the Centre for Research on the Epidemiology of Disasters at the Université Catholique de Louvain. EMDAT currently lists information on people killed, made homeless, affected

[5] To decrease variance a logarithmic transformation of GDP was performed at the beginning.

[6] In order to define the "event set" the threshold of stock losses is set as a share (1%) of flow effects (GDP). While it would have been more systematic to define an asset threshold, yet we responded to the larger intuitive appeal of using GDP as a denominator, and the fact that this threshold was also used by another paper in the EDRR working paper series which we wanted to be in line with.

and financial losses for more than 16,000 sudden-onset (such as floods, storms, earthquakes) and slow-onset (drought) events from 1900 to present. Primary data are compiled for various purposes, such as informing relief and reconstruction requirements internationally or nationally, and data are generally collected from various sources and, including UN agencies, non-governmental organizations, insurance companies, research institutes and press agencies. The other database is the proprietary Munich Re NatCat Service database, which mainly serves to inform insurance and reinsurance pricing. This database contains fewer entries focusing on the about 300 largest events since 1950, yet data exhibit a higher reliability as often crosschecked with other information. We focus on the monetary losses (direct impacts or risk) listed in constant 2000 USD terms. In both datasets, loss data follow no uniform definition and are collected for different purposes such as assessing donor needs for relief and reconstruction, assessing potential impacts on economic aggregates and defining insurance losses. We distinguish between sudden and slow onset events. Key sudden-onset events are extreme geotectonic events (earthquakes, volcanic eruptions, slow mass movements) and extreme weather events such as tropical cyclones, floods and winter storms. Slow-onset natural disasters are either of a periodically recurrent or permanent nature; these are droughts and desertification.

We broadly associate the loss data with asset losses, i.e. damages to produced capital. This is a simplification, as indirect impacts, such as business interruption, may also be factored into the data. Yet, generally, at least for the sudden onset events, analysts generally equate the data with asset losses, and an indication that this assumption can be maintained is the fact that loss data are usually relatively quickly available after a catastrophe, which indicates that flow impacts emanating over months to years are usually not considered. Losses are compared to estimates of capital stock from Sanderson and Striessnig (2009), which estimated stocks using the perpetual inventory method based on Penn World table information on investments starting in 1900 and assuming annual growth and depreciation of 4 percent.

3.3 Projecting disaster impacts on GDP

We project differences (in percent) between observed and projected GDP up to five years after a disaster event. A negative value indicates a situation where the projection surpasses the observation leading to a negative effect. Figure 4 charts out these differences for the years 1 to 5. Due to the heterogeneity of the data, it is not very surprising that the results are heavily skewed and as an average value the median should be looked at.

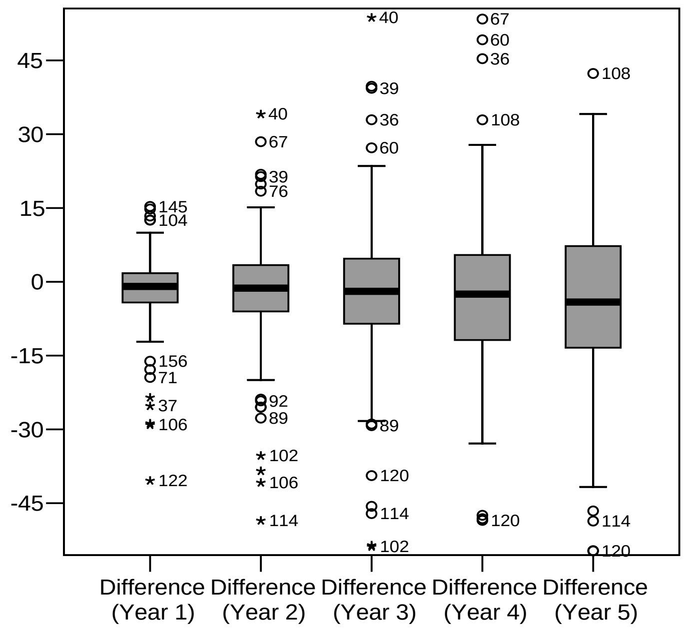

Fig. 4: Box-plots for differences between observed and projected GDP (in percent of observed, baseline GDP in the event year)

The mean, median, standard deviation as well as the skewness coefficients for the whole sample are shown in table 3.

Table 3: Summary results for differences of observed and projected GDP levels

	t+1	**t+2**	**t+3**	**t+4**	**t+5**
Mean	-1.27	-1.43	-1.68	-1.75	-2.02
Median	**-0.53**	**-1.03**	**-1.86**	**-2.27**	**-3.98**
Std. Dev	7.19	11.01	14.99	18.37	22.53

Skewness	-1.54	-0.76	-0.13	0.42	0.98

According to the skewness and standard deviation the results are asymmetric with a large spread. The results, however, clearly indicate a trend. All post-disaster years show negative values with an increasing "gap," indicating that "on average" one can expect negative economic follow-on consequences in the short-medium term, leading to a median reduction of GDP of about 4% points (of baseline GDP in to) in year 5 after the event.

We further test whether the differences are statistically different from zero and, due to non-normality of the data, used the non-parametric one-sample Wilcoxon test (table 4). The null hypothesis H0 is that the median is equal to zero, while the alternative hypothesis H1 is that the median is smaller than zero. Table 4 shows the p-values for this test using the (mean) projections.

Table 4: p-values of the Wilcoxon test for differences to be smaller than zero (H1) and H0: equal to zero.

	t+1	**t+2**	**t+3**	**t+4**	**t+5**
p-value	0.0138	0.0379	0.0258	0.0171	0.0129
Hypothesis	H1	H1	H1	H1	H1

Clearly, the null hypothesis is rejected for all post-disaster years, and therefore one can conclude that there are significant negative follow-on effects. Furthermore, also 95 percent forecast confidence intervals to include uncertainty of the projections within the analysis are used. Additionally, also sub-sample analysis to include uncertainty regarding the influence of multiple occurrences of disasters is performed. The sub-sample is chosen so that only events are considered with no other event (with losses higher than 1 percent of GDP) occurring 5 years before and 5 years after the event considered in the sample. Results related to this sub-sample corroborate our findings on the negative economic consequences (details can be found in Appendix D).

3.4 Explaining the variation: vulnerability predictors

As a next step, we test key variables, particularly those relating to economic vulnerability, as to their suitability as predictors for explaining the differences of projected and observed GDP in year 5 post event. Based on the literature review and discussion above, the following variables listed in table 5 are assessed.

Table 5: Predictor variables used in the analysis[7]

Predictors	**Variables**	**Source**
Direct impact and risk	Direct monetary losses	EMDAT, 2009, Munich Re, 2008 as compiled by Okuyama, 2009
	Losses in percent of GDP	Okuyama, 2009
	Losses in percent of capital stock	Own calculations
Exposure	GDP	WDI, 2008
	Capital stock	Sanderson and Striessnig, 2009
	Total number of population	WDI, 2008
Hazard	Hazard type: Storm, Flood, Earthquake, Drought, others	EMDAT, 2008 Munich Re, 2008
Economic vulnerability	Indebtedness	WDI, 2008
	Income level	WDI, 2006
	Land area	WDI, 2008
	Literacy rate	WDI, 2008
	Aid	WDI, 2008
	Remittances	WDI, 2008
	Small island development state (SIDS)	WDI, 2008

In the following, we first use multivariate models, then employ general linear regression modeling approaches (GLM) using fixed factors, covariates and mixed models as independent variables and Diff(5) as the dependent variable.

[7] We did not look at physical vulnerability factors (for example, the quality of building stock in an economy) as predictors, as those do not seem to be of importance in isolation and are accounted for in the direct impact variable.

First, exploratory analyses are performed (see tables A-1). Pearson correlation analysis (which assumes a linear relationship) between the continuous variables and Diff(5) leads to (highly) significant results with (log) capital stock losses (correlation of -0.317, p-value 0.000). Interestingly, such a correlation cannot be found for GDP losses, indicating that capital stock losses may serve as a better predictor. Furthermore, total population (correlation of 0.200, p-value 0.013) as well as aid (in percent of capital formation) are found to be significant (correlation of 0.187, p-value 0.032).

Descriptive statistics for Diff(5) within sub-groups according to the income, indebtedness, SIDS and hazard type indicators are considered next (see tables A-2 to A-6). Using the income indicator, the mean of Diff(5) for all sub-groups exhibits negative values. Also, with regards to the indebtedness indicator, there are negative mean (median) values. As to the type of hazard, storms and earthquakes as well as droughts (if the median is looked at) show negative values. In addition, additional "layers" (or sub-sub groups) are examined; however, the number of observations quickly becomes very small, and therefore average values should be treated with caution. Results of Diff(5) for the interaction of two indicators (which means 6 possible sub-groups) can be found in tables A-6 to A-11. For example, low income in combination with high indebtedness leads to more pronounced negative consequences. Overall, however, a general interpretation of these results is difficult as no clear trend can be discerned. Therefore, we use regression models in the following.

Multivariate regression model

A forward stepwise regression procedure to detect the most important independent variables from table 5 for the dependent variable Diff(5) is employed. In the first round of the iteration, the independent variables are each added to the starting model (i.e. intercept only model), and the improvement in the residual sum of squares for each of these resulting models is calculated. Next, for each model the p-value for the change in the sum of squares is determined (based on the F-distribution). The variable associated with the lowest p-value is the first model candidate. If the p-value is below 0.1 (significance at the 10% level), then this model is taken. In the next round, this model will be the starting model and the subsequent rounds follow the same procedure as the first. The forward procedure stops if the lowest candidate p-value in subsequent rounds is not lower than 0.1. Table 6 lists the initial model 1 and the final model 2 (all output tables for the full regression model can be found in Appendix B).

Table 6: Multivariate Regression results using a forward algorithm(Model=1: Starting model, Model=2: Final model)

Model		Coefficients (Unstandardized)		Standardized Coefficients	t	p-value
		B	Std. Error	Beta		
1	Constant	3.254	3.247		1.002	0.322
	Percent of Capital stock loss (log)	-4.600	2.076	-0.317	-2.216	0.032
2	Constant	-3.095	4.276		-0.724	0.473
	Percent of Capital stock loss (log)	-5.934	2.086	-0.409	-2.844	0.007
	Remittances	1.946	0.897	0.312	2.170	0.036

The final regression model is already reached at step 2, which indicates that the selected variables already have good predictive power. Regarding the fit of the model, while not very satisfactory from a predictive point of view (R square is around 19 percent), two variables are significant at the 5 percent level: capital stock losses (p 0.007) and remittances in the disaster year (p 0.036). While the capital stock loss variable has a negative coefficient suggesting a larger direct shock will lead also to larger negative GDP effects, the remittances parameter has a positive value suggesting that stronger remittances inflow will decrease negative consequences. In line with the exploratory analysis, the direct impacts variable (capital stock losses) seems to be a strong predictor.

To summarize, the size of the direct impact (losses) strongly predicts the magnitude of follow-on effects. The fact that it significantly explains the variation in Diff(5), which is based on the time series approach, seems to suggest some validity of the regression results so far. However, interdependencies between variables are not used in this model and are looked at next.

General linear regression model

A general linear regression modeling approach[8], which also allows for inclusion of interdependencies of several indicator variables, is used next. The model is restricted to selected key variables first identified in the literature review, the further limited by the exploratory analysis (partly presented already in the tables). The model has 4 fixed factors (indicators), including country income group, indebtedness, countries relating to SIDS and hazard type (see table 7).[9]

Table 7: Indicators used for the GLM regression

Name [abbreviation]	Value Label	Observations
Income [I_Income]	high income	19
	middle income	96
	low income	46
Indebtedness [debt]	Nan	20
	less indebted	59
	medium indebted	18
	highly indebted	62
SIDS [I_SIDS]	Yes	41
	No	118
Hazard [I_Hazard]	Storm	55
	Flood	41
	Earthquake	26
	Drought	24
	Other	13

[8] GLM underlies most of the statistical analyses used in applied and social research due to its widespread applicability. With general linear models many statistical tests can be handled as a regression analysis, including t-tests and ANOVA (Analysis of Variance).

[9] The covariates (continuous variables) are chosen based on table 2 and full order effects up to level 2 are included, i.e. relationships between up to two fix factors (indicators) and one covariate are explored within the model.

We thus define different sub-samples according to these indicator variables. For example, the whole sample can be split by the income group indicator into 3 sub-samples, the high income sub-sample (19 observations), the middle (94 observations) and low income sub-samples (46 observations). As mentioned, the limitation of higher order effects is mainly due to the decreasing number of observations within sub-groups. Table 8 shows the tests for the different main factors as well as their interactions with the indicators.[10] Full output details can be found in Appendix C.

Table 8: GLM Findings: tests of between-subjects effects

Dependent Variable: Difference (year 5)

Source	Type I Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	21220[a]	40	531	6.446	.023
Intercept	1337	1	1337	16.243	.010
Literacy rate	244	1	244	2.969	.145
Aid (capital formation)	13	1	13	.162	.704
Aid (percent of import and exports)	764	1	764	9.284	.029
Capital Stock loss (log) [logCapLoss]	1802	1	1802	21.888	.005
Aid (percent of GNI)	2230	1	2230	27.093	.003
Remittances [Remit]	1849	1	1849	22.467	.005
Capital Stock (log)	20	1	20	.238	.646
GDP (log)	80	1	80	.971	.370
Land Area (log)	0	1	0	.003	.956
I_debt * Remit	4108	2	2054	24.959	.003
I_Income * Remit	1	1	1	.008	.931
I_SIDS * Remit	97	1	97	1.174	.328
I_debt * I_Income * Remit	965	1	965	11.723	.019
I_debt * I_SIDS * Remit	653	1	653	7.932	.037
I_debt * I_Hazard * Remit	4155	8	519	6.310	.029
I_Income * I_SIDS * Remit	369	1	369	4.483	.088
I_Income * I_Hazard * Remit	106	1	106	1.291	.307
I_SIDS * I_Hazard * Remit	245	3	82	.991	.468
I_debt * logCapLoss	727	2	364	4.418	.079
I_Income * logCapLoss	698	1	698	8.475	.033
I_SIDS * logCapLoss	5	1	5	.063	.812
I_Hazard * logCapLoss	1805	4	451	5.482	.045
I_debt * I_Income * logCapLoss	82	1	82	.998	.364
I_debt * I_SIDS * logCapLoss	140	1	140	1.706	.248
I_debt * I_Hazard * logCapLoss	63	2	31	.381	.702
I_Income * I_SIDS * logCapLoss	0	0	.	.	.
I_Income * I_Hazard * logCapLoss	0	0	.	.	.
I_SIDS * I_Hazard * logCapLoss	0	0	.	.	.
Error	412	5	82		
Total	22969	46			
Corrected Total	21632	45			

a. R Squared = .981 (Adjusted R Squared = .829)

[10] A least squares criterion is used to obtain estimates of the parameters models.

As to the model specification (table 8 bottom), the model itself is significant (p-value 0.021) with about 83 percent of the variation explained (R-square 0.829), which is quite satisfactory. Significant variables (p-value smaller than 0.05) include aid (in percent of import and exports), capital stock loss (logged), aid (in percent of GNI), remittances, and interactions of capital stock losses and remittances with some of the other indicators, such as indebtedness, income and hazard.

The parameter estimates in Appendix C for the dependent variables cannot be used for interpretation purposes, because GLM models usually have systematic colinearity between the dependent variables and therefore the impact of one single dependent variable is not captured within the parameter estimate. Hence, the variables found to be significant in table 8 are analyzed according to scatter-plots, profile plots as well as comparisons of averages. In line with the observations made above the results lead to the conclusion that especially the direct impact, measured in percent of capital stock loss leads to negative long-term consequences. Remittances as well as various forms of aid decrease the negative effects, however, not as strongly as direct losses. Unfortunately, it has not been possible to refine the analysis with further sub-sub groups, such as looking at country debt levels which seems promising, as the number of observations became too small. Overall, we also find that in general natural disasters can be expected to entail negative consequences in the medium term (five years after an event). As in the multivariate regression, adverse macroeconomic effects can be related to the direct impact in terms of asset losses. Higher aid rates as well as higher remittances (pre-disaster) seem important in lessening the adverse macroeconomic consequences.

4 DISCUSSION

There is an ongoing debate on whether disasters cause significant macroeconomic impacts and are truly a potential impediment to economic development. Given the divergent positions, this analysis aimed at better defining a sort of “middle ground” identifying circumstances under which disasters have the potential to cause significant medium-term economic impacts. In a medium-term analysis, comparing counterfactual

GDP derived by time series analysis with observed GDP, natural disasters on average lead to significant negative effects on GDP. The negative effects may be small, yet can become more pronounced depending on the direct impact measured as a loss of capital stock. Using regression analysis, we further test a large number of predictors and find that higher aid rates as well as higher remittances importantly lessen the adverse negative macroeconomic consequences, while direct capital stock losses had the largest effects in causing adverse GDP effects. A number of other variables, such as country debt, seemed promising in terms of explaining the variability of GDP, yet it was not possible to further refine the analysis due to small number of observations. Beyond these findings, final conclusions are difficult to draw and the uncertainty in loss data and socioeconomic information has to be acknowledged. One reason is the challenge associated with determining the size and type of impacts as well as identifying additional key predictors. For example, particularly for middle and high income countries, capital stock losses probably play a minor role and other variables such as human and natural capital increasingly become important. Obvious steps for improving the analysis should thus focus on increasing the sample size and quality of data generated, particularly as relates to those lower income and hazard-prone countries supposed to be most vulnerable and of highest interest for the analysis. Finally, another key extension of the analysis would be to also look at disaster impacts on human and environmental capital and its economic repercussions, in isolation as well as in conjunction with produced capital.

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Appendix A: Tables

Table A-1: Correlation matrix

Correlations

		Difference (year 5)	Loss in percent of GDP	Capital Stock	GDP	Loss in monetary terms	Loss in percent of Capital Stock	Total Population	Literacy rate (percent of adult)	Government Aid
Difference (year 5)	Pearson Correlation	1	-.105	.051	-.128	-.142	-.184*	.200*	.098	-.092
	Sig. (2-tailed)		.195	.528	.117	.083	.025	.013	.388	.653
	N	155	155	155	150	150	149	155	80	26
Loss in percent of GDP	Pearson Correlation	-.105	1	-.102	-.052	.261**	.334**	-.099	.093	-.065
	Sig. (2-tailed)	.195		.131	.466	.000	.000	.152	.338	.689
	N	155	220	220	199	199	193	210	108	40
Capital Stock	Pearson Correlation	.051	-.102	1	.242**	.174*	-.025	.693**	.107	-.035
	Sig. (2-tailed)	.528	.131		.001	.014	.728	.000	.269	.832
	N	155	220	220	199	199	193	210	108	40
GDP	Pearson Correlation	-.128	-.052	.242**	1	.422**	.014	.101	.084	-.066
	Sig. (2-tailed)	.117	.466	.001		.000	.846	.156	.399	.692
	N	150	199	199	199	199	193	199	102	39
Loss in monetary terms	Pearson Correlation	-.142	.261**	.174*	.422**	1	.948**	.035	.073	-.071
	Sig. (2-tailed)	.083	.000	.014	.000		.000	.628	.463	.666
	N	150	199	199	199	199	193	199	102	39
Loss in percent of Capital Stock	Pearson Correlation	-.184*	.334**	-.025	.014	.948**	1	-.023	.017	-.057
	Sig. (2-tailed)	.025	.000	.728	.846	.000		.749	.864	.734
	N	149	193	193	193	193	193	193	99	38
Total Population	Pearson Correlation	.200*	-.099	.693**	.101	.035	-.023	1	.028	-.044
	Sig. (2-tailed)	.013	.152	.000	.156	.628	.749		.776	.789
	N	155	210	210	199	199	193	210	105	40
Literacy rate (percent of adult)	Pearson Correlation	.098	.093	.107	.084	.073	.017	.028	1	.112
	Sig. (2-tailed)	.388	.338	.269	.399	.463	.864	.776		.629
	N	80	108	108	102	102	99	105	108	21
Government Aid	Pearson Correlation	-.092	-.065	-.035	-.066	-.071	-.057	-.044	.112	1
	Sig. (2-tailed)	.653	.689	.832	.692	.666	.734	.789	.629	
	N	26	40	40	39	39	38	40	21	40

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Table A-1: Correlation matrix (continued)

Correlations

		Difference (year 5)	Aid (capital formation)	Aid (percent of imports and exports)	Land area	Loss in percent of GDP (log)	Loss in percent of Capital Stock (log)	Aid (% of GNI)	Remittances
Difference (year 5)	Pearson Correlation	1	.187*	.132	.118	-.149	-.317**	.061	.107
	Sig. (2-tailed)		.032	.162	.143	.064	.000	.494	.277
	N	155	132	113	155	155	149	130	106
Aid (capitall formation)	Pearson Correlation	.187*	1	.763**	-.171*	.034	-.034	.813**	.009
	Sig. (2-tailed)	.032		.000	.025	.661	.668	.000	.921
	N	132	171	133	171	171	160	161	122
Aid (percent of imports and exports)	Pearson Correlation	.132	.763**	1	-.147	.052	.049	.636**	.041
	Sig. (2-tailed)	.162	.000		.081	.540	.572	.000	.656
	N	113	133	142	142	142	133	136	121
Land area	Pearson Correlation	.118	-.171*	-.147	1	-.203**	-.338**	-.137	-.195*
	Sig. (2-tailed)	.143	.025	.081		.002	.000	.065	.016
	N	155	171	142	220	220	193	183	152
Loss in percent of GDP (log)	Pearson Correlation	-.149	.034	.052	-.203**	1	.714**	.208**	.355**
	Sig. (2-tailed)	.064	.661	.540	.002		.000	.005	.000
	N	155	171	142	220	220	193	183	152
Loss in percent of Capital Stock (log)	Pearson Correlation	-.317**	-.034	.049	-.338**	.714**	1	.100	.210*
	Sig. (2-tailed)	.000	.668	.572	.000	.000		.210	.015
	N	149	160	133	193	193	193	160	133
Aid (% of GNI)	Pearson Correlation	.061	.813**	.636**	-.137	.208**	.100	1	.172*
	Sig. (2-tailed)	.494	.000	.000	.065	.005	.210		.049
	N	130	161	136	183	183	160	183	132
Remittances	Pearson Correlation	.107	.009	.041	-.195*	.355**	.210*	.172*	1
	Sig. (2-tailed)	.277	.921	.656	.016	.000	.015	.049	
	N	106	122	121	152	152	133	132	152

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Table A-1: Correlation matrix (continued)

Correlations

		Difference (year 5)	Capital Stock (log)	GDP (log)	Money loss (log)	Land Area (log)
Difference (year 5)	Pearson Correlation	1	.117	-.065	-.177*	.043
	Sig. (2-tailed)		.147	.428	.030	.598
	N	155	154	150	150	155
Capital Stock (log)	Pearson Correlation	.117	1	.833**	.618**	.624**
	Sig. (2-tailed)	.147		.000	.000	.000
	N	154	204	193	193	204
GDP (log)	Pearson Correlation	-.065	.833**	1	.837**	.593**
	Sig. (2-tailed)	.428	.000		.000	.000
	N	150	193	199	199	199
Money loss (log)	Pearson Correlation	-.177*	.618**	.837**	1	.368**
	Sig. (2-tailed)	.030	.000	.000		.000
	N	150	193	199	199	199
Land Area (log)	Pearson Correlation	.043	.624**	.593**	.368**	1
	Sig. (2-tailed)	.598	.000	.000	.000	
	N	155	204	199	199	220

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Table A-2: Diff(5) vs. Income

Difference (year 5) * Income level

Difference (year 5)

Income level	N	Mean	Std. Deviation	Median	Skewness
high income	19	-10.0428	10.28454	-8.2346	-.610
low income	46	-1.5493	28.08414	1.8748	.661
middle income	90	-.1570	21.37437	-4.1126	1.075
Total	155	-1.7820	22.73418	-3.4932	.951

Table A-3: Diff(5) vs. Debt

Difference (year 5) * Indebtedness

Difference (year 5)

Indebtedness level	N	Mean	Std. Deviation	Median	Skewness
NanN	20	-8.5480	12.31746	-7.4272	-.033
highly indebted	62	-.6998	26.53054	1.7900	.629
medium indebted	17	1.4293	33.09615	-8.4707	1.283
less indebted	56	-1.5386	16.55988	-4.8505	.396
Total	155	-1.7820	22.73418	-3.4932	.951

Table A-4: Diff(5) vs. SIDS

Difference (year 5) * SIDS

Difference (year 5)

SIDS	N	Mean	Std. Deviation	Median	Skewness
no	114	-1.0722	21.51452	-2.5134	1.009
yes	41	-3.7554	26.01534	-3.9810	.944
Total	155	-1.7820	22.73418	-3.4932	.951

Table A-5: Diff(5) vs. Hazard type

Difference (year 5) * Hazard type

Difference (year 5)

Hazard type	N	Mean	Std. Deviation	Median	Skewness
Storm	53	-3.2304	15.29672	-5.1644	1.287
Flood	41	2.5940	22.90447	3.0448	-.032
Earthquake	25	-3.6452	23.32322	-4.4723	.998
Drought	23	4.6507	31.28664	-5.4178	1.711
other	13	-17.4760	23.65540	-9.8835	-.427
Total	155	-1.7820	22.73418	-3.4932	.951

Table A-6: Diff(5) vs. Income vs. Debt.

Difference (year 5)

Income level	Indebtedness level	N	Mean	Std. Deviation	Median	Skewness
high income	NanN	16	-9.8812	10.82718	-7.4272	-.679
	less indebted	3	-10.9044	8.45075	-11.5879	.362
	Total	19	-10.0428	10.28454	-8.2346	-.610
low income	highly indebted	41	-1.1036	29.47572	3.3870	.603
	medium indebted	5	-5.2039	12.89095	-8.1523	.716
	Total	46	-1.5493	28.08414	1.8748	.661
middle income	NanN	4	-3.2148	18.09280	-3.6352	.114
	highly indebted	21	.0887	20.20344	.4068	.857
	medium indebted	12	4.1931	38.78767	-10.0309	.991
	less indebted	53	-1.0084	16.79157	-4.5365	.331
	Total	90	-.1570	21.37437	-4.1126	1.075
Total	NanN	20	-8.5480	12.31746	-7.4272	-.033
	highly indebted	62	-.6998	26.53054	1.7900	.629
	medium indebted	17	1.4293	33.09615	-8.4707	1.283
	less indebted	56	-1.5386	16.55988	-4.8505	.396
	Total	155	-1.7820	22.73418	-3.4932	.951

Table A-7: Diff(5) vs. Income vs. Hazard type

Difference (year 5) * Income level * Hazard type

Difference (year 5)

Income level	Hazard type	N	Mean	Std. Deviation	Median	Skewness
high income	Storm	6	-9.9249	7.93491	-8.9508	-.233
	Flood	3	-8.7336	7.81854	-12.3034	1.626
	Earthquake	6	-15.3454	14.40122	-16.6655	.329
	Drought	3	-4.5909	4.97845	-6.6197	1.529
	other	1	.7820	.	.7820	.
	Total	19	-10.0428	10.28454	-8.2346	-.610
low income	Storm	14	1.4656	9.33077	4.1589	-.602
	Flood	16	4.5497	28.45303	7.6761	-.186
	Earthquake	3	-11.8533	37.53206	3.5834	-1.538
	Drought	9	.8741	39.00068	-7.8058	2.163
	other	4	-34.2222	24.94859	-41.9039	1.528
	Total	46	-1.5493	28.08414	1.8748	.661
middle income	Storm	33	-4.0054	17.78638	-6.9198	1.482
	Flood	22	2.7163	19.84732	1.7985	-.168
	Earthquake	16	2.2814	22.53234	.6409	2.057
	Drought	11	10.2610	29.30183	4.9994	1.213
	other	8	-11.3851	21.02976	-7.6592	-.918
	Total	90	-.1570	21.37437	-4.1126	1.075
Total	Storm	53	-3.2304	15.29672	-5.1644	1.287
	Flood	41	2.5940	22.90447	3.0448	-.032
	Earthquake	25	-3.6452	23.32322	-4.4723	.998
	Drought	23	4.6507	31.28664	-5.4178	1.711
	other	13	-17.4760	23.65540	-9.8835	-.427
	Total	155	-1.7820	22.73418	-3.4932	.951

Table A-8: Diff(5) vs. Income vs. SIDS

Difference (year 5) * Income level * SIDS

Difference (year 5)

Income level	SIDS	N	Mean	Std. Deviation	Median	Skewness
high income	no	16	-11.0912	10.62976	-9.9112	-.457
	yes	3	-4.4515	6.98729	-2.1327	-1.329
	Total	19	-10.0428	10.28454	-8.2346	-.610
low income	no	33	1.5991	21.89418	4.9307	.033
	yes	13	-9.5415	39.78641	-5.4178	1.464
	Total	46	-1.5493	28.08414	1.8748	.661
middle income	no	65	.0377	22.82711	-4.2906	1.281
	yes	25	-.6632	17.44403	-3.9810	-.339
	Total	90	-.1570	21.37437	-4.1126	1.075
Total	no	114	-1.0722	21.51452	-2.5134	1.009
	yes	41	-3.7554	26.01534	-3.9810	.944
	Total	155	-1.7820	22.73418	-3.4932	.951

Table A-9: Diff(5) vs. Hazard vs. SIDS

Report

Difference (year 5)

Indebtedness level	SIDS	N	Mean	Std. Deviation	Median	Skewness
NanN	no	17	-10.4743	11.15400	-8.2346	-.494
	yes	3	2.3679	15.35486	1.0816	.374
	Total	20	-8.5480	12.31746	-7.4272	-.033
highly indebted	no	42	.7537	23.01306	3.3392	.329
	yes	20	-3.7520	33.20379	-1.0841	1.013
	Total	62	-.6998	26.53054	1.7900	.629
middle indebted	no	12	6.2663	34.49705	-6.2215	1.500
	yes	5	-10.1795	29.49825	-11.5911	.481
	Total	17	1.4293	33.09615	-8.4707	1.283
low indebted	no	43	-1.1866	17.74184	-5.4348	.300
	yes	13	-2.7030	12.38017	-3.9810	1.078
	Total	56	-1.5386	16.55988	-4.8505	.396
Total	no	114	-1.0722	21.51452	-2.5134	1.009
	yes	41	-3.7554	26.01534	-3.9810	.944
	Total	155	-1.7820	22.73418	-3.4932	.951

Table A-10: Diff(5) vs. Debt. vs. SIDS

Difference (year 5)

Indebtedness level	SIDS	N	Mean	Std. Deviation	Median	Skewness
NanN	no	17	-10.4743	11.15400	-8.2346	-.494
	yes	3	2.3679	15.35486	1.0816	.374
	Total	20	-8.5480	12.31746	-7.4272	-.033
highly indebted	no	42	.7537	23.01306	3.3392	.329
	yes	20	-3.7520	33.20379	-1.0841	1.013
	Total	62	-.6998	26.53054	1.7900	.629
medium indebted	no	12	6.2663	34.49705	-6.2215	1.500
	yes	5	-10.1795	29.49825	-11.5911	.481
	Total	17	1.4293	33.09615	-8.4707	1.283
less indebted	no	43	-1.1866	17.74184	-5.4348	.300
	yes	13	-2.7030	12.38017	-3.9810	1.078
	Total	56	-1.5386	16.55988	-4.8505	.396
Total	no	114	-1.0722	21.51452	-2.5134	1.009
	yes	41	-3.7554	26.01534	-3.9810	.944
	Total	155	-1.7820	22.73418	-3.4932	.951

Table A-11: Diff(5) vs. Debt. vs. Hazard

Difference (year 5)

Indebtedness level	Hazard type	N	Mean	Std. Deviation	Median	Skewness
NanN	Storm	3	-8.9454	9.11666	-6.3138	-1.191
	Flood	5	-6.6942	7.78935	-10.3152	.548
	Earthquake	6	-15.3454	14.40122	-16.6655	.329
	Drought	5	-3.8723	15.37481	-6.6197	.333
	other	1	.7820	.	.7820	.
	Total	20	-8.5480	12.31746	-7.4272	-.033
highly indebted	Storm	28	.9441	17.26948	2.6662	.951
	Flood	16	4.6616	29.24047	7.6761	-.252
	Earthquake	4	-7.9115	31.64260	3.7486	-1.811
	Drought	9	2.7294	38.47571	-5.4178	2.081
	other	5	-27.4645	26.36579	-37.2340	.369
	Total	62	-.6998	26.53054	1.7900	.629
medium indebted	Storm	4	-9.1192	3.59991	-10.0309	1.009
	Flood	5	-7.6672	16.27240	-8.1523	.013
	Earthquake	1	71.3230	.	71.3230	.
	Drought	5	12.6623	43.04089	-12.3435	1.152
	other	2	-17.7618	43.65925	-17.7618	.
	Total	17	1.4293	33.09615	-8.4707	1.283
less indebted	Storm	18	-7.4628	12.97722	-8.3785	1.456
	Flood	15	6.9051	19.91528	6.3466	-.382
	Earthquake	14	-2.7668	13.83809	-2.2192	.650
	Drought	4	9.6128	13.16919	10.9818	-.443
	other	5	-11.0247	15.71403	-9.8835	-1.098
	Total	56	-1.5386	16.55988	-4.8505	.396
Total	Storm	53	-3.2304	15.29672	-5.1644	1.287
	Flood	41	2.5940	22.90447	3.0448	-.032
	Earthquake	25	-3.6452	23.32322	-4.4723	.998
	Drought	23	4.6507	31.28664	-5.4178	1.711
	other	13	-17.4760	23.65540	-9.8835	-.427
	Total	155	-1.7820	22.73418	-3.4932	.951

Appendix B: Linear (forward) regression: Details

Table B-1: Model Summary

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.317[a]	.100	.080	21.03051
2	.435[b]	.189	.151	20.19663

a. Predictors: (Constant), Loss in percent of Capital Stock (log)

b. Predictors: (Constant), Loss in percent of Capital Stock (log), Remittances

Table B-2: ANOVA

ANOVA[c]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2171.570	1	2171.570	4.910	.032[a]
	Residual	19460.421	44	442.282		
	Total	21631.991	45			
2	Regression	4092.124	2	2046.062	5.016	.011[b]
	Residual	17539.867	43	407.904		
	Total	21631.991	45			

a. Predictors: (Constant), Loss in percent of Capital Stock (log)

b. Predictors: (Constant), Loss in percent of Capital Stock (log), Remittances

c. Dependent Variable: Difference (year 5)

Table B-3: Coefficients

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.254	3.247		1.002	.322
	Loss in percent of Capital Stock (log)	-4.600	2.076	-.317	-2.216	.032
2	(Constant)	-3.095	4.276		-.724	.473
	Loss in percent of Capital Stock (log)	-5.934	2.086	-.409	-2.844	.007
	Remittances	1.946	.897	.312	2.170	.036

a. Dependent Variable: Difference (year 5)

Table B-4: Excluded Variables

Excluded Variables[c]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	Capital Stock (log)	-.163[a]	-.807	.424	-.122	.506
	GDP (log)	-.131[a]	-.878	.385	-.133	.916
	Money loss (log)	-.116[a]	-.807	.424	-.122	1.000
	Land Area (log)	-.221[a]	-1.332	.190	-.199	.728
	Remittances	.312[a]	2.170	.036	.314	.913
	Aid (% of GNI)	-.083[a]	-.570	.572	-.087	.983
	Loss in percent of GDP (log)	.043[a]	.211	.834	.032	.512
	Aid (capital formation)	.047[a]	.319	.751	.049	.968
	Aid (percent of imports and exports)	.102[a]	.696	.490	.105	.954
	Literacy rate (percent of adult)	.011[a]	.075	.940	.011	.908
2	Capital Stock (log)	-.123[b]	-.629	.533	-.097	.501
	GDP (log)	-.100[b]	-.688	.495	-.106	.906
	Money loss (log)	-.087[b]	-.629	.533	-.097	.990
	Land Area (log)	-.070[b]	-.376	.709	-.058	.561
	Aid (% of GNI)	-.027[b]	-.187	.853	-.029	.948
	Loss in percent of GDP (log)	.034[b]	.177	.861	.027	.512
	Aid (capital formation)	.108[b]	.756	.454	.116	.933
	Aid (percent of imports and exports)	.169[b]	1.183	.243	.180	.918
	Literacy rate (percent of adult)	-.049[b]	-.330	.743	-.051	.876

a. Predictors in the Model: (Constant), Loss in percent of Capital Stock (log)

b. Predictors in the Model: (Constant), Loss in percent of Capital Stock (log), Remittances

c. Dependent Variable: Difference (year 5)

Appendix C: General Linear Regression

Table C-1: Between-Subject factors

Name [abbreviation]	Value Label	N
Income [I_Income]	high income	19
	middle income	96
	low income	46
Indebtedness [debt]	Nan	20
	less indebted	59
	medium indebted	18
	highly indebted	62
SIDS [I_SIDS]	Yes	41
	No	118
Hazard [I_Hazard]	Storm	55
	Flood	41
	Earthquake	26
	Drought	24
	Other	13

Table C-2: Tests of between-Subject factors

Dependent Variable: Difference (year 5)

Source	Type I Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	21220[a]	40	531	6.446	.023
Intercept	1337	1	1337	16.243	.010
Literacy rate	244	1	244	2.969	.145
Aid (capital formation)	13	1	13	.162	.704
Aid (percent of import and exports)	764	1	764	9.284	.029
Capital Stock loss (log) [logCapLoss]	1802	1	1802	21.888	.005
Aid (percent of GNI)	2230	1	2230	27.093	.003
Remittances [Remit]	1849	1	1849	22.467	.005
Capital Stock (log)	20	1	20	.238	.646
GDP (log)	80	1	80	.971	.370
Land Area (log)	0	1	0	.003	.956
I_debt * Remit	4108	2	2054	24.959	.003
I_Income * Remit	1	1	1	.008	.931
I_SIDS * Remit	97	1	97	1.174	.328
I_debt * I_Income * Remit	965	1	965	11.723	.019
I_debt * I_SIDS * Remit	653	1	653	7.932	.037
I_debt * I_Hazard * Remit	4155	8	519	6.310	.029
I_Income * I_SIDS * Remit	369	1	369	4.483	.088
I_Income * I_Hazard * Remit	106	1	106	1.291	.307
I_SIDS * I_Hazard * Remit	245	3	82	.991	.468
I_debt * logCapLoss	727	2	364	4.418	.079
I_Income * logCapLoss	698	1	698	8.475	.033
I_SIDS * logCapLoss	5	1	5	.063	.812
I_Hazard * logCapLoss	1805	4	451	5.482	.045
I_debt * I_Income * logCapLoss	82	1	82	.998	.364
I_debt * I_SIDS * logCapLoss	140	1	140	1.706	.248
I_debt * I_Hazard * logCapLoss	63	2	31	.381	.702
I_Income * I_SIDS * logCapLoss	0	0	.	.	.
I_Income * I_Hazard * logCapLoss	0	0	.	.	.
I_SIDS * I_Hazard * logCapLoss	0	0	.	.	.
Error	412	5	82		
Total	22969	46			
Corrected Total	21632	45			

a. R Squared = .981 (Adjusted R Squared = .829)

Table C-3: Parameter estimates

Parameter Estimates

Dependent Variable: Difference (year 5)

Parameter	B	Std. Error	t	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Intercept	65.048	82.020	.793	.434	-145.791	275.886
Literacy	-.394	.362	-1.088	.326	-1.324	.537
Aidgdf	-.192	.242	-.796	.462	-.813	.429
Aidnex	.391	.424	.923	.398	-.698	1.479
logCapLoss	-21.650	229.545	-.094	.929	-611.715	568.414
AidGNI	-.297	.959	-.309	.770	-2.762	2.169
Remit	-16.487	194.754	-.085	.936	-517.120	484.145
logCapStock	2.950	6.885	.428	.686	-14.749	20.649
logGDP	-11.146	7.886	-1.414	.217	-31.417	9.124
logLandArea	11.320	4.287	2.640	.046	.299	22.340
[L_debt=1.00]*Remit	273.337	372.066	.735	.496	-683.088	1229.762
[L_debt=2.00]*Remit	122.872	232.243	.529	.619	-474.127	719.872
[L_debt=3.00]*Remit	0	.	.	.	.	.
[L_Income=76.00]*Remit	-245.669	506.327	-.485	.648	-1547.223	1055.886
[L_Income=77.00]*Remit	0	.	.	.	.	.
[L_SIDS=.00]*Remit	24.322	202.097	.120	.909	-495.183	543.828
[L_SIDS=1.00]*Remit	0	.	.	.	.	.
[L_debt=1.00]*[L_Income=76.00]*Remit	-65.834	125.906	-.523	.623	-389.487	257.818
[L_debt=1.00]*[L_Income=77.00]*Remit	0	.	.	.	.	.
[L_debt=2.00]*[L_Income=76.00]*Remit	0	.	.	.	.	.
[L_debt=2.00]*[L_Income=77.00]*Remit	0	.	.	.	.	.
[L_debt=3.00]*[L_Income=77.00]*Remit	0	.	.	.	.	.
[L_debt=1.00]*[L_SIDS=.00]*Remit	-163.417	473.051	-.345	.744	-1379.433	1052.599
[L_debt=1.00]*[L_SIDS=1.00]*Remit	0	.	.	.	.	.
[L_debt=2.00]*[L_SIDS=.00]*Remit	0	.	.	.	.	.
[L_debt=3.00]*[L_SIDS=.00]*Remit	0	.	.	.	.	.
[L_debt=3.00]*[L_SIDS=1.00]*Remit	0	.	.	.	.	.
[L_debt=1.00]*[L_Hazard=1.00]*Remit	-271.442	380.054	-.714	.507	-1248.401	705.517
[L_debt=1.00]*[L_Hazard=2.00]*Remit	55.542	65.961	.842	.438	-114.015	225.099
[L_debt=1.00]*[L_Hazard=4.00]*Remit	0	.	.	.	.	.
[L_debt=1.00]*[L_Hazard=5.00]*Remit	0	.	.	.	.	.
[L_debt=2.00]*[L_Hazard=2.00]*Remit	-32.420	143.687	-.226	.830	-401.780	336.940
[L_debt=2.00]*[L_Hazard=3.00]*Remit	-130.722	238.276	-.549	.607	-743.229	481.786
[L_debt=2.00]*[L_Hazard=4.00]*Remit	0	.	.	.	.	.
[L_debt=3.00]*[L_Hazard=1.00]*Remit	12.886	544.168	.024	.982	-1385.943	1411.715
[L_debt=3.00]*[L_Hazard=2.00]*Remit	55.172	190.856	.289	.784	-435.439	545.784
[L_debt=3.00]*[L_Hazard=3.00]*Remit	-5.385	7.599	-.709	.510	-24.919	14.149
[L_debt=3.00]*[L_Hazard=4.00]*Remit	103.618	228.818	.453	.670	-484.576	691.812
[L_debt=3.00]*[L_Hazard=5.00]*Remit	0	.	.	.	.	.
[L_Income=76.00]*[L_SIDS=.00]*Remit	306.871	481.720	.637	.552	-931.429	1545.171
[L_Income=76.00]*[L_SIDS=1.00]*Remit	0	.	.	.	.	.
[L_Income=77.00]*[L_SIDS=.00]*Remit	0	.	.	.	.	.
[L_Income=77.00]*[L_SIDS=1.00]*Remit	0	.	.	.	.	.
[L_Income=76.00]*[L_Hazard=1.00]*Remit	178.903	159.026	1.125	.312	-229.887	587.692
[L_Income=76.00]*[L_Hazard=2.00]*Remit	0	.	.	.	.	.
[L_Income=76.00]*[L_Hazard=4.00]*Remit	0	.	.	.	.	.
[L_Income=77.00]*[L_Hazard=1.00]*Remit	0	.	.	.	.	.
[L_Income=77.00]*[L_Hazard=2.00]*Remit	0	.	.	.	.	.
[L_Income=77.00]*[L_Hazard=3.00]*Remit	0	.	.	.	.	.
[L_Income=77.00]*[L_Hazard=4.00]*Remit	0	.	.	.	.	.
[L_Income=77.00]*[L_Hazard=5.00]*Remit	0	.	.	.	.	.
[L_SIDS=.00]*[L_Hazard=1.00]*Remit	-16.443	550.186	-.030	.977	-1430.741	1397.855
[L_SIDS=.00]*[L_Hazard=2.00]*Remit	-168.587	197.815	-.852	.433	-677.087	339.913
[L_SIDS=.00]*[L_Hazard=3.00]*Remit	0	.	.	.	.	.
[L_SIDS=.00]*[L_Hazard=4.00]*Remit	-113.086	237.732	-.476	.654	-724.195	498.024
[L_SIDS=.00]*[L_Hazard=5.00]*Remit	0	.	.	.	.	.
[L_SIDS=1.00]*[L_Hazard=1.00]*Remit	0	.	.	.	.	.
[L_SIDS=1.00]*[L_Hazard=2.00]*Remit	0	.	.	.	.	.
[L_SIDS=1.00]*[L_Hazard=4.00]*Remit	0	.	.	.	.	.
[L_SIDS=1.00]*[L_Hazard=5.00]*Remit	0	.	.	.	.	.
[L_debt=1.00]*logCapLoss	-89.034	114.835	-.775	.473	-384.226	206.159
[L_debt=2.00]*logCapLoss	-74.571	32.945	-2.264	.073	-159.258	10.116
[L_debt=3.00]*logCapLoss	0	.	.	.	.	.
[L_Income=76.00]*logCapLoss	59.254	34.853	1.700	.150	-30.339	148.848
[L_Income=77.00]*logCapLoss	0	.	.	.	.	.
[L_SIDS=.00]*logCapLoss	-137.896	79.075	-1.744	.142	-341.166	65.373
[L_SIDS=1.00]*logCapLoss	0	.	.	.	.	.
[L_Hazard=1.00]*logCapLoss	137.943	193.275	.714	.507	-358.886	634.772
[L_Hazard=2.00]*logCapLoss	153.894	202.842	.759	.482	-367.529	675.317
[L_Hazard=3.00]*logCapLoss	161.206	199.402	.808	.456	-351.375	673.786
[L_Hazard=4.00]*logCapLoss	160.106	202.766	.790	.466	-361.121	681.334
[L_Hazard=5.00]*logCapLoss	0	.	.	.	.	.
[L_debt=1.00]*[L_Income=76.00]*logCapLoss	-48.924	42.237	-1.158	.299	-157.498	59.649
[L_debt=1.00]*[L_Income=77.00]*logCapLoss	0	.	.	.	.	.
[L_debt=2.00]*[L_Income=76.00]*logCapLoss	0	.	.	.	.	.
[L_debt=2.00]*[L_Income=77.00]*logCapLoss	0	.	.	.	.	.
[L_debt=3.00]*[L_Income=77.00]*logCapLoss	0	.	.	.	.	.
[L_debt=1.00]*[L_SIDS=.00]*logCapLoss	114.522	102.978	1.112	.317	-150.192	379.235
[L_debt=1.00]*[L_SIDS=1.00]*logCapLoss	0	.	.	.	.	.
[L_debt=2.00]*[L_SIDS=.00]*logCapLoss	0	.	.	.	.	.
[L_debt=3.00]*[L_SIDS=.00]*logCapLoss	0	.	.	.	.	.
[L_debt=3.00]*[L_SIDS=1.00]*logCapLoss	0	.	.	.	.	.
[L_debt=1.00]*[L_Hazard=1.00]*logCapLoss	-20.244	40.697	-.497	.640	-124.860	84.371
[L_debt=1.00]*[L_Hazard=2.00]*logCapLoss	-26.591	33.445	-.795	.463	-112.564	59.382

Appendix D: Uncertainty analysis

To assess the uncertainty in the projections based on the ARIMA models, 95% forecast confidence intervals were calculated. For each observation in the sample, we calculated the 95% forecast confidence intervals and used the upper and lower bounds for comparison with the observed GDP data; i.e., we calculate the differences to observed data based on these two values. Hence, there are two additional samples: one on the upper and one on the lower confidence region. The mean and median for these two samples are shown in table D1.

Table D1: Mean and median of the sample differences using either the lower bound projections or the upper bound projections of the 95 percent forecast confidence intervals.

	t+1		**t+2**		**t+3**		**t+4**		**t+5**	
	low	up	low	up	low	up	low	up	low	up
Mean	-11.09	6.97	-22.95	14.18	-37.94	20.95	-56.15	27.06	-80.47	33.02
Median	-9.14	5.86	-19.10	13.10	-31.10	20.31	-44.95	27.79	-59.29	34.15

A large range can be found for the differences in the post-disaster years according to these 95 percent upper and lower confidence intervals of the projections; yet there is a clear trend to negative differences. The test for the lower and upper confidence bounds of the projections are however not useful for interpretational purposes due to the high standard errors associated with mean projections, leading either to a full rejection of the Null hypothesis or not.

One remaining question regarding the ARIMA model projections and the validity of the results above is the influence of multiple disaster events. We tackle this issue by looking at a sub-sample within the full sample where 5 years before and 5 years after the disaster event no other major disaster (with losses higher than 1 percent of GDP) occurred. Table D2 again shows the mean and median as well as the sample size.

Table D2: Summary results for differences of real and projected GDP levels for sub-sample

	t+1	**t+2**	**t+3**	**t+4**	**t+5**
Mean	-2.0558	-3.0284	-4.1281	-5.2683	-7.0973
Median	-.8355	-1.4487	-2.0793	-3.5084	-5.9910
Std. Dev.	7.75618	12.15134	17.14314	23.01776	30.86930
Skewness	-1.721	-1.764	-2.201	-3.200	-4.172
Observations	136	129	128	123	120

As in the full sample case, the average values are all negative, even with higher negative values. Statistical non-parametric Wilcoxon tests reveal that all of the average results are significantly lower than zero on the 95 percent confidence interval.