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Natural Disasters and Macroeconomic Performance: An Empirical Analysis Based on an Econometric Modelling Approach

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Abstract We investigate the short and medium term (up to 5 years) macroeconomic consequences due to natural disaster events. The focus is on the Gross Domestic Product (GDP) as the main economic performance measure on the country level. Consequences are estimated based on a comparison of the actual post-disaster economic performance with a counterfactual projected one using an econometric modelling approach. Furthermore, it is investigated which socio-economic and other disaster related dimensions are able to explain differences in consequences the most. In that regard, rather than focusing on the time shortly before the disaster (as usually done in such analysis) special emphasis on events (such as other hazards) or situations (including socio-economic dimensions) which happened some time before the actual disaster occurred but eventually influenced the post–disaster consequences is given. Positive as well as negative consequences to GDP due to disaster events were found within the sample. However, on average, the (accumulated) consequences due to disasters were neither significant negative nor positive. In other words, this analysis did not support the hypothesis that disasters in general lead to negative consequences (or positive consequences) but rather the consequences are likely to be dependent on the pre-disaster socio-economic situation. Private financial debt as well as the general macroeconomic situation was found to be significant here to explain part of the variance. Additionally, medium term consequences were found to be dependent on the direct losses experienced, the number of inter-annual hazards occurred, as well as the amount of losses due to disasters in previous years. Furthermore, there are some indications that education plays a role here too. Some recommendations for future research based on the results found are given.

Key words: Natural disasters, macroeconomic effects, econometric model, empirical analysis.

1. INTRODUCTION

In this paper we want to investigate the short and medium term (up to 5 years) macroeconomic consequences due to natural disaster events. The focus will be on Gross Domestic Product (GDP) as the main economic performance measure on the country level. Consequences are estimated based on a comparison of the actual post-disaster economic performance with a counterfactual projected one using

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an econometric modelling approach. Furthermore, we want to investigate which socio-economic and other disaster related dimensions are able to better explain differences in consequences. In that regard, rather than focusing on the time shortly before the disaster (as is usually done in such analysis) we give special emphasis on time-dependencies. Time dependency is defined here as events (such as other hazards) or situations (including socio-economic dimensions) which happened some time before the actual disaster occurred but influenced the post–disaster consequences (and cannot be understood without it). We start first with an overall introduction into this issue from an empirical as well as theoretical perspective.

A growing literature has emerged over the last years on the macroeconomic impacts of natural disasters. Looking at the past literature on macroeconomic impacts due to disaster events, two broad positions can be identified (see Hochrainer 2009). Position 1 broadly suggests the post-disaster trajectory will fall short of the planned trajectory, while position 2 contends that the planned GDP path can be achieved or even surpassed (Figure 1). One study for position one is Noy (2009). He empirically examined the reduction of GDP growth rates for a large sample of disaster events, for which, using a linear regression modelling 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. The classic opposing study to position 1 is Albala-Bertrand (1993), i.e., he concludes that natural disasters do not lower GDP growth rates and "if anything, they might improve them" (1993: 207). The results were based on a rather simple comparison of GDP (and other macroeconomic variables) growth rates before the disaster event with growth rates after the disaster event. Additionally, his analysis was built on only a small sample of 28 disaster situations in 26 different countries from 1960-1979. A re-examination of his analysis using a larger sample which consisted of 85 disaster events in 45 countries was done by Hochrainer (2006) but could not support the hypothesis of Albala-Bertrand (1993). We refer to Cavallo and Noy (2010) for a critical literature survey on the economics of natural disaster events and growth impacts (see also IPCC 2012). Generally speaking, the different empirical findings are difficult to be summarized, as different approaches, methodologies and definitions are used which "makes it almost impossible to compare or aggregate published estimates that are based on so many different assumptions and methods" (Hallegate and Przyluski 2010), although Cavallo and Noy (2010) tried to compare in a comprehensive manner the different results found.

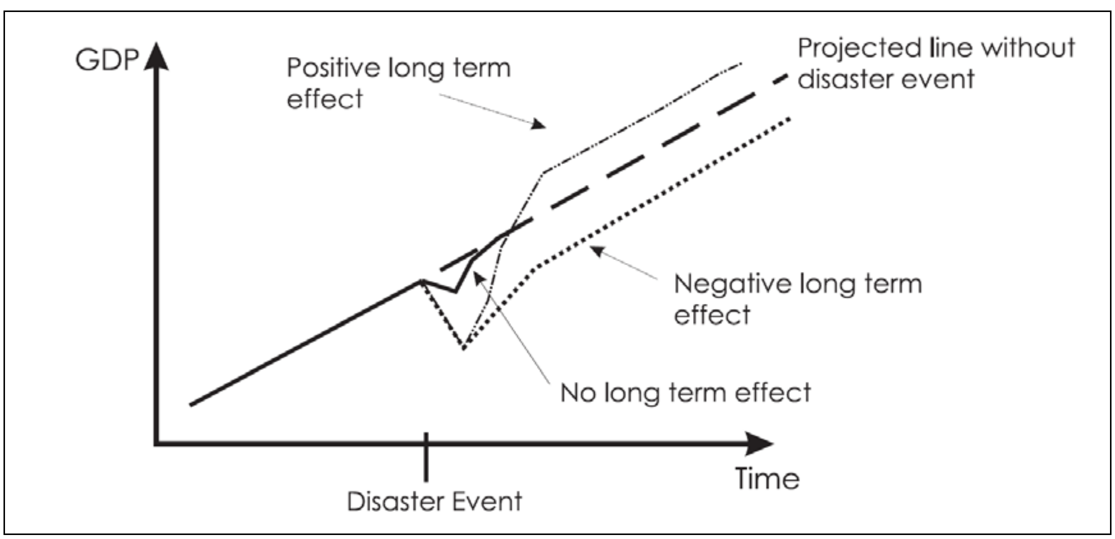

Fig. 1 Possible growth paths of GDP after a disaster. Source: Hochrainer (2006).

Regarding existing theories about natural disasters and socio-economic performance, they are usually divided into two strands, the Solow-Swan exogenous growth model approaches and the endogenous

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Schumpeterian growth model approaches. Combinations of these two, which critically examined the hypothesis of "creative destruction", can be found, for example, in Hallegate and Dumas (2009), who conclude that disasters are never positive economic events, and can also eventually lead to poverty traps. In more detail, in the exogenous growth model approaches, usually one starts with a production function such as the Cobb-Douglas function:

$$Y_t = A_t K_t{}^{\alpha} L_t{}^{(1-\alpha)}$$

where Y_t is total output at time t, A_t is a productivity parameter, K_T is capital stock, L_T is human capital (labour), and α and $1-\alpha$ are factor shares. If this is transformed to a growth equation, one gets

$$\dot{Y}_t / Y_t = \dot{A}_t / A_t + \alpha(\dot{K}_t / K_t) + (1-\alpha)(\dot{L}_t / L_t)$$

One can already see that long-term growth effects can be expected due to indirect changes, e.g., via the adoption of new technology (changes in A), or changes in human capital investment L, or changes in physical capital due to reconstruction (changes in K). All possible combinations of changes in growth within the right hand side of the production function are, in principle, possible, which makes the net effect "theoretically ambiguous" (Skidmore and Toya 2002). The endogenous growth models, most importantly here is the Schumpeterian and the non-equilibrium dynamic model (NEDyM), usually determine growth responses in relation to technological progress. For example, Hallegate and Dumas (2009) distinguish between non-destroyed capital and destroyed capital after a disaster within the Cobb-Douglas function, i.e.

$$Y_t = \delta_K A_t K_{t0}{}^{\alpha} L_t{}^{(1-\alpha)}$$

where δ_K is the non-destroyed capital and K_{t0} is the capital without the disaster event. Using the concept of mean capital productivity to model the creative destruction mechanism in the aftermath of a disaster, Hallegate and Dumas (2009) state that the assumptions usually made for providing positive growth effects are overly optimistic and therefore disasters have, at best, neutral effects on growth.

As growth theory does not seem to lead to a final answer as to whether (and how) disasters affect economic growth, this question is sometimes seen as "ultimately an empirical one" (Cavallo et al. 2010). Interestingly, focus on time-dependent dimensions (see also Figure 2) are rarely included (see as an exception Skidmore and Toya 2002), and also multi-risk situations are not very often incorporated (see for example Schumacher and Strobl 2011). Furthermore, the effects of small, but repeated, events were not looked at in a comprehensive manner. In addition, as indicated, except for Hochrainer (2009) and Cavallo et al. (2010), counterfactual comparisons are usually neglected in such studies, but still may be the most promising area to study the "real" costs of events (Cavallo and Noy 2010). Counterfactual in this context means that one compares the outcomes of a disaster with the situation that no disaster has occurred.

The standard empirical growth equation for such large scale analysis (e.g., using panel data) used within most of the disaster studies (see Loayza et al. 2012) can be stated as

$$Y_{i,t} - Y_{i,t-1} = \beta_0 Y_{i,t-1} + \beta_1 X_{i,t} + \beta_2 Z_{i,t} + \mu_t + \eta_i + \varepsilon_{i,t}$$

where the subscripts i and t represent the country and time, Y is output (usually the log is taken and divided by population to obtain output per capita), X is the capital investment rate, Z represents variables reflecting the economic heterogeneity between different countries, μ is a time-specific effect to allow for differences in the rate of world-economic growth and other non-disaster related shocks, η_i denotes unobserved country-specific effects, and ε is the error term (see Cavallo and Noy 2010 for a summary). Dependent variables, i.e., variables on the left-hand side of the above equation, used within the literature, include (i) most often the growth rate of GDP per capita (and also sector specific ones), either annually or averaged over some years, (ii) losses per capita (in log) (iii) people affected, as well as (iv) total factor productivity and public finance situations (see Cavallo and Noy 2010). On the right-hand side of the equation, a multitude of various predictor variables can be found which more or less are based on either theoretical conceptions or on past findings in the literature. Hence, not only are the outcomes for growth or other dependent variables uncertain, but also the influences are far from clear (see Cavallo and Noy 2010, Hallegate and Przyluski 2010).

As already indicated, time-dependencies, socio-economic dimensions, single and multi-risk situations are the primary focus of this article. The main idea is shown in Figure 2 where the effects of past events may cause consequences for future events which cannot be understood without the former ones.

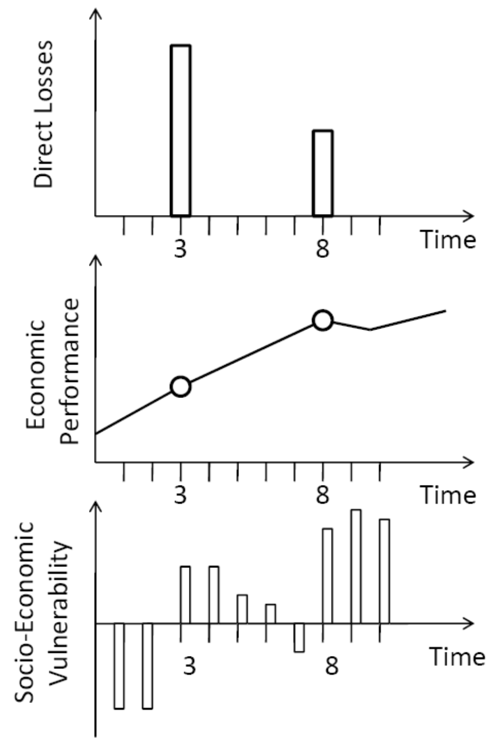

Fig. 2 Concept of time-dependent vulnerability

Conceptually, the second event (in Figure 2) in year 8 caused higher indirect effects, even if the direct losses are smaller compared to year 3, as the underlying vulnerability was higher in the second event. One problem is now how to define socio-economic vulnerability in such a way that the dynamics are explicitly included. Just from a conceptual point of view, many different ways of defining socio-economic vulnerability can be found in the literature (Parker et al. 2009). However, we are less interested here in the concepts and more on possible ways to empirically measure and test it for a large sample of panel data. We will discuss the socio-economic variables included and methodology used in the next section in more detail.

Summarizing, this article can be understood as providing a better basis for the discussion on economic consequences due to natural disasters by incorporating and comparing counterfactual vs. actual observed outputs for a large sample of disaster events. It is based on work done by Worthington and Valadkhani (2004), Hochrainer (2009), and Cavallo et al. (2010) and extends it to a larger dataset as well as includes new predictor variables. In addition, the article analyses the different possible drivers which could cause the different growth paths observed. One important and neglected aspect concerns human capital. We include this dimension (as well as others) to investigate if significant influences can be found when these new variables are incorporated. The article is organized as follows. Section 2 lays out the methodology applied and the proposed predictor and control variables as well as the response variable and dataset used. Section 3 then presents the results and section 4 ends with a conclusion and outlook to the future.

2. METHODOLOGY

We locate our discussion within the disaster risk management framework (Mechler 2004). Standard approaches (see for example Grossi and Kunreuther 2005; Woo 2011) estimate direct losses (caused by the disaster itself) as a function of the hazard, the exposure and the (physical) vulnerability. The most important hazard dimensions include the specific intensity and recurrence probabilities within certain areas. Exposure is usually related to assets such as houses, firms or populations which are exposed to the hazard. Physical vulnerability is related to the susceptibility to harm of people or engineered structures. Exposure and physical vulnerability levels are dependent on the socio-economic factors of the elements at risk and therefore disasters affect sub-groups within the society differently. This is immediately evident if one compares the average death tolls of high-, middle-, and low income country groups (Figure 3), where losses of the latter are orders of magnitude higher than in the others.

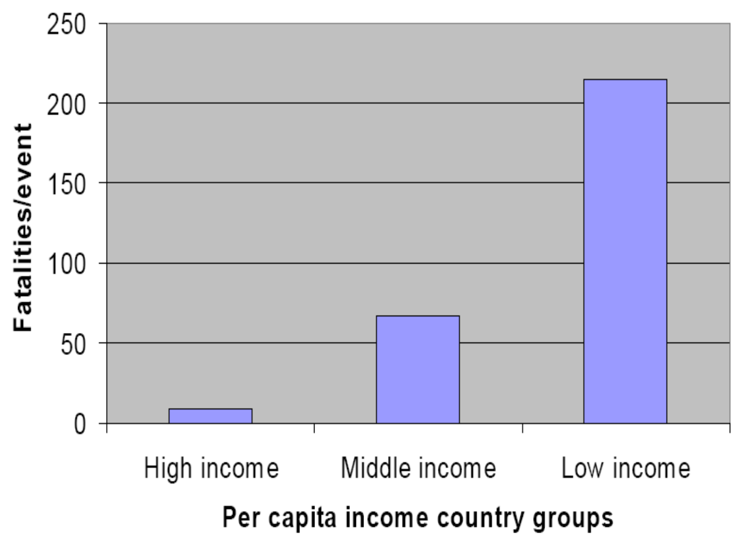

Fig. 3 Average fatalities per event for different income groups. Source: Linnerooth-Bayer et al. 2005.

As a consequence of such direct losses, follow-on effects may materialize, leading to indirect 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 activity path. It may relate to private households and businesses as well as governments that often bear 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 reducing and transferring disaster risks. Table 1 lists some studies and general factors that contribute to a discussion of (macro) economic disaster risk and economic vulnerability. Determinants of the impacts and risk can be distinguished according to (i) the type of natural hazard (*hazard* variable), (ii) geographical area and spatial scale of the 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 (all related to *economic vulnerability*) (see Table 1).

Table 1 Empirical studies assessing macroeconomic risk and economic vulnerability to natural hazards. Source: extended from Barrito (2008) and Hochrainer (2009).

Study	**Response variables**	**Potential variables for predicting adverse macro effects**
Charveriat (2000)	• GDP	• Size of the economy, degree of diversification and size of the informal and agricultural sectors.
ECLAC and IDB (2000); Freeman et al.(2002); Mechler (2004);Hochrainer (2006)	• GDP, fiscal variables	• Ability to refinance losses and provide relief to the affected population (financial vulnerability) • Availability of implicit (aid) and explicit (insurance) risk sharing arrangements
Burton et al.(1993); Kahn (2005)	• Deaths due to natural disasters	• Income
Benson and Clay (2004)	• Total GDP annual change • Agricultural GDP annual change • Non-Agric. GDP annual change	• Structure of the economy • Size • Income level and stage of development • Prevailing socioeconomic conditions
Toya and Skidmore (2007)	• Disaster-related deaths • Damages/GDP	• 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).
Noy (2009)	• GDP	• 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
Raschky (2008)	• GDP	• Availability of financial risk sharing institutions
Cavallo et al. (2010)	• Per capita GDP	• Only very negative events have short and long run effects • Political instability important
Schumacher and Strobl (2011)	• Damages/Population	• Loss and wealth relationship depends on level of hazard of natural disaster
Loayza et al. (2012)	• GDP per capita (5 year averages)	• Disasters do not always affect growth negatively • Moderate disasters can have positive growth effects, severs do not • Growth is more sensitive to disasters in developing cntry

All of the indicators used for explaining the response variables mentioned above are valid candidates as proxies for hazard, exposure and vulnerability (we will describe our selected independent variables in the next section). However, they are likely not to remain constant over time and therefore time-dependency (i.e. the dependency of consequences today from events in the past, see Figure 2 and corresponding discussion) comes into play (see Figure 4).

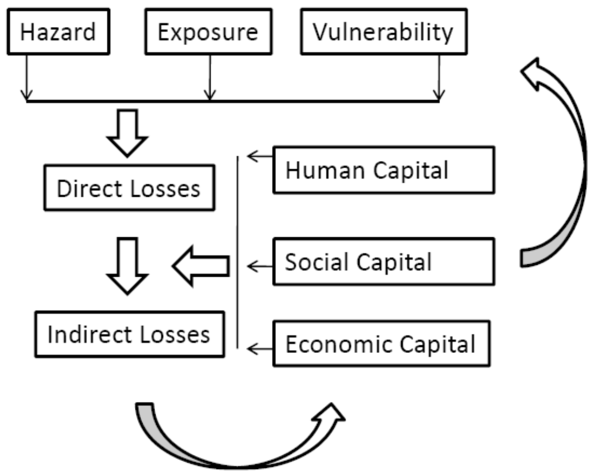

Fig. 4 Conceptual framework used in this study for explaining risk due to natural disasters.

Figure 4 additionally introduces different forms of capitals which can be used to cope with an event (see DFID 1999; Yazdanpanah et al. 2013). Human Capital refers, for example, to the knowledge, skills, and competencies of individuals whereas social capital refers to networks, features of social organization, such as norms, values, trust and understanding that facilitate co-operation. Economic capital includes financial capital which can be used and determines economic vulnerability. In this paper we focus mostly on human and economic capital dimensions. As indicated in Figures 3 and 4, the effects of disasters will likely increase future risk but only materialize if another disaster event (or another kind of downside risk, i.e. risk associated with losses) happens.

Regarding the actual estimation procedure, we will apply multivariate linear regression models to test which variables could explain the differences in consequences Δy_n . We use the following form of functional relationship

$$\Delta y_{n\_c,t} = \alpha + \sum_{i=1}^{I} \beta_i X_{Direct\_i,c,t} + \sum_{j=1}^{J} \beta_j X_{Exposure\_j,c,t} + \sum_{k=1}^{K} \beta_k X_{Hazard\_k,c,t} +$$

$$+ \sum_{l=1}^{L} \beta_l X_{Economic\_l,c,t} + \beta_m X_{HumanCapital\_c,t} + e_{c,t}$$

where c and t are the country and time index, respectively, and the β are the parameters estimated for the different response dimensions (see Table 2). In more detail, a generalized linear model using robust estimators is applied to the data (e.g. to account for possible heteroscedasticity and outliers as well as other influential observations). We first start with a discussion of the right hand side of the equation, i.e. the predictor and control variables used, and afterwards we will discuss the left hand side, i.e. how we estimate the consequences.

2.1. Predictor/Control Variables

The predictor/control variables are based on the discussion above (see Tables 1 and 2 for a summary) and Figure 4. While ideally the direct losses would be measured as a function of the hazard, the exposure and the (physical) vulnerability, this kind of data is often not available. Hence, most of the empirical studies today are using the EM-DAT database for calculating proxies of the intensity of a disaster. In this paper, we use the log (to avoid the results being driven by extreme values) of the loss to GDP and the log of loss per capita as a proxy for direct impact. Both distributions are approximately normal (tested via the Kolmogorov-Smirnov test as well as visual inspections). Since population values are available for nearly all countries and years, there are fewer missing values for these candidate proxies too. Furthermore, fatalities and people affected are also taken as a proxy and potential candidates for direct impacts. Both are summed up, whereas people affected are given a weight of 0.3 times that of fatalities (see Loayza et al. 2012). This number is then divided by the total population of the respective country.

Exposure predictors include the log of capital stock which is calculated based on the Penn World Tables (see Sanderson et al. 2009). In more detail, using the Penn World tables, the average of the first five years of each individual country's investment series are used to back-project investment until 1900, assuming an annual growth rate of 4 percent in investment. The sum of all previous investments, discounted by the number of years since they were made, was taken as the initial year's capital stock. Applying the perpetual inventory method, a rate of depreciation of 4 percent was assumed by Sanderson et al. (2009) and by aggregating countries regional physical capital stocks for the whole period were obtained. The distribution of the log of capital stock was found to be normally distributed. Furthermore, the log of population density was used as a possible predictor variable (see Schumacher and Strobl 2011). This variable is skewed to the right a bit, but will be assumed to be approximately normally distributed. Additionally, the log of land area is also taken as a possible control variable.

The hazard variables include the annual return period of an event over the given time horizon and is modelled via the Poisson distribution. Recall, a Poisson distribution with parameter $\lambda>0$, is defined as

$$P(X=n)=\frac{\lambda^n}{n!}e^{-\lambda}$$

For n=0, 1, 2, …. Observe that λ is equal to the expected value of X and calculated within the sample for the time period 1970-2012. The same was done for all disaster events which happened over the given time period, and can be interpreted as an indicator of how often multiple hazard events within a year have happened on average. Furthermore, the type of disasters, e.g., drought, flood, storms and earthquakes, that occurred during a given year are also provided. Hence, single as well as multiple hazardous events can be characterized and used as an additional response variable. For the human capital dimension, a recent constructed dataset from Lutz et al. (2010) is used, which not only gives the population's age distribution, but also the education by age. We use the ratio between the more highly educated people to total population within the 20 - 39 years age group which is calculated based on the back projections provided in Lutz et al. (2010).

The public sector situation is modelled via the CatSim (Catastrophe Simulation) approach (Hochrainer 2006; Mechler et al. 2009). In the CatSim approach, direct risk (losses and corresponding probability to experience such a loss) is combined with the available resources a government may use in the event of a disaster. The probability of the event where for the first time the government is no longer able to finance the losses is called the "resource gap return period" and represents the financial vulnerability of the government. We use the log of this return period as another response variable; for those countries with no financial resources (hence the resource gap year event would be 0) to keep them in the sample, we use the value of 1 (see for a similar approach Loayza, 2012). Additionally, we use the government consumption of GDP as an additional indicator of the financial burden of the government. Finally, the average of per capita loss (from other natural hazard events) (in log) 5 years prior to the disaster, as well as the average number of people affected 5 years prior to the disaster is used as an indication of pre-disaster shocks too.

Table 2 Predictors/control variables used in the study.

Predictors	Variables	Source
Direct Impact	Log (Loss per GDP) Log (Loss per capita) Log (People hurt per capita)	EMDAT 2012, Munich Re 2010, Okuyama, 2009, World Bank 2011, Own calculations
Exposure	Log (Capital Stock)	Penn World Tables; Sanderson et al. 2009; Own calculations
	Log(Population density)	WDI 2011
	Log(Land Area)	World Bank 2011
Hazard	Hazard type: Storm, Flood, Earthquake, Drought, Number and type of different hazards for given year	EMDAT, 2012 Munich Re, 2010
	Annual recurrence of loss events, log(λ_a), Lambda_1	EM-DAT, 2012, Own calculations, Poisson model
	Inter-annual recurrence of hazard events (e.g. within one year,) log(λ_y), Lambda_2 Inter-annual occurrence	EM-DAT, 2012, Own calculations, Poisson model
Economic/ Financial vulnerability	Government risk Critical resource gap event	CatSim approach, Mechler et al. 2009. Own calculations.
	Government burden Log(Gov. consumption to GDP)	World Bank 2011 Own calculations
	Macroeconomic stability Log(1+CPI growth)	World Bank 2011 Own calculations
	Private financial depth Log(Domestic Credit to GDP)	World Bank 2011 Own calculations
	Average per capita loss 5 years before disaster	Own calculations
	Average per capita hurt 5 years before disaster	Own calculations
	Trade Log(exp+imp to GDP)	WDI 2011
	Indebtedness level of country: Dummy variable	WDI 2011
	Income level of country Dummy variable	WDI 2011
Human Capital	Ratio of highly educated people to total population: Age Group: 20-39	Lutz et al., 2010, Own Calculations.

2.2. Response Variables

Regarding the response variables, in order to identify the net economic effects of disasters, we compare the counterfactual situation ex-post to the actual state of the system ex-post. This involves looking at the potential trajectory (unaffected economy without the disaster) compared to the actual state of the economy. This is in quite contrast to other studies which compare the actual economic performance post-event with the actual pre-event performance. The approach by Cavallo et al. (2010), while very promising as it is based on “synthetic control groups” to compare the counterfactual, is only possible for large scale events as the comparison cannot be done else wise (as the control group need to be unaffected countries) and therefore cannot be used here. Intervention analysis to analyse disaster effects could also be a possible candidate (see Worthington and Valadkhani, 2004), however, usually only the very short term can be examined and additionally it is only applicable for small samples or specific country studies, with a large number of observations, e.g., daily price returns. Albala-Bertrand (1993) and subsequently others (see Hochrainer 2006, and more recently Loayza et al., 2012) used averages of pre-disaster periods and compared them with the post disaster growth behaviour. Afterwards, the differences (or average values itself) are entered into some sort of qualitative or quantitative analysis to explain possible effects. We adopt here the approach of Hochrainer (2009) with a larger sample and include additionally (in case of better fits) the possibility to forecast via an exponential smoothing operator.

In more detail, we use either autoregressive integrated moving average models, also called ARIMA(p,d,q) models (Box and Jenkins, 1976) for forecasting GDP or perform exponential smoothing to make predictions of possible growth paths (in terms of GDP per capita, in log) without the disaster event or events. While such modelling may be criticized for its black box approach (Makridakis and Wheelwright, 1989), it serves well here due to the large amount of projections which have to be made and the difficulty in identifying suitable economic modelling approaches, such as Input-Output models, for all the different countries within the sample and over a time period starting from 1970. In the ARIMA approach, the autoregressive process of order AR(p) can be defined as

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

and the moving-average process of order MA(q) can be written as

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

which subsequently lead to an ARMA(p,q) process, with p autoregressive and q moving average terms, defined as

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

where ϕ and θ are parameters to be estimated and ε are white noise stochastic error terms. To account for non-stationarity, we use a first order difference estimator. 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 $B^k z_t = z_{t-k}$,then

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

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

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

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-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 to 4 (due to the limited amount of data available) 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. Furthermore, all models are tested to be stationary (usually d=1 suffices to assure a stationary process) and all series are demeaned. The data requirements were set to the case that at least 10 data points from the past are needed for projections into the future.

The projected growth paths are then compared to the actual ones. In accordance to the suggestions made by Hallegate and Przyluski (2010) we measure the combined effects of possible output loss (or gains) over a pre-defined post-disaster period. The conceptual framework is depicted in Figure 5.

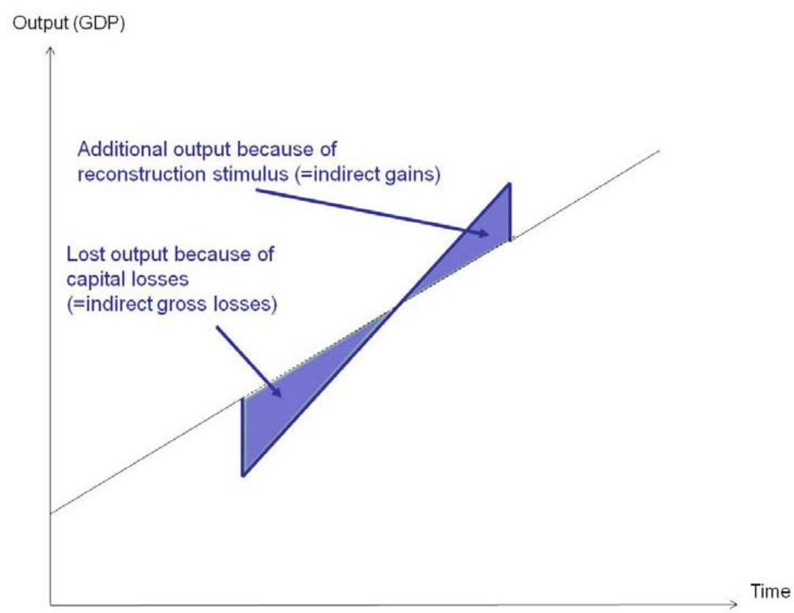

Fig. 5 Conceptual framework used for explaining the consequences of disasters over a given time period. Source: Hallegate and Przyluski (2010)

To calculate the net effect of the disaster, the differences in output between the projected no disaster event trajectory $\hat{y}_t$ and the actual (with disaster) trajectory y_t will be integrated over respective time intervals, i.e.

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$$\Delta y_n = \sum_{1}^{n} (y_i - \hat{y}_i)$$

where n is chosen to be 0,…,4 (including the disaster year), i.e., projections up to 4 years after the disaster event are looked at. Furthermore, to avoid biases in the results due to other events, for a given n, only those observations from the sample data are incorporated which did not had any additional disaster during that time period, e.g. if n is equal to 4 and the disaster year for a specific country is 1980, than this observation is only included if no other disaster events between 1980-1984 have happened.

2.3. Sample Data

The sample for our empirical analysis consists of (annual) natural disaster losses for events from 1970-2006 for all events which caused economic losses (in addition, people killed and affected are also observed), leading to a total of 1473 observations. The sample was compiled using the open-source EMDAT disaster database (EMDAT 2012) 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 and financial losses for more than 18,000 sudden-onset (such as floods, storms, earthquakes) and slow-onset (drought) events from 1900 to present. Data are compiled from various sources, including UN agencies, non-governmental organizations, insurance companies, research institutes and press agencies. At least one of 4 conditions have to be satisfied to be captured by EM-DAT: 10 or more casualties, 100 or more people affected, a declaration of a state of emergency, or a request for international assistance. It should be noted that only one third of the whole database has information on economic losses and therefore sometimes (see for example Loayza et al. 2012) the number of people affected is used as a proxy. Despite the caveats of EM-DAT (it is generally recommended not to use data before 1970, see for a discussion GAR 2013), it still constitutes the most comprehensive effort in collecting cross-country data on natural and man-made disasters (Cavallo and Noy 2010). Additional data resources come from the proprietary Munich Re NatCat Service database (Munich Re 2010), which mainly serves to inform insurance and reinsurance pricing, but based on such information also calculates economic losses. This database contains fewer entries, focusing on the about 300 largest events since 1950, yet this data exhibits a higher level of reliability as it is often crosschecked with other information.

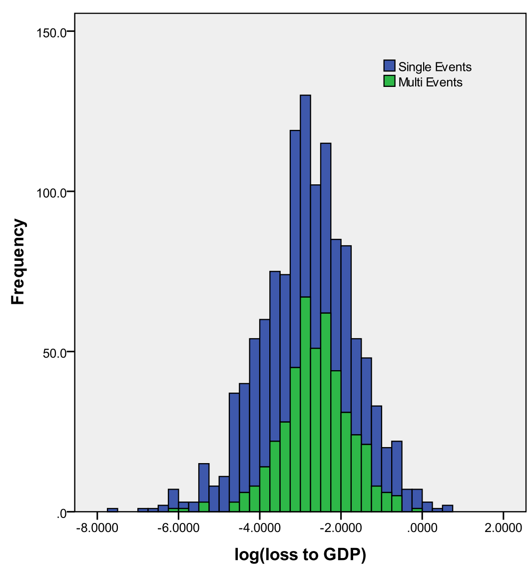

Fig. 6 Distribution of losses (in log per GDP) separated into single and multi hazard events.

As discussed, annual disaster losses are looked at and as such, these losses can be caused due to a single hazard or due to multi hazard events which have happened in the respective year. Regarding the distribution of single and multi-hazard events in the sample, within the 1473 observations, more than 220 earthquake events can be found, most of them (184) are single earthquake events (i.e. only one earthquake which caused losses happened during the year) but there are additional 38 cases with more than 1 earthquake incidence during the year too (Figure 6). Furthermore, with nearly half of the total observations in the sample flood and storm losses are the most prominent hazard. Only a small number of drought events (100) can be found in the sample (around 7 percent of the total sample). This already indicates that there are a considerable number of observations with more than one disaster event occurrence during the year. In more detail, 63 percent of the sample consists of single (annual) loss observations, 17 percent consist of observations where 2 loss events occurred, 6 percent consist of observations where 3 loss events occurred during the year, and around 13 percent of the sample experienced more (or equal) than 4 loss events. Unsurprisingly, combinations of storm losses with flood losses as well as earthquake losses with flood losses are most often represented within the multi hazard event sub-sample. Also the average losses are higher for the multi risk sample (log of losses per GDP for single events is -2.95 compared to -2.61 for multi events) however, also large variance in losses can be observed.

3. RESULTS

We start with an examination of the dependent variable without any considerations of the response variables first (Table 3).

Table 3 Summary results for Δy_n

	Δy_0	Δy_1	Δy_2	Δy_3	Δy_4
Mean	-0.0008	-0.0032	0.0097	0.0324	0.0598
Median	0.0017	0.0052	0.0123	0.0173	0.0382
St.Dev.	0.0500	0.1317	0.2469	0.3943	0.5365
Skewness	-0.6455	-0.8050	-0.7263	-0.5420	-0.1578
Wilcoxon Test p-value	0.328	0.435	0.90	0.76	0.092

Using the mean first, one can see that during and one year after the disaster, a negative sign appears and afterwards a positive sign. This indicates that in the disaster year and one year post disaster, negative flow consequences can be expected (on average). Due to the outliers and general skewness of the data, however, the median more adequately reflect the average behaviour. Here, all signs are positive, and this would indicate an increase in macroeconomic performance compared to the no disaster event projections. This rather surprising result must be treated with caution as the numbers are very close to zero, raising the question if the median is significantly different from zero. Due to the skewed data we use the non-parametric Wilcoxon signed-rank test on the dependent variable. As Table 3 indicates, the hypothesis that the median of the dependent variable is zero cannot be rejected. Hence, no general statements about net macro-economic effects with and without disaster events based on the dependent variable alone can be given with the sample at hand. Based on our previous discussion this comes with no surprise as the consequences are assumed to be dependent on the underlying socio-economic vulnerabilities which will be discussed next. We start with some summary statistics of the response variables listed in Table 4.

The first variable, i.e. the log of losses to GDP, as well as the number of earthquake, flood, storm and drought events during the disaster year, were already discussed in the previous section. Loss to capita is little bit skewed to the left, the same holds true for people hurt per capita, which needs to be taken into account in the regression analysis. The hurt per capita variables for the four different hazards indicate that drought affect large proportions of the population, followed by floods, earthquake and storms. Number of years with disaster losses compared to the whole time period suggests that every second year disaster events occur on average and that most countries experienced, on average, at least one or more than 1 disaster in the same year in the past.

Table 4 Summary statistics

Variable	Mean	Median	St.Dev
log(loss to GDP)	-2.81	-2.79	1.15
log(loss to capita)	0.63	0.70	1.21
log(People hurt per capita)	-3.32	-3.11	1.51
log(hurtpercapita)_EQ	-3.74	-3.66	1.43
log(hurtpercapita)_Flood	-3.30	-3.23	1.52
log(hurtpercapita)_Storm	-3.90	-3.91	1.70
log(hurtpercapita)_Drought	-1.83	-1.69	1.34
log of capital stock	11.23	11.39	1.08
log(pop2area)	1.80	1.90	0.62
log (land area)	5.41	5.48	1.03
Number_EQ	0.19	0.00	0.50
Number_Flood	0.68	0.00	0.99
Number_Storm	0.86	0.00	1.55
Number_Drought	0.07	0.00	0.26
Number_All	1.80	1.00	2.22
log(Lambda_1)	-0.49	-0.41	0.36
log(Lambda_2)	0.13	0.15	0.53
log (financing gap event)	1.57	1.20	0.65
Gov expend to GDP	2.42	2.58	0.79
Inflation	4.31	4.67	1.40
Private financial depth	3.23	3.37	1.32
Trade	1.74	1.75	0.28
Ratio (high educated to total for 20-39 yr)	0.60	0.58	0.29

The response variables in Table 4 do have some interesting correlation structures which are discussed next. As expected, the loss to GDP and loss per capita variables are highly and significantly correlated (correlation of 0.831, p-value < 0.01). Hence, we use loss per capita as well as people hurt per capita for the direct impact part only (as they showed only small correlations). Furthermore, due to high correlations between the hurt per capita and hazard type variables, we start with the total number of people hurt first and perform robustness tests later for the specific hazards. Also, not too surprising is the significant correlation between the average number of disasters and capital stock (as the more capital stock is available the higher is the possibility that something valuable gets destroyed) with a significant correlation estimated to be 0.699 (p-value <0.01). Additionally, the average number of disasters within a year and land area (as larger land areas increase the possibility that different hazards can occur) showed a significant correlation of 0.677 (p-value <0.01). The number of disasters (measured through the Poisson distribution) and number of disasters during a year are also highly correlated at 0.877, which could be interpreted that the more disasters within a year, the higher the chance that one of them is also causing economic losses. Interestingly, the human capital response variable showed a negative significant correlation (-0.475) with the number of people hurt per event, which gives indications that an increase in

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education could be an important factor in reducing human losses due to disasters (see also Striessnig, Lutz and Patt 2013). It should be noted, however, that the human capital variable is also highly correlated with capital stock, i.e., a better educated society shows higher levels of wealth (also found to be the same for the pre-disaster GDP per capita variable). Which line of reasoning here is the right one, e.g. either higher education brings wealth or the other way round is controversially discussed in the literature and cannot be tested via our empirical model (see for a discussion Crespo and Lutz 2007).

Table 5 Logistic regression model results.

	(1)	(2)	(3)	(4)	(5)
Dep. var.	Δy_0 (-1,1)	Δy_1 (-1,1)	Δy_2 (-1,1)	Δy_3 (-1,1)	Δy_4 (-1,1)
log(loss to capita)	0,0809 (0,1903)	-,044 (,279)	-,110 (,547)	-,140 (23,888)	-1,024 (4407,265)*
log(hurt per capita)	0,0051 (0,1453)	,107 (,223)	,094 (,418)	,209 (23,822)	,798 (1344,874)**
log (capital stock)	-0,8486 (0,8807)	-1,951 (1,215)*	-1,481 (2,213)	-1,888 (141,935)	-,171 (4497,854)
log (pop2area)	1,5367 (1,0319)*	2,484 (1,399)**	1,992 (2,347)	2,887 (176,012)	2,555 (3484,673)
log (land area)	1,9952 (1,0701)**	2,977 (1,443)**	2,397 (2,481)	3,582 (195,736)*	4,667 (14603,758)**
log(Lambda_1)	0,7722 (1,0965)	1,352 (1,410)	1,940 (2,479)	2,565 (196,521)	1,560 (20345,783)
log(Lambda_2)	-1,0876 (1,0105)	-1,307 (1,464)	-2,419 (2,820)	-3,195 (185,699)	-6,278 (27858,867)*
log (financing gap)	0,3994 (0,2575)*	,260 (,418)	-,123 (,706)	-,337 (53,972)	-,115 (1984,538)
Government burden	-1,0369 (0,5465)**	-,844 (,764)	-2,559 (1,626)**	-2,153 (117,290)*	-2,061 (1126,490)*
Inflation	-1,9435 (0,8770)***	-3,355 (1,786)***	-4,462 (3,679)***	-2,962 (276,113)*	-4,618 (6167,981)**
Private financial debt	-0,5075 (0,2759)**	-1,027 (,452)***	-1,334 (,887)**	-1,551 (92,657)	-1,717 (5816,267)**
Trade	1,2850 (1,0528)	1,457 (1,271)	-,387 (2,458)	1,277 (175,349)	1,218 (9692,972)
Education ratio	1,7193 (1,0925)*	1,126 (1,538)	,984 (2,805)	-,164 (200,018)	1,939 (1805,095)
5years average loss	-0,3559 (0,2419)*	-,101 (,331)	-,200 (,655)	-,122 (39,017)	-1,154 (5416,728)*
5years average hurt	0,2293 (0,1283)**	-,003 (,195)	,065 (,416)	,038 (36,196)	,126 (596,796)
No. of observations	323	216	136	106	85
Pseudo (Nagelker.) R^2	0.229	0.274	0.392	0.410	0.573
Right Classification	65%	69%	75%	76%	84%

(i) Standard errors in parentheses, (ii) ***, **, and * are 1, 5, and 10 percent significance levels.

With the discussed variables a generalized (multivariate) linear regression model with robust standard errors is built, treating Δy_n (n=0,...,4) as independent variable and the discussed response variables as the dependent ones. As the distributions of the variables were not too skewed (especially if the outliers are removed), histogram checks suggested that the assumption of a normal distribution could be reasonable

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for most of them. Hence, outlier detection was performed and observations that gave unreasonably large deviations (checked also via box-plots) were deleted from the sample set. To deal with the potential heteroscedasticity and correlation of the observations across time, we used bootstrapping methods to calculate robust standard errors. The full model was then tested (see Table in Appendix A). The respective model estimated was significant but showed significant values only for the inflation and private financial depth response variables, and no influences of the hazard impact, education level, and/or the recurrence intervals of single or multi hazard events were found.

Table 6 Multivariate regression results.

	(1)	(2)	(3)	(4)	(5)
Dep. var.	**Growth rate T+1**	**Growth rate T+2**	**Growth rate T+3**	**Growth rate T+4**	**Average growth T0-T4**
Constant	2,953 (6,371)	-3,590 (4,091)	-8,762 (4,689)*	-10,247 (4,634)**	-3,590 (4,091)
log(loss to capita)	,028 (,160)	-,146 (,099)	-,213 (,145)	-,195 (,142)	-,146 (,099)
log(hurt per capita)	-,024 (,133)	,061 (,084)	,267 (,128)**	,138 (,106)	,061 (,084)
log (capital stock)	-,295 (,877)	,881 (,522)*	1,505 (,835)*	,667 (,813)	,881 (,522)*
log (pop2area)	2,009 (1,073)*	1,192 (,619)**	,752 (1,011)	1,546 (,948)*	1,192 (,619)**
log (land area)	2,452 (1,107)**	1,466 (,623)**	1,059 (1,012)	1,526 (,979)	1,466 (,623)**
log(Lambda_1)	,014 (1,097)	-,809 (,847)	-1,946 (1,214)	-1,231 (1,142)	-,809 (,847)
log(Lambda_2)	-1,454 (,886)*	-1,440 (,577)**	-1,255 (,892)	-1,422 (,878)*	-1,440 (,577)***
log (financing gap)	,006 (,242)	-,004 (,147)	-,124 (,226)	,145 (,214)	-,004 (,147)
Government burden	-1,045 (,561)*	-1,188 (,341)***	-1,117 (,600)*	-,516 (,560)	-1,188 (,341)***
Inflation	-3,022 (1,091)***	-2,371 (,755)***	-1,850 (,770)***	-,691 (,764)	-2,371 (,755)***
Private financial debt	,156 (,292)	-,042 (,197)	-,224 (,268)	-,314 (,240)***	-,042 (,197)
Trade	2,683 (,866)***	2,942 (,530)***	3,025 (,720)***	2,461 (,812)***	2,942 (,530)***
Education ratio	1,938 (,977)**	1,938 (,654)***	2,897 (,819)***	2,462 (,897)***	1,938 (,654)***
5years average loss	,023 (,209)	,187 (,133)	,070 (,210)	,477 (,191)	,187 (,133)
5years average hurt	-,011 (,089)	,016 (,064)	,126 (,097)	-,089 (,085)	,016 (,064)
No. of observations	796	796	796	796	796
Model F	6.264***	6.260***	8.032***	7.267****	15.498***
R^2	0.151	0.151	0.186	0.171	0.306

(i) Standard errors in parentheses, (ii) ***, **, and * are 1, 5, and 10 percent significance levels.

Hence, in a next step specific hazards were looked at, although no significant results were found for earthquakes, floods, storms and drought either. Several other groups/dummy variables were constructed to see if significant results could be found for some sub-groups (e.g., to differentiate between smaller and larger disasters, multi-hazard or single event). However, also here again no significant results were found with the hazard, exposure or education parameters. In a next step, the Δy_n (n=0,...,4) were re-coded to -1 or +1 dependent on its sign, and a logistic regression model, similar to the multivariate one, was calculated (again using bootstrapping methods to calculate robust standard errors). Results are presented in Table 5.

Similar to the results in the multivariate regression model, inflation and private financial depth, as well as land showed to be significant. However, for consequences in the medium term, loss to capita and people hurt during the event, as well as the frequency of disasters within one year, in combination of loss events in the recent past gain significant importance. To further investigate these findings (and also for testing the robustness of the results and comparison with results found in similar approaches using the growth rates only), we used the average growth rate, as well as the single growth rates after the disaster years to see any influences of our selected response variables. The model used is as described in the beginning of this paragraph (see Table 6). Interestingly, the education variable plays a significant role for high growth rates even 4 years after the disaster. As this is controlled for initial GDP per capita level (and years), this is irrespective of the economic development stage. Furthermore, the higher the numbers of disaster which can hit the country, the lower the growth rates that can be expected. Government burden and inflation play a very negative role (as expected) for growth.

Summarizing, with the approach adopted here, positive as well as negative consequences to GDP due to disaster events were found within the sample. However, on average, the (accumulated) consequences due to disasters did not showed to be either significant negative noir positive. In other words, this analysis did not support the hypothesis that disasters in general lead to negative consequences (or positive consequences) but rather the consequences are likely to be dependent on the pre-disaster socio-economic situation. Private financial debt as well as the general macroeconomic situation was found to be significant here to explain part of the variance. Additionally, medium term negative consequences can be expected the larger the losses are, the higher the number of inter-annual hazards occurrences, and the larger pre-disaster losses were. There seem also some indications that the education ratio may also play a role here.

4. CONCLUSION

In this article we investigated the question about short and medium term consequences (up to 4 years in the future) due to natural disaster events. The consequences were estimated by comparing the actual economic performance with a counterfactual projected line using an econometric modelling approach. Explanation of consequences was based on past events from the EM-DAT database as well as other databases. The econometric modelling approach did not revealed a significant deviation (positive or negative) of accumulated GDP differences from the counterfactual situation on average. In other words, there can be positive as well as negative effects experienced depending on the socio-economic vulnerability of the system. Regarding the question as to which variables could explain the differences the most, there are indications that not only losses per capita will play a role, but also the losses which have happened in the recent past, as well as the average number of total hazard events per year (multi risk situations). Furthermore, growth rates were found to be higher after disaster events with higher educated societies. One reason for this observation may be the fact that past losses drains resources away from other investments and multi risk situations, e.g. where more than one hazard or repeating hazards occur often, put an additional pressure on the economic performance. It was also found that societies with low education will be more susceptible to long-term effects in case of disaster events. Hence, conceptual approaches such as the one in Figure 2 showed some value for explaining medium term consequences based on a capital approach and can provide valuable new research angles for multi risk analysis too. However, it should also be noted that the econometric approach here exhibits large uncertainties in the projections and as an appropriate next step one should investigate in more detail specific case studies. Furthermore, no cascading effects, such as was the case in Japan due to the 2011 Tohoku earthquake, can be found in the EMDAT database, hence it seems appropriate that for risk management purposes, empirical data is of less use here. One therefore could conclude that while the question of effects of natural disasters still will be “ultimately an empirical one” (Cavallo et al. 2010) the use of large scale samples as used here are of limited importance to determine which factors will play a significant role. Partly contributing to this argument is the fact that the consequences are very much context specific and influenced in a more complex way by other dimensions than linear regression approaches are able to handle. There is the challenge to bridge the gap between anecdotal evidences from case specific analysis and broad based statements from large scale samples. One way forward could be to determine suitable sub-samples of groups dealing with disaster events and apply a more nuanced approach of coping capacities. One approach currently is discussed within the “resilience” concept and may provide a good way to move forward on the issue of natural disasters and development in general.

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Appendix A:

Table A1 Generalized linear model results (robust regression).

	(1)	(2)	(3)	(4)	(5)
Dep. var.	Δy_0	Δy_1	Δy_2	Δy_3	Δy_4
log(loss to capita)	-.002 (0.0022)	-.001 (0.0074)	.004 (0.0185)	.024 (0.0298)	.020 (0.0404)
log(hurt per capita)	-.001 (0.0018)	-.002 (0.0056)	-.002 (0.0098)	-.010 (0.0190)	.044 (0.0330)
log (capital stock)	.008 (0.086)	.015 (0.0253)	.045 (0.0562)	-.009 (0.0997)	.088 (0.1368)
log (pop2area)	-.003 (0,0108)	-.003 (0.0318)	.042 (0.0677)	.067 (0.1204)	.156 (0.1692)**
log (land area)	.002 (0,0107)	.018 (0.0292)	.037 (0.0622)	.119 (0.1119)	.303 (0.1592)
log(Lambda_1)	-.008 (0.0173)	-.041 (0.0473)	-.069 (0.1150)	.015 (0.1697)	.070 (0.2354)
log(Lambda_2)	.000 (0.0159)	-.006 (0.0513)	-.100 (0.1121)	-.102 (0.1863)	-.348 (0.2877)
log (financing gap)	.005 (0.0047)	.016 (0.0125)	.032 (0.0276)	.035 (0.0482)	.056 (0.0766)
Government burden	-.014 (0.0094)	-.042 (0.0262)	-.128 (0.0582)**	-.150 (0.0964)	-.200 (0.1332)
Inflation	-.038 (0.0097)*	-.170 (0.0310)*	-.419 (0.0348)*	-.625 (0.1066)*	-.837 (0.1661)*
Private financial debt	-.014 (0.0050)*	-.044 (0.0163)*	-.125 (0.0338)*	-.276 (0.0570)*	-.343 (0.0860)*
Trade	.009 (0.0181)	.011 (0.0467)	-.065 (0.0889)	.131 (0.1508)	.247 (0.2181)
Education ratio	.007 (0.0168)	.038 (0.0589)	.125 (0.1219)	.352 (0.2072)***	.503 (0.2990)***
No. of observations	323	216	136	106	85
Log Likelihood	579.999	176.793	31.659	-14.125	-31.152

(i) Standard errors in parentheses, (ii) ***, **, and * are 1, 5, and 10 percent significance levels.