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Quality of Government and the Relationship between Natural Disasters and Child Poverty

A Comparative Analysis

Adel Daoud, Björn Halleröd, and Debarati Guha Sapir

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About the authors

Adel Daoud is Associate Professor at the Department of Sociology and Work Science, University of Gothenburg, Sweden. He was a visiting researcher at the Max Planck Institute for the Study of Societies, Cologne, in 2014.
Email: adel.daoud@socav.gu.se

Björn Halleröd is Professor in Sociology at the Department of Sociology and Work Science, University of Gothenburg, Sweden.
Email: bjorn.hallerod@socav.gu.se

Debarati Guha Sapir is Director of the Centre for Research on the Epidemiology of Disasters (CRED) and Professor at University of Louvain School of Public Health, Brussels, Belgium.
Email: debby.sapir@uclouvain.be

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Max-Planck-Institut für Gesellschaftsforschung
Max Planck Institute for the Study of Societies
Paulstr. 3 | 50676 Cologne | Germany

Tel. +49 221 2767-0
Fax +49 221 2767-555

www.mpifg.de
info@mpifg.de

Abstract

This paper explores the degree to which exposure to reoccurring natural disasters of various kinds explains seven dimensions of severe child poverty in 67 middle- and low-income countries. It also analyzes how certain institutional conditions, namely the quality of government (QoG), have moderating effects on the relationship between disasters and child poverty. Two main hypotheses are tested. The first is that disasters do have an adverse average effect on severe poverty. The second is that disasters reveal a positive coefficient (i.e., more disasters, more deprivation) but that higher levels of QoG negatively moderate this effect, i.e., the adverse effect of disasters is diminished by increasingly high QoG levels. From 70 possible combinations of relationships (7 types of deprivation combined with 10 types of natural disaster measures), 11 have the expected correlation between disasters and child deprivation and only one has the expected interactive correlation between quality of government, disasters, and child poverty. Several unexpected results could also be observed which are discussed in the paper along with recommendations for future research.

Zusammenfassung

Das Papier untersucht den Zusammenhang zwischen hoher Kinderarmut und Ausmaß und Häufigkeit von Naturkatastrophen. Hierzu werden sieben Dimensionen der Kinderarmut in 67 Ländern mit mittlerem und niedrigem Pro-Kopf-Einkommen analysiert, die wiederholt von Naturkatastrophen betroffen sind. Am Beispiel der Regierungsqualität (Quality of Government, QoG) wird weiterhin untersucht, ob und inwieweit institutionelle Rahmenbedingungen den Zusammenhang zwischen Katastrophen und Kinderarmut beeinflussen. Zwei Haupthypothesen werden getestet: (1) Katastrophen haben generell einen negativen Effekt auf schwere Armut; (2) Katastrophen haben einen positiven Koeffizienten (mehr Katastrophen, mehr Deprivation), aber höhere QoG-Werte mildern diesen Effekt, das heißt, die negativen Auswirkungen von Katastrophen werden von höheren QoG-Werten abgeschwächt. Von siebzig möglichen Beziehungskombinationen (sieben Deprivationstypen kombiniert mit zehn Schweregraden von Naturkatastrophen) weisen elf die erwartete Korrelation zwischen Katastrophen und Deprivation bei Kindern auf, aber nur eine besitzt die erwartete interaktive Korrelation zwischen QoG, Katastrophen und Kinderarmut. In dem Discussion Paper werden darüber hinaus verschiedene unerwartete Ergebnisse sowie Empfehlungen für die weitere Forschung diskutiert.

Contents

Quality of Government and the Relationship between Natural Disasters and Child Poverty: A Comparative Analysis

1 Introduction

In this paper we explore the degree to which exposure to reoccurring natural disasters of various kinds is associated with different dimensions of severe child poverty across sixty-seven low- and middle-income countries (LMICs). Of special interest here is the relationship between governance, often referred to as the *quality of government,* and natural disasters. A natural disaster is always a threat to people, not least to children, and once the disaster hits there are direct effects on peoples' lives; in fact, it is the interaction between people's ability to deal with disasters and the magnitude of the disaster that might turn a natural event into a disaster. If and how people are affected varies between countries. People in rich countries are generally less affected, even though the economic damage can be considerable (Neumayer/Plümper/Barthel 2014; Klomp/Valckx 2014). The adverse effects of disasters also hinges on the governmental capacity and institutional settings to act pro-actively by providing good infrastructure, healthcare systems, etc., and to react promptly and properly once the disaster has occured (Strömberg 2007; Kim/Guha Sapir 2012; Keefer/Neumayer/Plümper 2011; Kenny 2009; Paul 2011). In this study, we translate preparedness into the well-known concept of quality of government (QoG), that is, the administrative effectiveness of a state's capacity to act effectively (Holmberg/Rothstein/Nasiritousi 2009), and we test how QoG fares in protecting people against the adverse effects of disasters.

Our basic assumption, therefore, is that a natural disaster of a given type and magnitude does affect children, increasing their risk of being deprived of basic necessities such as food, sanitation, and healthcare, but also that the impact differs, depending on the countries' economic development and their QoG. The assumed mechanisms in play are, first, that economic development and QoG have an impact on the direct effects of the disaster and, second, that the recovery phase is shorter and progresses more smoothly in relatively rich and well-governed countries, as compared with poor and ill-governed ones. The second mechanism also implies that in poor and not very well-governed countries, recurring disasters might exhaust or create a scarcity of resources that are needed to protect children from poverty in other areas (Daoud 2007, 2010). Hence, depending on the economic development and QoG, a disaster might have detrimental effects also on children in general, not only those directly affected by the disaster.

We want to thank Thomas Plümper and Filippo Reale for providing us with insightful and constructive comments in their role as non-anonymous reviewers. We also want to thank the editor for the MPIfG Discussion Papers Series, Martin Höpner, and the production team at the Editorial and PR Unit at the MPIfG, Astrid Dünkelmann and Ian Edwards, for helping us improve the general quality of the paper. All remaining obscurities are entirely our responsibility.

A second assumption, or possibility, is that recurrent exposure to disaster has detrimental effects on both the economic development and the ability to develop an efficient governance structure – similar to the effects armed conflict has (e.g., Besley/Reynal-Querol 2014). In this paper we cannot test if such a causal relationship exists; what we can see is whether there are correlations between exposure to disaster and economic development and QoG, however this reasoning does offer yet another possible explanation why children living in countries that are frequently affected by disasters, apart from being directly affected, possibly suffer from more deprivation because of the lack of resources and the lack of good governance.

The analysis is an important contribution to the general discussion about why peoples' living conditions vary between countries and, more specifically, to the increasing interest in understanding the detrimental effects of bad governance. Today there is ample evidence that the lack of QoG has a negative impact on a range of aspects, including health, access to healthcare, education, and mortality (Holmberg/Rothstein 2010, 2012; Rothstein 2011; Grindle 2007; Weiss 2000).[1] A central question for this paper is whether QoG is truly the cause for the detrimental living conditions we witness in some countries; it might, after all, not be governance but nature that makes the difference. Hence, this paper is mainly a contribution to the research on the political economy of natural disasters but bears relevance for spatial sociology, development studies, and human geography (Neumayer/Plümper/Barthel 2014; Anbarci/Escaleras/Register 2005).

The analysis is unique because it combines country-level data about disasters with micro data about children's exposure to deprivation across a large number of LMICs. In this paper, we will mainly focus on between-country variations because the data on disasters is collected at country levels. So, This approach therefore means we will not be able to test for within-country variations of disasters, nor are we able to test for the longitudinal effect of disasters upon child poverty since we only have cross-sectional data on poverty.

In the following section, we discuss some of the key findings on the relationship between natural disasters, institutional conditions, and child poverty. We outline the underlying theoretical model of this paper, the two main hypotheses we test, and how they are tested. We also point to some of the main limitations of this study. In section three, we discuss both macro data (natural disasters, institutions, etc.) and micro data (child poverty data) used in this study. An account of how the natural-disaster variables have been constructed is also discussed here. In section four, we outline the analyses that have been made. In conjunction with this section, we conclude by discussing our interpretation of the results and offering further recommendations for future research.

1 See Agnafors (2013) for a critical appraisal of the concept of quality of government.

2 Background: Natural disasters, institutions, and child poverty

The idea that natural disasters lead to poverty and possibly to mass death is – or at least has been – central to some areas of development studies; its roots can be found in basic Malthusian conceps (Malthus 1826; cf. Sen 1981; Dobkowski/Wallimann 1998). In contemporary research, it is clear that a natural disaster has a social, economic, and natural component (Cannon 1994; Stallings 2006; Paul 2011; Neumayer/Plümper/Barthel 2014). It is not purely natural, and thus its adverse effects can be counteracted by technological and institutional mechanisms (cf. Kim/Guha Sapir 2012). A natural hazard becomes a disaster when it interacts with human beings in a negative way: for example, earthquakes occur in many places, but an earthquake only becomes a disaster when people with no means to protect themselves are affected by it (resilience), which then leads to casualties. Lal et al. make the causal and conceptual distinction between "natural disasters leading to poverty," on the one hand, and "poverty [that] may lead to increased vulnerability to natural hazards," on the other (López-Calva/Ortiz-Juárez 2009; Lal/Singh/Holland 2009). Both causal directions are viable.

Most research seems to focus on the role that governments play in preparing for forthcoming disasters and in organizing help when disasters occur (e.g., Anbarci/Escaleras/Register 2005; Kahn 2005; Keefer/Neumayer/Plümper 2011; Kenny 2009). Strömberg (2007), for example, shows that both developed countries and LMICs are affected by natural disasters almost to the same degree, but still people are injured or killed to a far less extent in developed countries. Moreover, he shows that a country's quality of government and its economic development play a significant role; democracy (cf. Sen 1991) and inequality, however, have little or no significant effect (Strömberg 2007). The dependent variable in this study was the number of people killed in natural disasters. An absent or insignificant effect of democracy on the proportion of children living in poverty is also observed in our latest study on child poverty, quality of government, and democracy (Halleröd et al. 2013).

Other studies show that there is a strong relationship between economic factors and natural disasters (cf. Guha Sapir/Santos 2012; Kahn 2005; Klomp/Valckx 2014; Schumacher/Strobl 2011). One interesting contribution is that disasters do not always have only adverse effects on economic development; GDP output may initially decrease but later increase if reconstruction of the old mode of production is replaced by new technology (cf. Hallegatte/Przyluski 2010). Yet other studies have focused on identifying the incentives donor countries have to give aid in the event of a natural disaster; for example, they study whether it makes a difference if the receiving country is a former colony or not (e.g., Eisensee/Strömberg 2007). There are a number of country-specific studies that link different kinds of natural disasters to the social, economic, and epidemiological impacts, such as those on Indonesian earthquakes (Sudaryo et al. 2012), Vietnamese floods, (Bich et al. 2011), crop production in Tanzania (Rowhani et al. 2011), Fiji disasters (Lal/

Singh/Holland 2009), poverty traps in Ethiopia and Honduras (Carter et al. 2007), economic impacts of disasters in Dominica, Bangladesh, and Malawi (Benson/Clay 2004), and the gendered nature of disasters (Neumayer/Plümper 2007).

In one of the relatively few studies that focus on children's living conditions, Kudamatsu et al. investigate the link between weather fluctuations in Africa, malaria, malnutrition, and infant mortality over the last fifty years (Kudamatsu/Persson/Strömberg 2010). They find a clear statistical correlation; infants born in areas with epidemic malaria during the rainy season face a higher risk of death. Similar studies have been conducted in India on the relationship between children living in flooded areas, the prevalence of diarrhea, and the risk of malnutrition. One result is that children in these areas are at a greater risk of suffering from stunted growth than children in non-flooded ones (Rodriguez-Llanes et al. 2011). However, diarrhea was found to have no significant effect (Joshi et al. 2011).

Previous research tends to focus on certain isolated regions found in Africa, Latin America, or Asia (López-Calva/Ortiz-Juárez 2009; Rodriguez-Oreggia/de la Fuente/de la Torre 2010; Skoufias 2003). Smaller numbers of studies can be found that make a global comparison with reference to children (cf. Benson 2003; Toya/Skidmore 2007; Kahn 2005). Our aim is to contribute to this kind of comparison from a political economic point of view. We will now proceed to discuss the data we use in this paper, our theoretical assumptions, and the research design we used to analyze to our questions.

3 Data

Micro data on severe child deprivation

Our individual-level data on child deprivation come from the Demographic and Health Survey (DHS) organized by US-AID and UNICEF's Multiple Indicator Cluster Survey (MICS), two well-established household survey programs. UNICEF works closely with the DHS program to harmonize survey questions and modules and to ensure a coordinated approach to survey implementation. These surveys are nationally representative with large sample sizes, high quality, and high response rates (Boerma 1996). We focus on seven outcomes listed in Table 1 (all tables are available in Appendix: Tables). This table also describes how the indicators are operationalized. Operationalization follows the so-called Bristol Approach (Gordon et al. 2003, 2010). Data on child deprivation is compiled from the 67 countries included in Table 2. The table also shows the average rate of child deprivation across these countries. Our combined sample contains information on 1,941,734 children under the age of 18.[2]

2 A reviewer pointed out a potential bias in the paper with regard to reporting of child depriva-

Measuring natural disasters

Data on natural disasters have been collected from EM-DAT, which is maintained by the Centre for Research on the Epidemiology of Disasters (CRED) at the University of Louvain.[3] EM-DAT contains core data on the occurrence and effects of more than 17,000 disasters in the world from 1900 to the present (our analysis stretches to the year 2012). It contains, for example, data on the type of disaster, the number of people killed and injured, and the number affected. For a disaster to be entered into the database at least one of the following criteria must be fulfilled: ten or more people were reported killed; a hundred or more people were reported affected; a state of emergency was declared; or a call for international assistance was issued. Figure 1 shows the total number of registered disasters between 1900 and 2012. An improved reporting system and increasing population are the main factors driving the dramatic increase in the prevalence of disasters. The gray bars show the frequency of disasters for all countries, while the black bars shows the figures for our sample. We chose 1988 as the starting date for our sample, since this is the year CRED created the EM-DAT and thus started to collect disaster data in a more systematic manner. One would therefore expect that the monitoring of disasters, data collection, and validation to be of higher quality than disaster data before this date (Guha Sapir/Hargitt/Hoyois 2004).

Since we are mainly interested in the reoccurring tendency of natural disasters, we have calculated two kinds of yearly average for the defined twenty-five year interval from 1988 to 2012. A country with a frequency of ten earthquakes during these twenty-five years will have an earthquake rate of ten divided by twenty-five, which is 0.4. The same logic applies to the number of people affected. If earthquakes affected 25,000 individuals within a country during the time period of our study, the country will have an average of a thousand individuals affected per year. As a result, two types of variables were constructed: one capturing the average occurrence or disaster frequency (DisFre) that a country has had during our observation period, and another one capturing the average number of disaster victims (DisVic), i.e., those killed and otherwise affected during the same period. Since we are comparing countries that differ substantially when it comes to both geographical and population size, we also need to adjust for country size. So, for the DisFre we have adjusted for the countries' geographical size, and for the DisVic, for the countries' population size. Figure 2 and Figure 3 give a graphical representation of the distribution of values in the sample across the globe: see Table 3 and Table 4 for a detailed breakdown of disasters per country.

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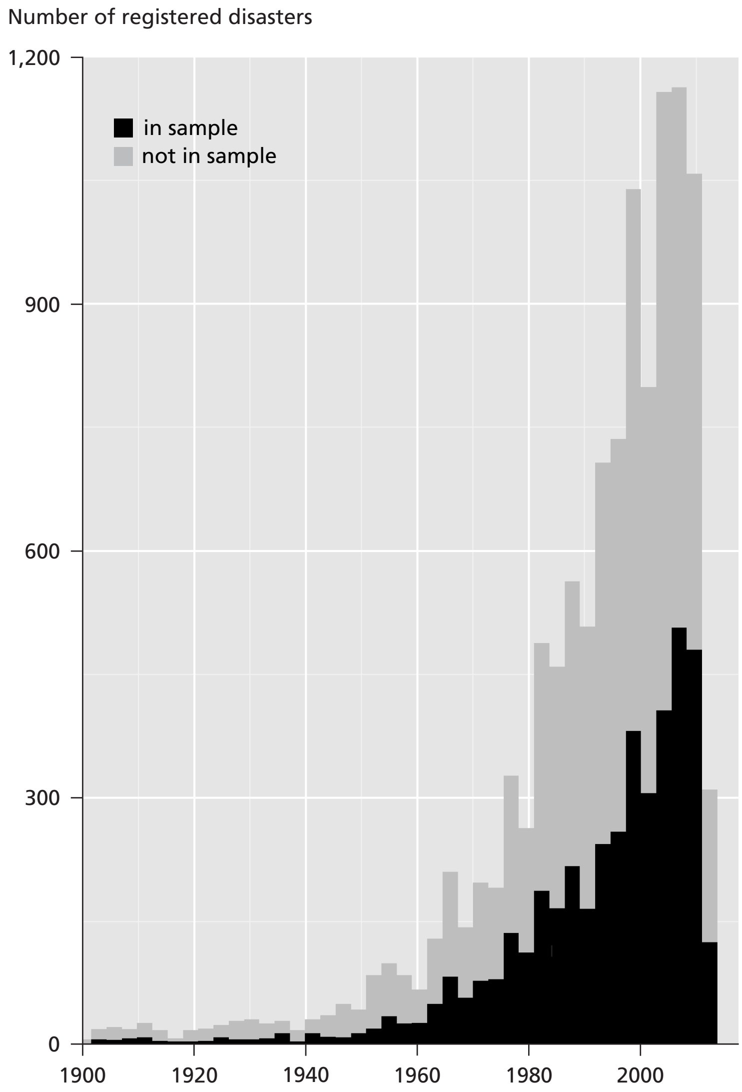
tion: a deceased child cannot be reported to the surveys. This would lead to some sort of a Darwinian mechanism where countries with higher rates of disasters can therefore have lower rates of child poverty because the weak are killed. We agree that this could be the case, but this line of argument assumes that those who are not poor, stay not poor. We assume that disasters could lead to the death of those (weak) people who have been exposed, but it also leads to poverty among sectors of the population who are not otherwise deprived.

3 For a discussion of data problems and a comparison of available data sources, see Kron et al. (2012).

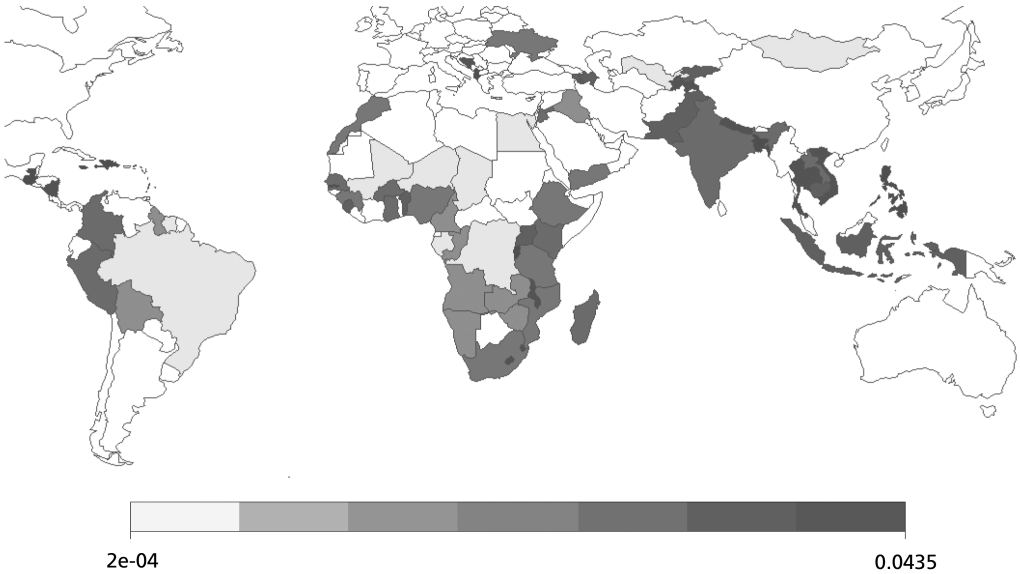
Figure 1 EM-DAT registered natural disaster frequency (excluding biological disasters) over the period 1900–2012



There are many kinds of natural disasters and there are no a priori reasons to believe that all types have the same effect. Therefore, apart from the aggregated measures that summarize all natural disasters, we also created the following submeasures:

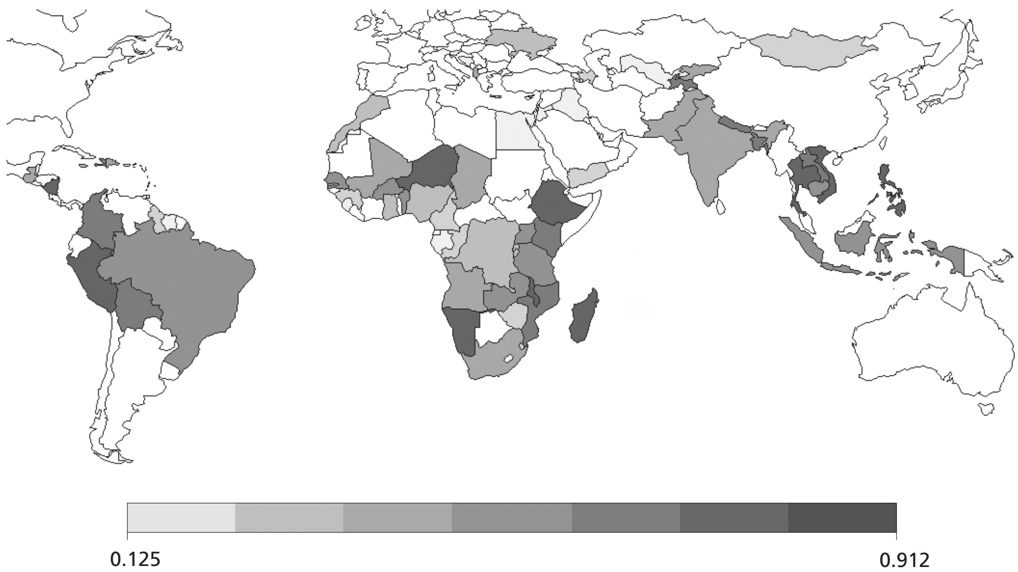
- climatological disasters (DisFre_climo and DisVic_climo)
- geophysical disasters (DisFre_geo and DisVic_geo)
- hydrological disasters (DisFre_hydro and DisVic_hydro)
- meteorological disasters (DisFre_meteo and DisVic_meteo)

Figure 2 Disaster frequency in sample countries across the globe



Note: Figures are yearly disaster frequency (all disasters), log 10-base adjusted, and country area adjusted (divided by the geographical area of a country).

Figure 3 Disaster victims in sample countries across the globe



Note: Figures are yearly disaster victims (all disasters), log 10-base adjusted, and country population adjusted (divided by population size).

For the sake of brevity we will henceforth refer to the aggregate measures as DisFre_all and DisVic_all.[4] The substantial EM-DAT definitions of these measures are outlined in Table 5.

4 The category "biological disaster" was omitted since its classification as a *natural* disaster is not entirely solid.

As mentioned above, the increase of registered disasters shown in Figure 3 is mainly driven by a more efficient reporting system, not an exponential increase of natural disasters. Thus, neither DisFre nor DisVic is exogenous in relation to social conditions. However, when we compare the two measures, DisFre is more exogenous than DisVic since DisFre hinges only on the probability that a disaster is reported, whereas the reporting of DisVic is known to have a stronger relationship to economic and political factors.

All disaster variables were transformed using the 10-base logarithm in order to force the data to have a smaller spread and to avoid extreme cases. First the raw unadjusted disaster figures were calculated (for frequency and victims), then these measures were either divided by population (for victims) or by country size (for frequency). Only then was the 10-base logarithm used to make yet another transformation. The following graphs highlight the distribution of the ten disaster variables. We can see that that the DisFre measures in particular still have a somewhat skewed distribution towards zero, with a number of outliers. This is not an ideal distribution, but there is very little one can do about it since the variables have both been adjusted for country size and log transformed (10-base).[5] Figure 4 outlines the distribution of the ten types of disasters.

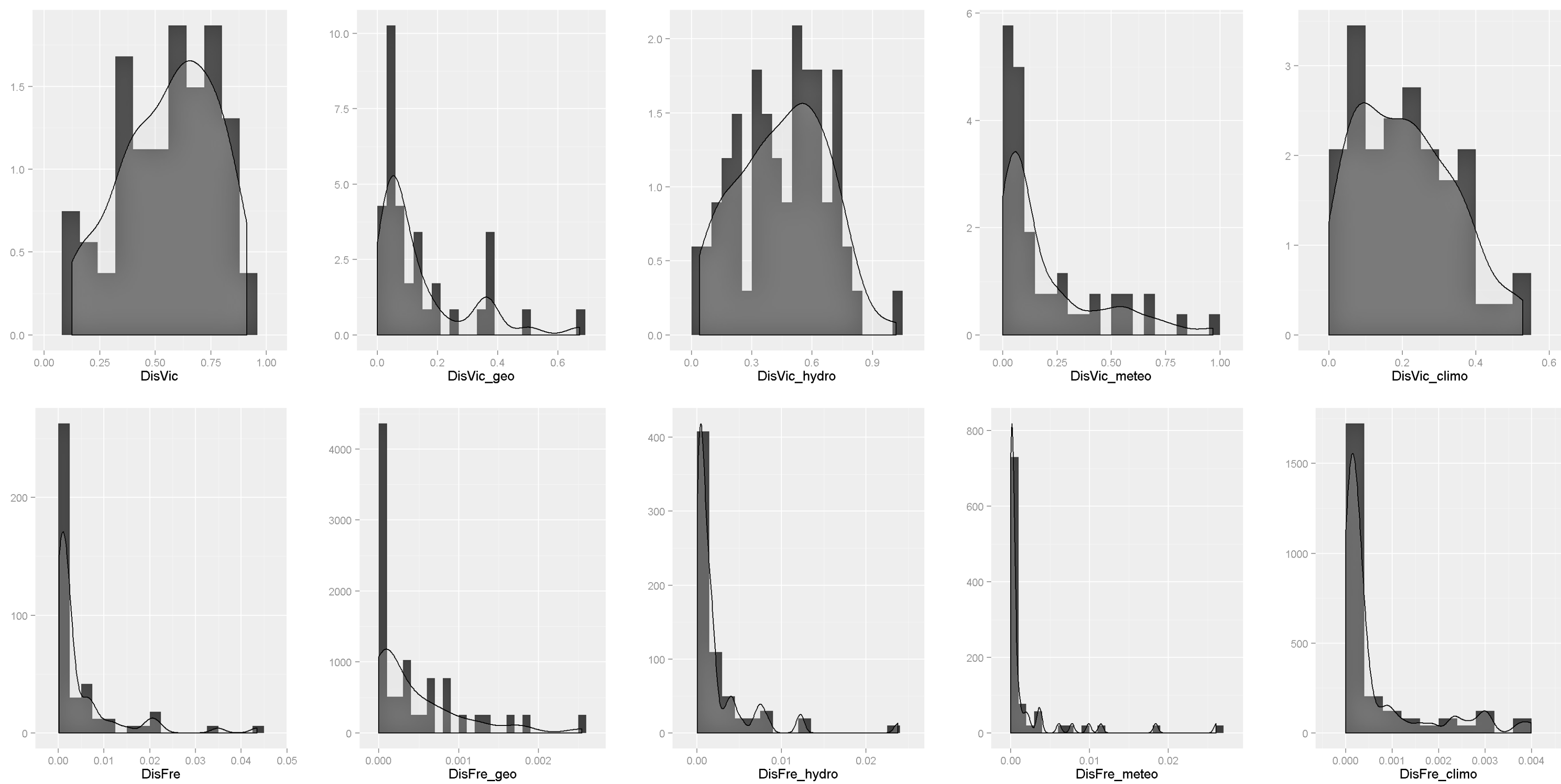
Measuring quality of government

Other country-level data have been collected from the quality of government database, QoG institute, University of Gothenburg. The QoG database covers 194 countries and is probably the most complete existing database on social policy and the quality of government, which is essentially a result of data harvesting from many sources such as the World Bank, the UN, and its suborganizations (Holmberg/Rothstein/Nasiritousi 2009). To measure the quality of government we use the government effectiveness estimate (wbgi_gee) of Kaufmann, Kraay, and Mastruzzi (2009, 2010). The measure is based on a compilation of information from survey data and expert assessments supplied by a range of organizations. In total, 36 components have been gathered from 15 different organizations, which

> combines into a single grouping responses on the quality of public service provision, the quality of the bureaucracy, the competence of civil servants, the independence of the civil service from political pressures, and the credibility of the government's commitment to policies. The main focus of this index is on "inputs" required for the government to be able to produce and implement good policies and deliver public goods. (Teorell et al. 2013: 123)

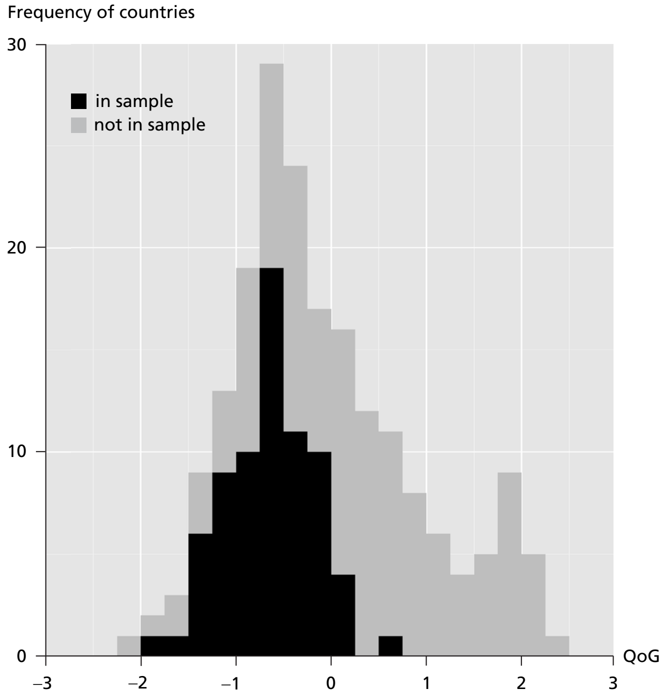
5 Other transformations were tested too, but we settled for the 10-base logarithm since its interpretation is more intuitive and has also been used in such classical work as Richardson (1960).

Figure 4 Histograms (frequency and density) for the ten disaster variables – sample distribution



Note: The histograms show the distribution of the various disasters. All disaster-victim related measures are yearly victims, log 10-base adjusted, and country population adjusted (divided by population size). All disaster-frequency related measures are yearly disaster frequency, log 10-base adjusted, and country area adjusted (divided by the geographical area of a country).

Figure 5 The distribution of quality of government



Note: Quality of government stands for "government effectiveness" combines into a single grouping responses on the quality of public service provision, the quality of the bureaucracy, the competence of civil servants, the independence of the civil service from political pressures, and the credibility of the government's commitment to policies. The main focus of this index is on "inputs" required for the government to be able to produce and implement good policies and deliver public goods. The governance estimates are normally distributed with a mean of zero and a standard deviation of one each year of measurement. This implies that virtually all scores lie between –2.5 and 2.5, with higher scores corresponding to better outcomes.
Source: Teorell et al. (2013: 123); Kaufmann/Kraay/Mastruzzi (2009).

This measure comes as a standardized measure in which the mean is zero and standard deviation is set to one. (See Arndt 2008, or Agnafor 2013, for a critical review of available governance measures.) In this study we have taken the historical average for each and every country as a new proxy for the quality of government, since we have a corresponding historical average for the natural disaster variables. Note that Kaufman and his colleagues standardize the measure with a mean of zero, which means that the historical average we are using is based on the relative ranking of the country, not some kind of absolute quality-of-government indicators. The distribution of our QoG measure is shown in 5. Again, the gray bars indicate the distribution for all countries, and the black bars show the values for the 67 countries included in the study. As can be seen, the countries under study are mainly found in the lower end of the distribution.

Additional control variables

In the two final models, namely *m3* and *m4,* we add a set of additional control variables. At the country level we add a measure of democratization controlling for the assumption that, in democracies, politicians tend to implement policies improving the living conditions even for the poor because they are held accountable in free and open elections (Sen 1991). In an assessment of alternative indices of democracy, Hadenius and Teorell (2005) conclude that the measures provided by Freedom House and Polity IV Project (2013) provide the most valid and consistent albeit not perfect measures of the procedural aspects of democratization. They further suggest that a combination of these two measures generates the most preferable measure. It is this combination we use as our indicator of democratization (for more detailed information, see Hadenius/Teorell 2005, and Teorell et al. 2013). The scale ranges from 0 to 10, in which 0 is least democratic and 10 most democratic. Also, since occurrence of natural disasters varies between years, we also include a survey year as a control variable. At the individual level, we use survey data to control for household composition, using two variables; one measuring the number of children (age $<$ 18) in the household and the other being the ratio between number of children and number of adults in the household. We also control for the children's age and sex. Finally, since child poverty still is a predominantly rural phenomenon (Halleröd et al. 2013), we include a variable that measures whether children live in urban or rural areas.[6]

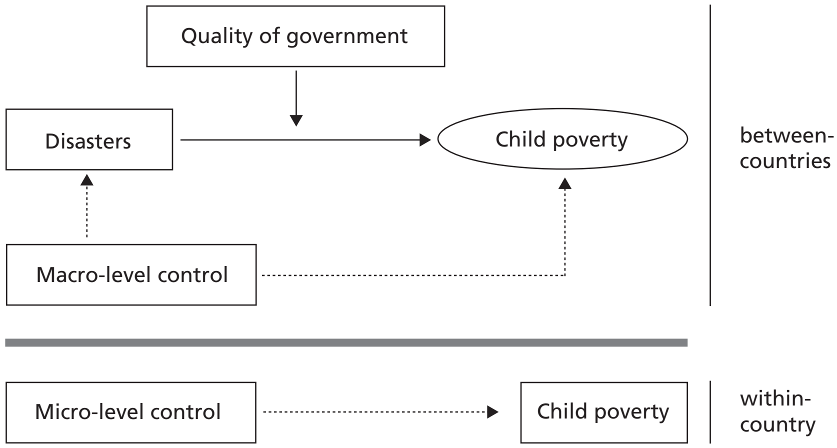
4 Theoretical assumptions and research design

Our basic theoretical analytical model is outlined in Figure 6. We assume that more disasters should lead to higher proportions of poverty (cf. Dobkowski/Wallimann 1998). We assume the following causal mechanisms in which natural disasters affect children: the first line of defense against the adverse effect of a disaster is the household (the capabilities of the adults); the second line of defense is the protective measures that governments take to empower households and to set up the necessary infrastructure.

Natural disasters affect children either by harming them directly, by killing or severely harming their parents, by significantly reducing the income of their parents, by destroying property that needs to be replaced, or by affecting sources of income for the children themselves. Effective (good) governments can influence the effect of disasters on family livelihood expenses in at least two ways: they can reduce the potential damage

6 In an earlier version of these models, we included several other variables that we had to exclude in the end because of non-convergence problems. For example, we controlled for regional geographical differences, including a dummy for continent; most importantly, we experimented with the inclusion of a random slope with regard to GDP as well as the interaction between GDP and disasters.

Figure 6 The basic theoretical model



of future disasters by enforcing certain policies (e.g., anti-earthquake building policies), and they can moderate the effects of disasters, for example, by providing financial support to households and by other economic policies that re-establish the functioning of the economy (e.g., repair of the infrastructure).

In terms of statistical effects, if we find that disasters are associated with severe child deprivation in a bivariate model, we will expand the model to include measures of QoG and an interaction between QoG and disasters. From previous research we know that QoG plays an important role in explaining country differences in child deprivation (Halleröd et al. 2013). If the QoG effects disappear once disasters are part of the equation, we can conclude that earlier research results on QoG were based on spurious observations. If QoG wipes out the impact of disasters, we firstly can conclude that it is QoG that matters for child deprivation but, because of the initial bivariate effect, also that countries with a high degree of child deprivation are more exposed to natural disasters (i.e., we get some tentative support for our second assumption). To further explore and test the robustness of this relationship between disasters and QoG, we include a set of other micro- and macro-level variables as controls in the relevant model.

Hypotheses specification

Given our analytical model, we need to specify two main models. In addition, we estimate a third and fourth model which include additional controls. The formal specifications of the models are shown below. The first model *(m1)* tests the hypothesis that there is an adverse effect of disasters on child deprivation in a bivariate relationship. Higher disaster rates should correlate positively with higher deprivation rates, i.e., we expect β_1 to be positive.[7]

$$y_{(d)}=\beta_0+\beta_1 X_{Dis} \qquad (m1)$$

$$y_{(d)}=\beta_0+\beta_1 X_{Dis}+\beta_2 X_{QoG}+\beta_3 X_{QoG}*X_{Dis} \qquad (m2)$$

$$y_{(d)}=\beta_0+\beta_1 X_{Dis}+\beta_2 X_{QoG}+\beta_4 X_{controls} \qquad (m3)$$

$$y_{(d)}=\beta_0+\beta_1 X_{Dis}+\beta_2 X_{QoG}+\beta_3 X_{QoG}*X_{Dis}+\beta_4 X_{controls} \qquad (m4)$$

All models are random intercept models with two random terms: one term for the child level εij (child i in country j) and one for the country level μj, for the *j*th country.

Indices

- *d*=deprivation measure, where *d*~(food, water, education, shelter, information, sanitation, health)
- *Dis*=disaster measure, where *Dis*~(DisFre, DisVic, DisFre_hydro, DisVic_hydro, DisFre_climo, DisVic_climo, DisFre_meteo, DisVic_meteo, DisFre_geo, and DisVic_geo).
- *QoG*=quality of government measure
- *controls*=a set of control variables (see Table 6).

The second model *(m2)* tests the hypothesis that the association between disasters and child deprivation is conditioned by QoG. We still assume there will be a positive coefficient (β_1) for the disasters parameter but that the interaction parameter (β_3) should damper this effect. In other words, higher levels of QoG (better governance) are assumed to decrease the adverse effect of disasters. In the two final models, *m3* and *m4*, we add a larger set of control variables in order to test the robustness of previous results.

When one merely estimates β_1 one is, strictly speaking, not fully testing the conditional effect of disasters on poverty moderated by QoG (Berry/Golder/Milton 2012; Brambor/Clark/Golder 2006; Kam/Franzese 2007).[8] What can be determined from a t-test of β_3 is whether a conditional relationship is present[9] (Kam/Franzese 2007), but one

7 However, we will still rely on a two-tailed interpretation of the relevant coefficients.

8 To reiterate, if we have the following regression model, where $\beta_4 X_{controls}$ designates a set of control variables: $y_{(d)}=\beta_0+\beta_1 X_{QoG}+\beta_2 X_{Dis}+\beta_3 X_{QoG} X_{Dis}+\beta_4 X_{controls}$, then the marginal effect of disasters on deprivation is then acquired by a differentiation with regard to disasters, which yields $\frac{\partial y_{(d)}}{\partial X_{Dis}}=\beta_2+\beta_3 X_{QoG}$. Likewise, the marginal effect of QoG on poverty moderated by disasters is then $\frac{\partial y_{(d)}}{\partial X_{QoG}}=\beta_1+\beta_3 X_{Dis}$.

9 A second differentiation of the regression model, with respect to QoG this time, will give $\partial\left(\frac{\partial y_{(d)}}{\partial X_{Dis}}\right)/\partial X_{QoG}=\beta_3$. Therefore, a simple t-test will suffice when testing for moderation effect.

will not know from this test for which subset of QoG values this moderation is statistically significant. Nevertheless, it is only meaningful to analyze the marginal effect plots fully if the β_3 parameter is significant. We will thus limit ourselves (a) to checking if a conditional interaction exists by conducting a simple t-test of the coefficient of interaction term *(*β_3*)*, and (b) to checking the direction (sign) of the interaction term and the disaster parameter, and (c), only when these two previous conditions are substantively interesting, to checking with marginal effect plots.

Hence, since each disaster measure was correlated with each and every of the seven deprivations, we produced seventy different models for each modelling step *(m1, m2, m3,* and *m4),* alternating the focal independent variables (disaster) with the focal dependent (deprivation) one; which then means that we produced two-hundred and eighty different models for all ten disaster measures. Accordingly, other than these focal variables, the same model specification was used over the entire list of models.

We want to emphasize again that the main focus of this paper is to investigate if there is a unique effect of each disaster type on each kind of poverty potentially conditioned by QoG and not to explain as much variation as possible in the different poverty measures. In other words, we are not maximizing the coefficient of determination (R square) but rather analyzing the unique effect of the disaster parameters (Aneshensel 2013).

Estimation strategy

This study utilizes multilevel statistical modeling (Luke 2004; Goldstein 2011). Such techniques capture the partitioning of variance for the different nested levels and thus more clearly highlight where the strongest associations exist between variables. All the models are multilevel with two levels since there is a significant amount of variation partitioned on each level (children and countries).[10] Moreover, our dependent variable is defined on the micro-level, and our focal independent variable is defined on the macro-level. In such a design, we are testing between-country variation rather than within-country: we cannot test how disasters within a country affect the population in various ways. What we are testing is how child poverty in a country, on average, is associated with that country's level of disasters, on average. Our causal claims (between disasters and poverty) do not commit an ecological fallacy: that is, generalizing group (country)-level characteristics to the individual (child) level. Statistically, the reason for

10 We experimented with four-level models (children in households, in sample clusters in countries) and indeed significant variation could be found between the various levels in a simple variance component model. But many of the models we ran found it difficult to converge in a more complex specification. Thus, we chose to reduce the complexity of the models.

this is simple; our country-level variables can only explain variations that exists on the country level (aggregated from the child-level dependent variable). We cannot use QoG or disasters to explain variations between individuals (Blakely/Woodward 2000).

All the models are defined as linear probability models. We chose to work with this kind of specification over a logit model since linear probability models allow for a more a straightforward interpretation of the coefficients across models compared with a logit model. The interaction term will also have a direct interpretation which is not admissible in a logit version (Ai/Norton 2003). Simulation studies have also shown that linear probability models tend to be robust (Mood 2010; Hellevik 2009). Also, in this study, we are only interested in the sign of the coefficients and not the size; for this reason, a linear probability model suffices. All models were estimated using the MLwiN (Rasbash et al. 2009) engine, relying on the Iterative Generalised Least Squares (IGLS) algorithm.[11] The R2MLwinN[12] package (Zhang et al. 2013) was used in the R software (R Core Team 2014) to call MLwiN and thus to manage as well as to analyze the results. The samples used were adjusted according to the relevant age span for the corresponding deprivation; see Table 1.

5 Results

The main results from the analysis are summarized and presented in Table 7 and Table 8: all of the 280 regression models on which these tables build are available online.[13] Only the disaster estimates are shown in these tables; the β_1 always refers to the disaster parameter in the corresponding focal relationship, whereas the β_3 estimate always refers to the interaction terms between disasters and QoG. The β_3 parameter is thus only relevant for *m2* and *m4*. The p-values show the corresponding significance but only to a maximum of $p \leq 0.10$ level, and the sign in the parenthesis symbolizes the direction of the correlation. We focus on the p-values here since we are mainly interested in analyzing the statistical likelihood that a relationship exists between deprivations, QoG, and disasters as well the direction of this relationship.

Starting with Table 7 and the bivariate DisFre estimates in models *m1*, we can conclude that only two out of thirty-five *m1* estimates were significant at the $p \leq 0.10$ level. Since we had anticipated a much stronger association between the occurrence of disasters and

11 In order to check for robustness, we used a Markov Chain Monte Carlo (MCMC) estimation algorithm (Zhang et al. 2013) to check a random pick of the models we ran. They all did indeed show the same result.

12 R2MLwiN is an R command interface to the MLwiN multilevel modelling software package, allowing users to fit multilevel models using MLwiN from within the R environment <www.bris.ac.uk/cmm/software/r2mlwin/>.

13 See <www.mpifg.de/pu/mpifg_dp/dp15-4_appendix.pdf>.

child deprivation, the result is clearly not in line with our theoretical expectations. The fact that one of these significant estimates goes in the opposite direction (the model estimate suggests that geological disasters improve children's access to sanitation) underlines that we have not obtained any conclusive results from the DisFre *m1* analysis. Modeling stage *m3* tests whether the *m1* results are robust by including a set of micro and macro control variables. Interestingly, now eight out of thirty-five focal relationships demonstrate a correlation, which indicates some kind of suppression effect. Nevertheless, only two relationships have a sign that correlates with what was expected by the hypothesis (viz. between DisFre_climo and malnutrition as well as DisFre_geo and sanitation). As we will discuss below, there are a number of possible reasons why the other six relationships have that correlation sign.

Looking at the *m2* estimates, i.e., testing for an interaction between QoG and disasters, we can see that only malnutrition demonstrates an interactive effect between QoG and disasters for four out of five disaster types (the exception being DisFre_meteo). But again, the outcome is unexpected. All interactive estimates are positive, which supports the counterintuitive idea that increased levels of good governance increase child deprivation. A marginal effect plot would demonstrate in which QoG-interval this effect is present and if it is at all substantially relevant. Before doing that, we added a number of controls again; the same ones as in the *m3* model. Accordingly, what we find at modeling stage *m4* is that the results at *m4* hold, albeit with somewhat decreased likelihood, since some of the focal relationships lost their constitutive term, such as between DisFre_hydro and malnutrition, where the β_1 parameter is no longer significant. What this indicates is that the average level of the effect of disasters (the intercept) is the same between a non-interactive and an interactive model, whereas the conditional effect of disasters on deprivation (the slope) is indeed changing as QoG changes. Nonetheless, all these effects are still going in an unexpected direction. We will discuss this counterintuitive result further below.

Moving on to Table 8 and the DisVic estimates, we can first conclude that DisVic is more systematically associated with child deprivation than was the case for DisFre. At *m1,* fourteen out of thirty-five focal relationships demonstrate a bivariate correlation between disaster and deprivation. Twelve of these show a correlation which has a theoretically expected sign. Of these twelve, eight still remain significant and with expected signs when tested with a larger set of controls at modeling stage *m3;* the relationship between DisVic_hydro and information deprivation also turns out to be significant now, indicating that it was suppressed. The most systematic association between disasters and child deprivation is found for climatological disasters. Children living in countries that score high on DisVic_climo suffer from a higher risk of being deprived of safe water, adequate nutrition, education, shelter, sanitation, and information. Thus, six out of the seven deprivation indicators are related to climatological disasters.

Looking at shelter deprivation, we can see that there is an adverse relationship between this deprivation dimension and three of the disaster measures, namely, DisVic_all, DisVic_hydro, and DisVic_climo. Shelter deprivation is associated with the latter two. Thus, the most systematic relationship seems to be between disasters and children's access to shelter and sanitation. DisVic_geo is only associated with malnutrition when controls are introduced. However, this estimate has a negative sign; in other words, it indicates a lower degree of deprivation in countries where many people are affected by these types of disasters.

In analyzing the interaction hypothesis between disasters and QoG on deprivation, starting at *m2,* we can see that only six of thirty-five have a significant interaction term (β_3). Five of these have the sign we expected. All these five belong either to DisVic_all or DisVic_hydro. Most of the constitutive β_1 estimates are insignificant – nevertheless, it is really the β_3 term which is the most central. When running these models in a larger set of controls, it is only the relationship between DisVic_hydro and shelter that remains intact and in the expected direction. What is noteworthy is that four of the seven deprivations now show that there is a significant interaction between DisVic_geo and QoG. This would lead us to the fairly unexpected conclusion that a larger fraction of the population would be affected by increased rates of disaster victims as that country is gaining better levels of QoG.

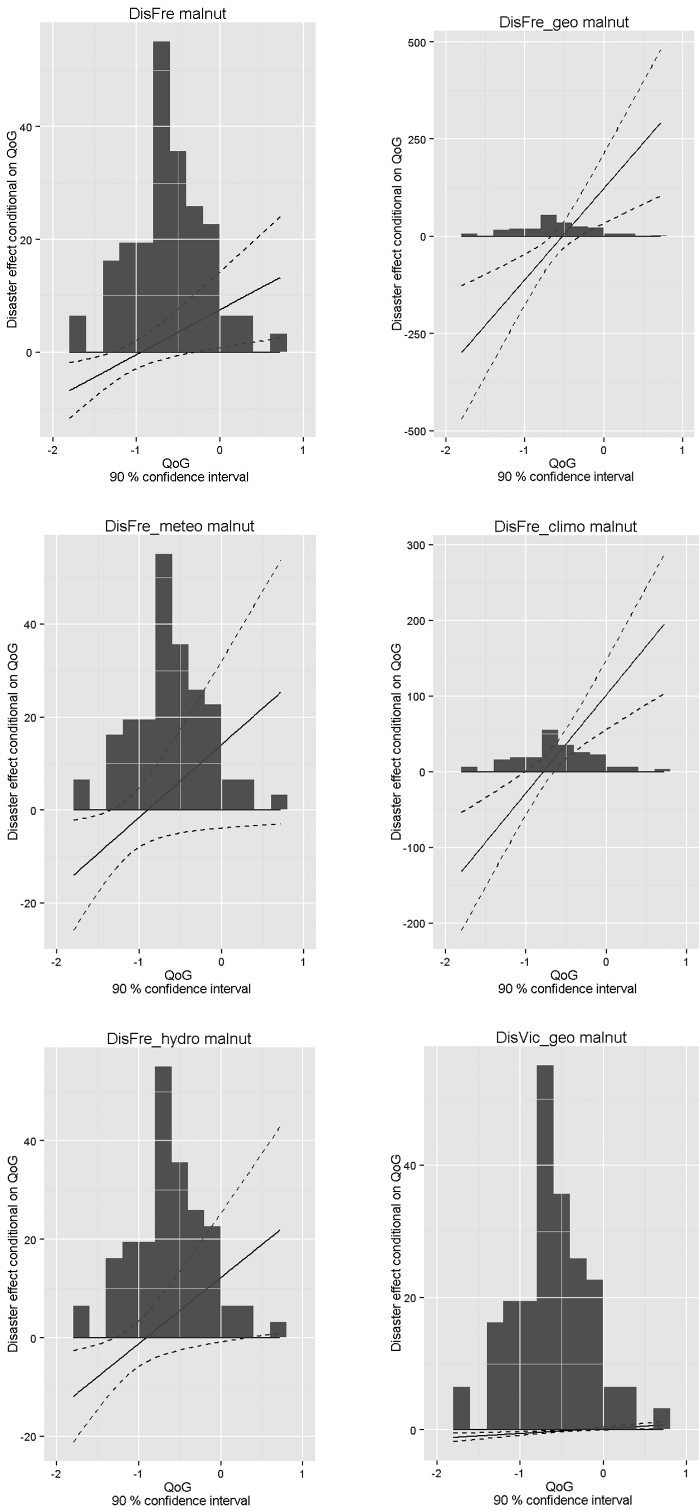
Marginal effect plots

Some unexpected results were produced in model *m4* that need further analysis. We need to know the range of QoG values for which this result holds true statistically and if this is substantively interesting. To know this we need to produce marginal effect plots with corresponding standard errors for all the relevant models and check the range where the effect is different from zero (Kam/Franzese 2007; Berry/Golder/Milton 2012; Brambor/Clark/Golder 2006). In Figure 7 we have plotted the five significant *m4* malnutrition models from Table 7 and Table 8.

Out of the seventy focal relationships, DisVic_hydro-shelter is the only relationship where we can confirm a relationship. Figure 8 illustrates the marginal effect of disasters upon poverty over the substantive range of QoG values. The effect is both statistically and substantively relevant for the range (–1.8 to 0.8). Better QoG levels will produce a dampening effect of the hydrological disasters measured.

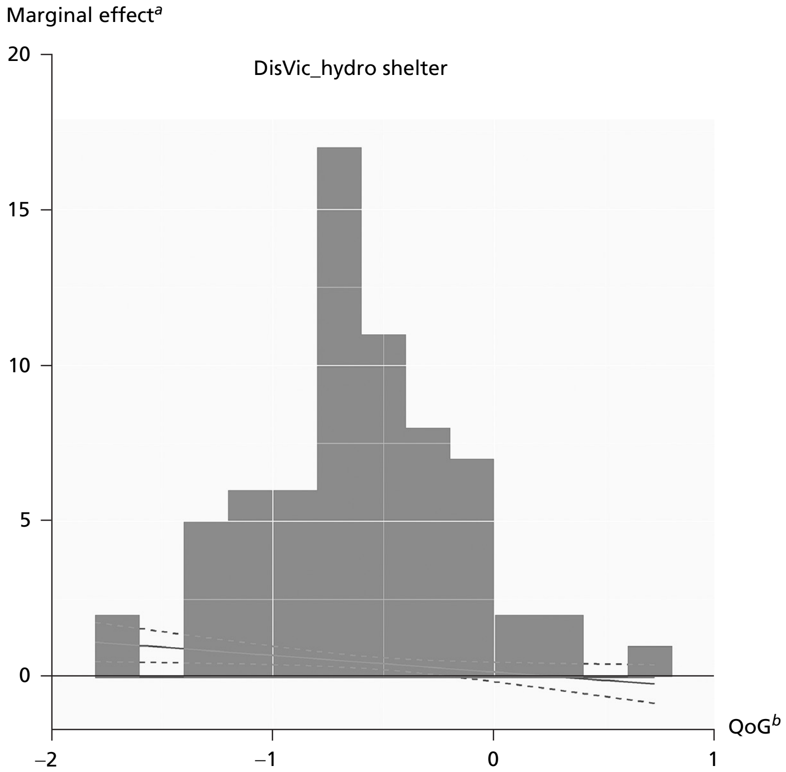
The plot in the upper left-hand corner of Figure 7 is the marginal effect plot for DisFre_all-malnutrition over a range of QoG values (sample max 0.8 and min –1.8). From this plot we can see that the effect is not different from zero at a 90%-confidence interval around the QoG values of –1.5 to about –0.25. To the left of this interval (–1.8 to –1.5), lies only a small portion of the QoG distribution, as shown by the histogram, which

Figure 7 Marginal-effect plots for focal relationships with positive correlations



Note: The figure captures the marginal effect of disasters (see type in the rubric) on malnutrition depending on the values of QoG. The histograms show the distribution of QoG values in the sample and thus where the effect is substantively relevant.

Figure 8 Marginal-effect plot for the only focal relationship with a negative correlation



a The marginal effect of hydrological disaster victims on shelter deprivation: ME(Disaster | QoG) = δ deprivation/δ disaster.
b 90 percent confidence interval of the measure disaster victims hydrological disasters on shelter deprivation. Depending on the values of QoG. The histograms show the distribution of QoG values in the sample and thus where the effect is substantively relevant.

makes the effect substantively uninteresting. The same is true for the right side of this interval (–0.25 to 0.8), where the effect is statistically significant but not of any great substantive interest since only a small part of the distribution lies there. Moreover, the error margin seems to be relatively large around the whole distribution, a fact that calls for caution. Similar problems apply for DisFre_meteo and DisFre_hydro. Therefore, for these, we will not regard the results as being surprising findings.

Where the results seem to be of both substantive and statistical interest are for DisFre_geo and DisFre_climo in relation to malnutrition. This is clearest in the latter case, where in the lower interval the effect of climatological disaster frequency on malnutrition is negatively moderated by the lower QoG interval (–1.8 to –1); this means that, in this QoG interval, the effect of disasters is actually having a remedial or relieving effect on malnutrition. Conversely, in the other significant interval (–0.6 to 0.8), the same disaster effect is positive and increases across higher QoG values. In other words, disasters are now having an expected adverse effect on malnutrition, albeit one that diminishes over better QoG values.

When it comes to disaster victims (from Table 8), this kind of effect can be substantively confirmed only for DisVic_geo-malnutrition. The substantively interesting interval goes from (−1.8 to 0.5) and the effect is all negative; meaning the more disasters there are, the more they will have a relieving effect on malnutrition. However, no substantive effect can be found for DisVic_meteo-malnutrition, DisVic_geo-health, DisVic_geo-sanitation, DisVic_geo-information (the marginal effect plots are not shown here).

To sum up the analysis of the interaction effect, firstly, DisVic_hydro-shelter is the only relationship where we can confirm a hypothesized relationship; secondly, we can confirm substantively as well as statistically interesting results for DisFre_geo, DisFre_climo, and DisVic_geo all in relation to malnutrition. However, none of the relationships have the sign expected.

Explaining unexpected results

We will here briefly outline an explanation about why we observe some unexpected results, disregarding methodological explanations for the moment.[14] Three of the central points we address are, firstly, why it is only the relationship of disasters to malnutrition that shows both a statistically and substantively interesting but unexpected result when interacted with QoG *(m4);* secondly, why we observe a considerable number of main effects having an unexpected sign *(m3);* and thirdly, why QoG did not turn out to have more of an effect than it did.

For the first two points, especially models related to malnutrition, we suggest that the line of argumentation will largely rely on previous research which argues that it can be rational for some countries to remain inactive when facing disasters (Plümper/Neumayer 2009; Clay/Stokke 2000; Cohen/Werker 2008; Mesquita/Smith 2007; Plümper/Martin 2003; Healy/Malhotra 2009). This propensity for inactivity is partly determined by whether a country is a democracy or autocracy, of public and popular pressure, of public finance, as well as of international food aid.

Natural disasters have a political dimension. Such events are used and misused to promote some political or ideological interest. Democratic governments are more prone to act against a disaster than autocratic ones, since democratically elected parties are

14 A reviewer pointed out, for example, that the QoG variable might have too small of a variance (since we only have countries from the lower end of the QoG distribution), which might explain why we are not picking up a significant effect in the interaction variables.

more sensitive to both elite and popular pressure. This is generally true if we assume that they want to stay in power (Mesquita/Smith 2007). But both governance types have an incentive to call for or await international aid in a situation where fiscal capacity is limited (Plümper/Neumayer 2009). If so, this means that disasters do not only correlate with aid (which they do) but also that the positive effect of aid seems to outstrip the negative effect of disasters. This will then lead to a correlation between disasters and deprivations which is unexpected – that is, where the former will have a relieving effect on the latter. This will, we suggest, explain the positive correlations in the *m3* models. Most of the interactive effects turned out to be insignificant or of nonsubstantive value, but where the effect turned out differently, a similar story to the one outlined above can be applied. The QoG distribution for our sample is at the lower end of the global distribution, see Figure 6. Most of these countries are also at the lower end of the democracy distribution and thus the same incentives apply to inactivity. Nevertheless, we do control for the level of democratization in our models but have no specific control for budget balance, corruption, international food aid, and voter support, since the purpose of our study is different. Hence, further research is needed to understand these kinds of relationships and how the effect of disasters can yield increasing poverty rates when QoG increases.

All in all, where disasters have an effect, it seems to be more about governments and politics rather than administrative institutions and their quality (viz. QoG). The evidence collected in this paper seems to support a line of research that suggests that the choices and behavior of governments are more important than the overall quality of government. The form and the quality of the institutions seem to play a role only in one of the hypothesized focal relationships. For the rest we cannot find such a relationship. This suggests that the content of politics is probably more important than its form. We have not tested this proposition in this paper but intend to do so in future research.

6 Concluding discussion

Our aim was to analyze the degree to which the occurrence of natural disasters is associated with severe child deprivation, i.e., we asked whether children living in disaster-stricken countries are more likely to be deprived of safe water, adequate nutrition, education, shelter, sanitation, healthcare, and access to information. We also wanted to test whether such a connection was mainly conditioned by the quality of government or also by economic development. The idea was that richer countries and countries with well-functioning governance are more able to protect their populations from the adverse effect of disasters. However, at this stage we are not making any assumptions about the causality between the exposure to natural disasters, on the one hand, and GDP and QoG, on the other. Thus, it could be that economic resources and good governance alleviate the effects of disasters, but it could also be that recurrent exposure to disasters hampers both economic development and the prerequisites for good QoG (Schumacher/Strobl 2011; Klomp/Valckx 2014; Haber/Menaldo 2011). There is today a growing body of literature that points to the importance of QoG. In order to test the idea that it is vital to good governance to protect the population, in this case children, from the adverse effect of disasters, we have analyzed the interactions between the exposure to disasters and QoG, assuming that good QoG would offset the impact of disasters on child deprivation (Halleröd et al. 2013). We used two different sets of measures for disasters, one measuring the frequency with which disasters occur and the other measuring the percentage of the population within a country who were affected. For both sets of measures we produced indicators for different types of disasters – hydrological, climatological, meteorological, and geological – plus an aggregate measure for all disasters.

Starting with disaster frequency (DisFre) we conclude that only two of the thirty-five focal relationships between disasters and deprivation *(m3)* have the expected correlation, DisFre_Climio-malnutrition and DisFre_geo-sanitation. No expected interactive relationship between QoG, child deprivation, and malnutrition could be found *(m4)*. However, we found two relationships that are both statistically and substantively interesting, namely, DisFre_geo and DisFre_climo both in relation to malnutrition. Yet the problem was that these relationships did not appear as we expected because they had an unexpected correlation direction. Adding the interaction did indeed lead to positive estimates for the disaster measures; i.e., the more disasters there were, the more malnutrition. The interaction effect indicates that children in disaster-stricken countries actually did worse if QoG was good. Since housing production, water provisioning, and healthcare are more often influenced by governments than, say, food production, we expected to observe several more examples of a statistical moderation effect here, but no evidence of such could be found, for example, for shelter.

When it comes to disaster victims (DisVic), we found only one focal relationship which behaved in the same way as the DisFre intereactions, namely DisVic_geo-malnutrition. Otherwise, no interactive relationship could be confirmed. We can confirm that nine out of the thirty-five direct relationships between disasters and severe child deprivation exist. These are: DisVic_all-shelter; DisVic_hydro in relation to shelter, sanitation and health; DisVic_climo in relation to water, malnutrition, shelter, sanitation, and information. Climatological disasters obviously dominate these relationships, which is in line with previous research showing that "climatic disasters in developing countries have the most significant adverse impact on economic growth" (Klomp/Valckx 2014: 183) and thus also obviously on severe child poverty.

Previous research has shown (e.g., Callaghan et al. 2007) that there is a direct link between natural disasters and the health condition of the effected population, but no such link can be verified in this study. Specifically, one would expect a direct link between geological disasters and shelter deprivation, but no such link can be established. Maybe this statistical effect is not detected because this study is not designed to measure the effect of a disaster immediately after a disaster, but rather focuses on the annually repeated impact of disasters. More research is needed here as well.

It is somewhat unexpected that the kind of institutional characteristics this paper set out to test, namely administrative effectiveness (QoG),[15] had such a limited effect on the relationships between reoccurring natural disasters and severe child deprivation: in only one case did it produce an interaction with the expected effect. Given the design of the study, we cannot fully investigate why this is the case, but this is a point that future research needs to answer.

This paper has taken an exploratory approach to analyzing the relationship between reoccurring natural disasters, institutional conditions, and severe child deprivation. We therefore combined several different measures of child poverty and natural disasters. The specification of the statistical models has also been the same across all focal relationships – in a more sophisticated design, one would choose to vary the specification according to the theoretical understanding of a specific deprivation relationship to another specific disaster. For example, one would want to include measures of aid received, the social welfare system, migration, and displacement, and other socioeconomic and institutional conditions. Moreover, in this study we used a cross-sectional approach to analyze the data; with a longitudinal one we would be able to say much more about changes over time. Instead of aggregating all disasters up to the country level, we recommend a more sophisticated methodology given data availability on both child poverty and disasters. One could also test different thresholds for the child deprivation, such as a less strict one; we chose the severe one.

The methodology of this paper is also relatively crude. An aggregation of data to the country level takes away an important portion of the within-country variation. Another more sophisticated approach would then be to use geographical information system techniques (e.g., geographically weighted regression) to locate disasters and child poverty data in order to get a more precise geographical approximation. Statistical tests of this sort would be much more reliable. Nevertheless, since only some instances of the data on child poverty and natural disasters have this kind of information, we chose to work with the design at hand.

Nevertheless, to sum up, does this study show that there is no relationship between natural disasters and child poverty and that quality of government has little to do with this effect? No, we do not hold that this conclusion is warranted. One of the main things

15 As pointed out by a reviewer, QoG as defined by the World Bank might be culturally biased: we have a measure which is defined by a Western international organization (The World Bank) and the standards it is setting are simply not found in all corners of the world. This could mean that good governance still matters but what and how this type of governance manifests itself empirically varies widely.

this study shows is that there seems to be little effect between natural disasters measured as a reoccurring phenomenon, measured on a yearly basis, and severe child poverty. This research design reveals very little about the effect from a specific or sudden natural disaster on poverty and where poverty rates are measured longitudinally.

Appendix: Tables

Table 1 Individual level indicator: Dependent variables – seven types of child deprivation

Child deprivation	n	Proportion severely deprived
Water: Children who had access only to surface water (for example, rivers) for drinking or who lived in households where the nearest source of water was more than 15 minutes away. Children < 18 years old.	1,941,734	0.24
Food: Children whose heights and weights for their age were more than –3 standard deviations below the median of the international reference, that is, severe anthropometric failure. Children < 5 years old.	815,264	0.07
Education: Children who had never been to school and were not currently attending school, i.e., no professional education of any kind. Children 7 to 12 years old.	1,476,235	0.11
Shelter: Children in dwellings with more than five people per room and/or with no flooring material. Children < 18 years old.	1,926,435	0.51
Sanitation: Children who had no access to a toilet of any kind in the vicinity of their dwelling, that is, no private or communal toilets or latrines. Children < 18 years old.	1,940,599	0.28
Health: Children who had not been immunized against diseases or young children who had a recent illness involving diarrhea and had not received any medical advice or treatment. Children < 5 years old	944,895	0.13
Information: Children who had no access to radio, television, telephone or newspapers at home. Children 3 to 12 years old.	1,837,578	0.18

Table 2 Countries in the study, sample year and sample size: Percent of children (unweighted) in the sample suffering from severe deprivation

Country	Year	n	Wat.	Malnut.	Educ.	Shelt.	Sanit.	Heal.	Info	Country	Year	n	Wat.	Malnut.	Educ.	Shelt.	Sanit.	Heal.	Info
Albania	2000	6,683	4.9	19.0	2.1	6.9	0.0	19.8	n.a.	Madagascar	2004	36,625	56.6	8.0	12.7	10.3	49.7	11.9	25.4
Angola	2001	16,535	43.5	24.6	12.4	73.8	39.6	10.0	49.9	Malawi	2006	71,425	38.1	20.7	6.7	81.9	12.6	19.6	27.3
Azerbaijan	2000	9,732	24.3	9.9	2.9	14.2	0.1	29.2	12.5	Mali	2006	40,095	7.5	22.0	51.8	79.2	23.5	24.3	8.6
Armenia	2000	8,300	9.4	3.0	0.8	1.6	0.1	12.8	1.1	Mongolia	2000	11,576	29.1	6.9	2.5	52.0	14.1	8.1	7.0
Bangladesh	2006	127,250	3.9	n.a.	8.7	82.6	28.1	16.7	44.5	Morocco	2004	24,439	13.1	10.1	11.6	28.0	23.1	14.5	4.2
Benin	2001	16,215	24.9	13.4	19.8	42.7	70.1	18.4	n.a.	Mozambique	1997	23,245	48.5	2.6	15.0	72.7	52.8	5.3	46.7
Bolivia	2004	37,856	10.8	8.9	1.4	48.4	36.4	18.3	4.1	Namibia	2000	15,031	21.9	2.0	4.9	62.5	56.6	4.1	n.a.
Bosnia and Herzegovina	2000	9,486	2.3	4.9	2.9	n.a.	0.0	12.6	n.a.	Nepal	2006	19,935	18.2	20.7	7.9	81.7	55.1	12.6	3.9
Brazil	1996	22,732	0	3.3	1.8	12.4	17.1	13.8	2.4	Nicaragua	2001	29,673	13.1	7.4	13.2	62.9	21.1	16.6	6.7
Burkina Faso	2003	32,831	43.0	6.8	35.2	60.0	71.0	8.7	13.6	Niger	2006	27,180	24.6	28.6	53.0	83.2	70.7	30.7	15.8
Burundi	2005	22,799	51.8	n.a.	17.7	87.4	2.8	28.0	45.6	Nigeria	2007	63,188	41.7	23.8	32.9	52.5	30.3	49.1	19.6
Cambodia	2006	33,463	16.7	17.1	10.9	68.9	75.9	23.2	9.6	Pakistan	2007	32,994	8.7	n.a.	24.9	52.9	28.3	19.2	20.7
Cameroon	2006	21,303	35.7	14.9	10.5	55.8	7.4	20.8	24.8	Peru	2004	11,040	27.3	0	0.4	52.4	23.8	3.8	2.9
Chad	2000	16,209	48.8	5.6	0.0	90.7	51.2	36.7	0.0	Philippines	2003	26,768	7.5	n.a.	2.4	13.9	12.1	17.7	3.4
Colombia	2005	60,392	6.8	0.6	1.1	12.0	11.2	2.9	7.4	Rwanda	2000	24,911	64.2	20.4	10.6	80.4	3.0	17.5	21.1
Congo, Republic of	2005	14,526	30.9	11.0	3.9	44.4	10.6	13.2	9.6	Senegal	2005	35,446	12.0	7.2	38.3	44.3	24.9	20.3	2.2
Congo, DR	2007	25,219	57.6	22.8	16.8	74.8	11.0	29.6	21.0	Sierra Leone	2006	21,022	48.6	23.5	25.2	73.3	32.0	33.5	46.0
Dominican Republic	2002	47,253	9.6	0.5	1.7	11.6	8.0	4.3	4.4	South Africa	1998	24,019	30.5	0.0	1.3	26.0	18.2	2.3	n.a.
Egypt	2005	45,155	0.6	9.2	5.7	21.7	2.0	8.0	1.3	Sudan	2000	81,451	34.5	31.6	17.0	90.6	40.9	39.5	58.1
Ethiopia	1992	34,439	81.2	7.1	33.5	87.7	77.6	13.6	48.8	Suriname	2000	6,603	11.4	1.5	0.1	7.5	10.5	2.5	0.0
Gabon	2000	15,687	37.6	0.1	1.1	30.3	2.7	0.4	9.1	Swaziland	2000	12,557	63.4	3.8	4.5	25.7	27.4	2.0	n.a.
Gambia	2000	14,191	30.9	6.2	0.1	48.5	12.4	16.7	20.6	Tajikistan	2000	12,711	54.9	0.0	0.0	51.2	0.8	3.7	0.0
Ghana	2006	12,742	24.3	9.7	14.3	42.5	39.1	20.5	19.9	Tanzania	2005	25,022	32.5	13.6	18.8	75.3	19.5	11.2	11.9
Guatemala	1999	16,239	16.5	5.9	6.8	55.4	22.7	8.5	11.8	Thailand	2006	38,954	1.6	2.7	0.6	11.1	1.1	6.9	1.2
Guinea	1999	18,745	40.9	2.3	29.7	52.8	32.3	9.5	25.4	Uganda	2001	21,448	74.5	3.8	3.4	73.0	11.3	8.3	22.5
Guyana	2001	8,733	25.1	2.5	0.0	28.8	3.1	3.1	0.0	Ukraine	2005	5,830	0.4	n.a.	0.3	2.0	0.0	n.a.	0.3
Haiti	2000	22,983	52.6	2.3	7.4	52.6	44.3	12.5	18.0	Uzbekistan	2006	19,906	3.1	5.4	1.3	10.3	0.0	3.7	0.8
India	2006	198,294	9.8	23.1	10.8	59.6	43.8	13.3	10.5	Vietnam	2006	12,736	8.7	n.a.	2.3	28.7	20.9	9.1	13.8
Indonesia	2003	56,726	18.1	0.0	1.4	9.1	25.8	5.9	7.4	Yemen	2006	13,637	28.8	n.a.	20.1	41.8	19.9	45.3	16.8
Iraq	2000	50,775	22.4	3.4	0.0	5.8	9.2	4.4	0.0	Zambia	2002	20,220	28.2	24.6	21.5	66.6	28.3	17.4	24.0
Jamaica	2005	5,813	5.9	n.a.	0.2	n.a.	0.8	7.5	n.a.	Zimbabwe	2006	21,218	28.1	11.3	2.0	46.1	38.2	30.1	20.0
Jordan	1997	22,114	0.9	2.2	0.6	14.3	0.7	12.0	0.8										
Kenya	2003	18,779	60.9	3.3	6.2	68.8	23.4	7.8	15.0										
Kyrgyzstan	2006	10,015	16.3	5.4	1.7	16.1	0.0	12.5	1.6										
Lao People's DR	2006	16,263	26.6	19.9	14.3	34.8	58.2	43.7	27.3										
Lesotho	2000	14,352	46.8	8.2	0.0	50.3	41.8	13.2	n.a.										

Table 3 Disaster frequency per country (mean and standard deviation for period 1988–2012)

Country	DisFre_ mean	DisFre_ sd	DisFre_ climo_ mean	DisFre_ climo_sd	DisFre_ geo_ mean	DisFre_ geo_sd	DisFre_ hydro_ mean	DisFre_ hydro_ sd	DisFre_ meteo_ mean	DisFre_ meteo_ sd
Albania	1.46	0.52	0.38	0.65	0.23	0.44	0.69	0.63	0.15	0.38
Angola	2.27	1.33	0.33	0.49	0.00	0.00	1.93	1.44	0.00	0.00
Armenia	1.25	0.50	0.25	0.50	0.25	0.50	0.75	0.50	0.00	0.00
Azerbaijan	1.56	0.88	0.22	0.44	0.44	0.53	0.89	0.93	0.00	0.00
Bangladesh	7.52	2.24	0.96	0.84	0.28	0.46	2.44	1.00	3.84	1.82
Benin	1.14	0.53	0.00	0.00	0.00	0.00	1.07	0.27	0.07	0.27
Bolivia	2.14	1.06	0.71	0.78	0.10	0.30	1.24	1.04	0.10	0.30
Bosnia and Herzegovina	1.80	0.79	0.70	0.67	0.00	0.00	0.90	0.88	0.20	0.42
Brazil	4.83	2.04	0.71	0.91	0.04	0.20	3.71	2.05	0.38	0.58
Burkina Faso	1.27	0.46	0.40	0.51	0.00	0.00	0.87	0.74	0.00	0.00
Burundi	2.54	1.66	0.46	0.52	0.08	0.28	1.54	1.51	0.46	0.66
Cambodia	1.44	0.51	0.25	0.45	0.00	0.00	1.00	0.52	0.19	0.54
Cameroon	1.31	0.48	0.23	0.44	0.08	0.28	1.00	0.41	0.00	0.00
Chad	1.64	0.84	0.36	0.50	0.00	0.00	1.14	0.66	0.14	0.36
Colombia	4.20	1.94	0.16	0.37	0.96	1.27	2.92	1.47	0.16	0.37
Congo, Republic	1.25	0.46	0.00	0.00	0.12	0.35	1.12	0.35	0.00	0.00
Congo, DR	2.06	1.29	0.12	0.34	0.25	0.45	1.38	0.96	0.31	0.60
Dominican Republic	2.39	1.29	0.06	0.24	0.06	0.24	1.06	0.80	1.22	1.06
Egypt	1.67	0.89	0.25	0.45	0.42	0.51	0.75	0.75	0.25	0.45
Ethiopia	2.57	1.90	0.48	0.51	0.13	0.34	1.96	1.82	0.00	0.00
Gabon	1.00	0.00	0.00	0.00	0.00	0.00	0.50	0.58	0.50	0.58
Gambia The	1.27	0.47	0.18	0.40	0.00	0.00	0.73	0.65	0.36	0.50
Ghana	1.36	0.50	0.00	0.00	0.00	0.00	1.36	0.50	0.00	0.00
Guatemala	2.90	1.58	0.38	0.59	0.76	0.70	1.24	1.14	0.52	0.75
Guinea	1.09	0.30	0.18	0.40	0.00	0.00	0.82	0.60	0.09	0.30
Guyana	1.00	0.00	0.33	0.50	0.00	0.00	0.67	0.50	0.00	0.00
Haiti	3.32	2.03	0.14	0.35	0.05	0.21	1.77	1.34	1.36	1.33
India	12.84	4.84	1.60	0.91	0.56	0.65	7.92	4.23	2.76	1.83
Indonesia	10.24	4.68	0.44	0.58	3.88	2.05	5.80	3.49	0.12	0.44
Iraq	1.12	0.35	0.12	0.35	0.12	0.35	0.88	0.64	0.00	0.00
Jamaica	1.53	0.74	0.07	0.26	0.00	0.00	0.33	0.49	1.13	0.92
Jordan	1.50	0.84	0.67	0.82	0.00	0.00	0.33	0.52	0.50	0.55
Kenya	2.65	1.84	0.45	0.51	0.10	0.31	2.05	1.88	0.05	0.22
Kyrgyzstan	1.38	0.62	0.12	0.34	0.44	0.73	0.75	0.86	0.06	0.25
Lao People's DR	1.50	0.76	0.21	0.43	0.00	0.00	0.93	0.62	0.36	0.50
Lesotho	1.62	0.74	0.50	0.53	0.00	0.00	0.38	0.74	0.75	0.89
Madagascar	2.37	1.26	0.26	0.45	0.00	0.00	0.26	0.56	1.84	1.07
Malawi	1.90	1.07	0.30	0.47	0.15	0.49	1.35	0.99	0.10	0.31
Mali	1.56	0.73	0.38	0.50	0.00	0.00	1.19	0.54	0.00	0.00
Mongolia	1.64	0.67	0.36	0.50	0.00	0.00	0.45	0.52	0.82	0.75
Morocco	1.62	0.81	0.19	0.40	0.12	0.34	1.19	1.05	0.12	0.34
Mozambique	2.50	1.57	0.50	0.69	0.05	0.22	1.10	1.07	0.85	1.04
Namibia	1.13	0.35	0.33	0.49	0.00	0.00	0.80	0.68	0.00	0.00
Nepal	2.29	1.49	0.38	0.65	0.12	0.34	1.67	0.92	0.12	0.34
Nicaragua	2.14	1.13	0.32	0.48	0.36	0.66	0.64	0.73	0.82	0.73
Niger	1.39	0.61	0.39	0.50	0.00	0.00	0.94	0.64	0.06	0.24
Nigeria	2.82	2.04	0.12	0.33	0.00	0.00	2.47	1.91	0.24	0.44
Pakistan	4.76	2.44	0.52	0.65	0.64	0.81	3.00	2.27	0.60	0.71
Peru	3.24	1.81	0.56	0.58	0.72	0.94	1.84	1.28	0.12	0.33
Philippines	13.52	6.76	0.20	0.50	1.16	1.11	5.24	3.83	6.92	3.13
Rwanda	1.46	0.52	0.31	0.48	0.15	0.38	1.00	0.71	0.00	0.00
Senegal	1.25	0.45	0.12	0.34	0.00	0.00	0.94	0.44	0.19	0.54
Sierra Leone	1.12	0.35	0.00	0.00	0.00	0.00	1.00	0.53	0.12	0.35
South Africa	2.87	1.49	0.65	0.65	0.17	0.39	1.13	0.87	0.91	1.00
Sudan	1.95	1.10	0.35	0.49	0.10	0.31	1.40	1.10	0.10	0.31
Suriname	1.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
Swaziland	1.14	0.38	0.57	0.79	0.00	0.00	0.29	0.49	0.29	0.49
Tajikistan	2.38	1.24	0.19	0.51	0.48	0.60	1.62	1.07	0.10	0.30
Tanzania, UR	2.30	0.86	0.40	0.50	0.25	0.44	1.45	0.76	0.20	0.52
Thailand	4.04	2.20	0.38	0.58	0.12	0.34	2.38	1.79	1.17	1.05
Uganda	1.94	0.73	0.33	0.49	0.22	0.55	1.17	0.99	0.22	0.55
Ukraine	1.62	0.81	0.38	0.62	0.00	0.00	0.81	0.66	0.44	0.89
Uzbekistan	1.20	0.45	0.20	0.45	0.60	0.89	0.40	0.55	0.00	0.00
Vietnam	5.68	2.58	0.20	0.50	0.00	0.00	2.64	1.66	2.84	1.57
Yemen	2.07	1.07	0.00	0.00	0.14	0.36	1.79	0.97	0.14	0.53
Zambia	1.36	0.63	0.21	0.43	0.00	0.00	1.14	0.77	0.00	0.00
Zimbabwe	1.78	0.97	0.67	0.50	0.00	0.00	0.89	0.60	0.22	0.44

Table 4 Disaster victims per country (mean and standard deviation for period 1988–2012)

Country	DisVic_ mean	DisVic_ sd	DisVic_ climo_ mean	DisVic_ climo_sd	DisVic_ geo_ mean	DisVic_ geo_sd	DisVic_ hydro_ mean	DisVic_ hydro_ sd	DisVic_ meteo_ mean	DisVic_ meteo_ sd
Albania	3.85	1.30	1.12	2.22	0.64	1.24	2.35	2.01	0.82	2.01
Angola	3.77	1.40	1.58	2.52	0.00	0.00	2.98	1.61	0.00	0.00
Armenia	2.99	2.25	1.37	2.74	1.04	2.09	1.58	1.79	0.00	0.00
Azerbaijan	4.02	1.31	0.09	0.26	1.95	2.39	2.61	2.27	0.00	0.00
Bangladesh	3.90	0.67	1.97	1.74	0.70	1.29	5.20	1.04	3.52	0.94
Benin	4.52	1.27	0.00	0.00	0.00	0.00	4.56	1.27	0.21	0.78
Bolivia	3.50	1.19	1.66	2.12	0.24	0.94	2.97	2.03	0.38	1.19
Bosnia and Herzegovina	2.77	1.37	1.09	1.71	0.00	0.00	2.20	1.96	0.37	0.96
Brazil	3.41	1.01	0.86	1.86	0.10	0.50	3.60	1.17	1.18	1.78
Burkina Faso	4.32	1.52	1.82	2.72	0.00	0.00	2.83	2.14	0.00	0.00
Burundi	3.33	1.35	1.72	2.70	0.16	0.58	2.89	1.35	1.24	1.72
Cambodia	4.35	2.06	1.49	2.67	0.00	0.00	3.91	2.54	0.27	0.78
Cameroon	2.90	1.48	0.41	1.46	0.27	0.96	2.62	1.44	0.00	0.00
Chad	4.27	1.35	2.11	2.94	0.00	0.00	3.48	1.89	0.38	0.98
Colombia	3.46	0.87	0.29	1.08	1.67	1.90	3.50	1.33	0.51	1.38
Congo, Republic	4.10	0.53	0.00	0.00	0.40	1.12	4.11	0.52	0.00	0.00
Congo, DR	3.33	0.95	0.35	0.98	0.74	1.65	2.95	1.42	0.81	1.60
Dominican Republic	3.23	1.61	0.00	0.00	0.18	0.78	2.60	1.91	2.40	2.05
Egypt	2.65	1.21	0.41	0.76	1.22	1.68	1.58	1.72	0.46	0.83
Ethiopia	4.26	1.61	2.61	3.27	0.37	1.06	3.20	1.85	0.00	0.00
Gabon	3.76	0.88	0.00	0.00	0.00	0.00	2.22	2.59	1.54	1.78
Gambia The	3.35	1.47	0.51	1.70	0.00	0.00	2.18	1.87	1.23	1.74
Ghana	4.77	1.06	0.00	0.00	0.00	0.00	4.77	1.06	0.00	0.00
Guatemala	2.87	1.14	0.96	2.01	1.77	1.66	2.19	1.62	1.25	1.91
Guinea	3.45	1.44	0.36	0.90	0.00	0.00	3.03	2.03	0.06	0.21
Guyana	2.93	2.58	0.64	1.93	0.00	0.00	2.29	2.50	0.00	0.00
Haiti	3.33	1.45	0.48	1.57	0.30	1.41	2.50	1.65	2.50	2.18
India	3.76	0.63	2.08	1.39	2.09	2.53	4.09	1.00	3.22	1.56
Indonesia	3.48	0.56	1.03	1.89	3.56	0.67	3.34	1.04	0.29	1.01
Iraq	2.67	1.55	0.00	0.00	0.34	0.96	2.33	1.81	0.00	0.00
Jamaica	2.97	1.49	0.00	0.00	0.00	0.00	1.17	2.05	2.23	1.91
Jordan	2.28	1.69	1.60	2.17	0.00	0.00	0.79	1.71	0.72	0.98
Kenya	4.10	1.80	2.94	3.34	0.02	0.07	2.88	1.89	0.09	0.38
Kyrgyzstan	3.17	1.50	0.46	1.58	0.96	1.74	1.75	1.72	0.25	0.99
Lao People's DR	4.71	1.18	0.73	1.87	0.00	0.00	3.72	2.44	1.66	2.46
Lesotho	3.33	1.86	2.84	3.04	0.00	0.00	0.40	0.75	1.08	1.56
Madagascar	4.42	0.93	1.43	2.48	0.00	0.00	0.90	1.79	3.79	1.63
Malawi	4.59	0.99	1.92	3.02	0.43	1.34	3.70	1.73	0.25	0.88
Mali	3.86	1.12	1.76	2.73	0.00	0.00	3.41	1.24	0.00	0.00
Mongolia	3.01	1.84	1.39	2.43	0.00	0.00	1.22	1.66	2.09	2.27
Morocco	3.03	1.30	0.58	1.62	0.35	1.08	2.24	1.74	0.09	0.30
Mozambique	4.08	1.47	1.96	2.76	0.16	0.71	2.91	2.31	2.27	2.37
Namibia	4.22	1.49	1.37	2.36	0.00	0.00	2.85	2.24	0.00	0.00
Nepal	3.42	1.24	1.00	1.72	0.55	1.56	3.31	1.59	0.24	0.65
Nicaragua	3.81	1.34	0.90	1.97	0.84	1.62	2.12	2.22	2.42	2.24
Niger	4.84	0.90	2.36	3.11	0.00	0.00	3.55	2.00	0.17	0.73
Nigeria	3.79	1.34	0.18	0.52	0.00	0.00	3.86	1.62	0.62	1.27
Pakistan	3.09	0.96	0.84	1.16	1.87	2.29	3.28	1.80	1.26	1.69
Peru	3.49	1.15	2.17	2.52	1.59	1.95	3.11	1.61	0.48	1.49
Philippines	4.28	0.54	0.39	1.37	2.45	2.02	3.59	1.17	4.72	0.73
Rwanda	3.91	1.07	1.67	2.62	0.47	1.14	2.71	1.68	0.00	0.00
Senegal	4.11	1.30	0.71	1.95	0.00	0.00	3.62	1.89	0.41	1.13
Sierra Leone	2.72	1.58	0.00	0.00	0.00	0.00	2.57	1.80	0.15	0.44
South Africa	2.89	1.17	1.63	2.18	0.28	0.63	2.74	1.72	1.55	1.53
Sudan	4.62	1.30	1.95	2.91	0.26	0.90	4.08	1.92	0.16	0.50
Suriname	4.11	0.41	0.00	0.00	0.00	0.00	4.11	0.41	0.00	0.00
Swaziland	4.50	1.13	2.25	2.85	0.00	0.00	1.26	2.23	0.98	1.69
Tajikistan	3.48	1.15	0.61	1.89	1.21	1.69	3.19	1.41	0.29	0.92
Tanzania, UR	3.71	1.20	2.08	2.93	0.69	1.31	3.12	1.35	0.44	1.07
Thailand	4.30	1.25	1.40	2.80	0.26	1.02	4.22	2.10	2.67	2.17
Uganda	3.81	1.40	1.91	2.79	0.44	1.32	2.52	1.93	0.35	0.80
Ukraine	3.46	1.55	0.68	1.49	0.00	0.00	2.72	2.40	0.62	1.25
Uzbekistan	3.20	1.70	1.16	2.58	1.13	1.65	0.91	1.40	0.00	0.00
Vietnam	4.26	0.75	0.85	2.07	0.00	0.00	3.83	1.64	3.92	1.22
Yemen	2.83	1.35	0.00	0.00	0.42	1.25	2.87	1.32	0.09	0.32
Zambia	4.92	1.21	1.32	2.61	0.00	0.00	3.95	2.01	0.00	0.00
Zimbabwe	4.19	2.12	4.11	3.14	0.00	0.00	2.49	2.15	0.11	0.32

Table 5 EM-DAT definitions of natural disaster types

Disaster	Definition	Main Type
Geophysical	Events originating from solid earth	Earthquake, volcano, mass movement (dry)
Meteorological	Events caused by short-lived/small to meso-scale atmospheric processes (in the spectrum from minutes to days)	Storm
Hydrological	Events caused by deviations in the normal water cycle and/or overflow of bodies of water caused by wind set-up	Flood, mass movement (wet)
Climatological	Events caused by long-lived/meso- to macro-scale processes (in the spectrum from intraseasonal to multidecadal climate variability)	Extreme temperature, drought, wildfire

Source: www.emdat.be

Table 6 Model specification: The same model will be run for each kind of deprivation (seven times)

	Motivation
Focal (basic) relationship	
Disaster frequency/country size (used one at a time)	Greater natural-disaster frequency (adjusted for geographical country size) has adverse effect on poverty. There are five different measures, and each are used one at a time. The disaster frequency and victim measures are never applied simultaneously.
Disaster victims/population size (used one at a time)	(1) More natural-disaster victims (adjusted for country population size) will be associated with more poverty. (2) More poverty will be associated with more natural-disaster victims. There are five different measures, and each are used one at a time. The frequency and victim measures are never applied simultaneously.
QoG (wbgi_gree)	Stronger QoG institutions reduce poverty.
QoG*Disaster (interaction)	The adverse effect of disasters depends on different levels of QoG. (Included only in the models if they passed modelling stage *m3*).
Control variables	
Country level	
GDP	More economically developed countries will have less poverty.
Democracy (fh_ipolity2)	More democracy gives the poor more say, which leads to less poverty.
Year (DHS/MICS)	To account for differences in DHS/MICS measurements.
Household level	
Urban	Rural population is more exposed than urban population to poverty.
Adults per child	More adults per children should give the household more resources (caring, potential income, etc.) to meet children´s needs.
Number of children	More children in a household lead to increased pressure on the household's resource pool.
Child level	
Sex	Sex differences
Age	Younger children are more dependent on their parents.

Table 7 Regression estimates – disaster frequencies

	m1	*m2*		*m3*		*m4*
	β_1	β_1	β_3	β_1	β_1	β_3
DisFre_all						
Water	–	–		–		
Malnutrition	–	$p \leq 0.06$ (+)	$p \leq 0.03$ (+)		$p \leq 0.06$ (+)	$p \leq 0.02$ (+)
Education	–			$p \leq 0.02$ (–)		
Shelter	–	–		–		
Sanitation	–	$p \leq 0.09$ (–)		$p \leq 0.04$ (–)	$p \leq 0.08$ (–)	
Health	–	–		–		
Information	–	–		–		
DisFre_hydro						
Water	–	–		–		
Malnutrition	–	$p \leq 0.07$ (+)	$p \leq 0.04$ (+)	–		$p \leq 0.05$ (+)
Education	–			$p \leq 0.03$ (–)		
Shelter	–	–		–		
Sanitation	–	$p \leq 0.07$ (–)		$p \leq 0.04$ (–)	$p \leq 0.03$ (–)	–
Health	–	–		–		
Information	–	–		–		
DisFre_climo						
Water	–	–		–		
Malnutrition	–	$p \leq 0.00$ (+)	$p \leq 0.00$ (+)	$p \leq 0.09$ (+)	$p \leq 0.00$ (+)	$p \leq 0.00$ (+)
Education	–	–		–		
Shelter	–	–		–		
Sanitation	–			–		
Health	–	–		–		
Information	$p \leq 0.02$ (+)			–		
DisFre_meteo						
Water	–	–		–		
Malnutrition	–	–		–		$p \leq 0.08$ (+)
Education	–	–		–		
Shelter	–	–		–		
Sanitation	–	–		–		
Health	–	–		–		
Information	–	–		–		
DisFre_geo						
Water	–	$p \leq 0.07$ (–)		$p \leq 0.05$ (–)		
Malnutrition	–	$p \leq 0.09$ (+)	$p \leq 0.04$ (+)	–	$p \leq 0.02$ (+)	$p \leq 0.01$ (+)
Education	–			$p \leq 0.03$ (–)		
Shelter	–	–		–		
Sanitation	$p \leq 0.02$ (–)			$p \leq 0.03$ (+)		
Health	–	–		–		
Information	–	–		–		

1. (+) means that the disaster parameter in question has a positive correlation with the relevant deprivation, and (–) means that this correlation is negative.
2. β_1 refers always to the main effect (or the constitutive term in an interaction model) of the disaster variable; β_3 refers always to the parameter of the interaction term between QoG and the disaster in question.
3. The p-values show the actual rounded two-tailed significance of the parameter in question. The p-value is only shown if it is below $p \leq 0.1$ otherwise.
4. "–" means that the disaster variable or the interaction term (depending on modelling step) is not significant at a $\alpha = 10\%$.
5. *m1* represents the basic bivariate model; *m2* is a basic interaction model; *m3* is the *m1* but with a set of controls included; and, *m4* is *m2* with a set of controls. See the section on research design for a full explanation.

The complete statistical results are presented in the online appendix: <www.mpifg.de/pu/mpifg_dp/dp15-4_appendix.pdf>.

Table 8 Regression estimates – disaster victims

	m1	*m2*		*m3*		*m4*
	β_1	β_1	β_3	β_1	β_1	β_3
DisVic_all						
Water	–	–	–	–	–	–
Malnutrition	–		–	–	–	–
Education	$p \leq 0.05$ (+)		–	–	–	–
Shelter	$p \leq 0.00$ (+)		$p \leq 0.06$ (–)	$p \leq 0.00$ (+)	–	–
Sanitation	$p \leq 0.00$ (+)	$p \leq 0.07$ (+)	–	–	–	–
Health	–	–	$p \leq 0.06$ (–)	$p \leq 0.01$ (–)	–	–
Information	–	–	–	–	–	–
DisVic_hydro						
Water	–	–		–	–	–
Malnutrition	–	–	$p \leq 0.06$ (–)	–	–	–
Education	$p \leq 0.09$ (+)	–		–	–	–
Shelter	$p \leq 0.00$ (+)		$p \leq 0.01$ (–)	$p \leq 0.00$ (+)	–	$p \leq 0.06$ (–)
Sanitation	$p \leq 0.00$ (+)			$p \leq 0.01$ (+)	–	–
Health	–	–	$p \leq 0.06$ (–)	–	–	–
Information	–	–		$p \leq 0.05$ (+)	–	–
DisVic_climo						
Water	$p \leq 0.01$ (+)	$p \leq 0.01$ (+)	–	$p \leq 0.02$ (+)	$p \leq 0.01$ (+)	–
Malnutrition	$p \leq 0.04$ (+)		–	$p \leq 0.04$ (+)	–	–
Education	$p \leq 0.09$ (+)	–	–	–	–	–
Shelter	$p \leq 0.00$ (+)	$p \leq 0.00$ (+)	–	$p \leq 0.00$ (+)	$p \leq 0.01$ (+)	–
Sanitation	$p \leq 0.00$ (+)		–	$p \leq 0.00$ (+)	–	–
Health	–	–	–	–	–	–
Information	$p \leq 0.01$(+)	–	–	$p \leq 0.02$ (+)	–	–
DisVic_meteo						
Water	–	–	–	–	–	–
Malnutrition	–	–	–	–	–	$p \leq 0.09$ (+)
Education	–	–	–	–	–	–
Shelter	–	–	–	–	–	–
Sanitation	–	–	–	–	–	–
Health	–	–	–	–	–	–
Information	–	–	–	–	–	–
DisVic_geo						
Water	$p \leq 0.10$ (–)	–		–	–	–
Malnutrition	$p \leq 0.05$ (–)	–	$p \leq 0.05$ (+)	$p \leq 0.05$ (–)	–	$p \leq 0.01$ (+)
Education	–	–		–	–	–
Shelter	–	–		–	–	–
Sanitation	–	–			–	$p \leq 0.04$ (+)
Health	–	–		–	–	$p \leq 0.06$ (+)
Information	–	–		–	–	$p \leq 0.09$ (+)

1. (+) means that the disaster parameter in question has a positive correlation with the relevant deprivation, and (–) means that this correlation is negative.
2. β_1 refers always to the main effect (or the constitutive term in an interaction model) of the disaster variable; β_3 refers always to the parameter of the interaction term between QoG and the disaster in question.
3. The p-values show the actual rounded two-tailed significance of the parameter in question. The p-value is only shown if it is below $p \leq 0.1$ otherwise.
4. "–" means that the disaster variable or the interaction term (depending on modelling step) is not significant at a $\alpha = 10\%$.
5. *m1* represents the basic bivariate model; *m2* is a basic interaction model; *m3* is the *m1* but with a set of controls included; and, *m4* is *m2* with a set of controls. See the section on research design for a full explanation.

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