Forthcoming, Journal of Operations Management

Natural disasters, the economy and population vulnerability as a vicious cycle with exogenous hazards

ManMohan S. Sodhi <m.sodhi@city.ac.uk>
Cass Business School, City University London
106 Bunhill Row, London EC1Y 8TZ, UK

Phone: +44 (0)20-7040-0276

20th March, 2016

Abstract: One way to understand the growing impact of disasters is as the output of a positive feedback, or reinforcing, loop. This paper hypothesizes that population vulnerability of a country transforms exogenous hazards to disaster impact for that country, which negatively impacts its economy as measured by per capita income and its growth. This impact in turn increases the vulnerability of the country's population thus creating a reinforcing loop. Therefore, like the output of any positive feedback loop, disaster impact would grow exponentially. Having analysed data over 50 years (1963-2012) and 179 countries, we find the results to be consistent with this conceptual model. We also find that disaster impact worldwide has indeed grown exponentially over this period even after normalizing for the growing global population and global income. These findings indicate the existence of a feedback loop that requires strategic rethinking about disaster management and development jointly to break this vicious cycle.

Keywords: Disasters, natural hazards, strategic humanitarian operations, development, country-level analysis, vulnerability.

1. Introduction

The increasing number and impact of natural disasters over time has led many to posit *vicious cycles* comprising disaster impact and any subset of deforestation, poverty, urbanisation, vulnerability and other factors (cf. Manuel-Navarrete et al. 2007; McEntire 2001; Barrett and Carter 2000; Vatsa 2004). So far, however, little empirical evidence has been provided to support the existence of these vicious cycles. This paper seeks to provide some initial evidence.

One way to model a simple vicious cycle is as a positive feedback loop (cf. Sudling 2013), i.e., a reinforcing loop, as in control theory. We conceptualize such a loop with disaster impact as the output and natural hazards as the exogenous input. We posit that population vulnerability is positively linked to disaster impact, disaster impact negatively impacts the economy of a country as measured by per capita income and its growth, and these in turn affect the vulnerability of the country's population. As with any positive feedback loop, we expect the output, in this case the disaster impact, to grow exponentially over time.

By analysing country-level disaster, economic and hazard data for five decades (1963-2012), we find our threefold results to be consistent with this conceptual model: *First*, the population's vulnerability transforming a given hazard (an earthquake) is positively linked to disaster impact for the country (Peduzzi et al. 2012). *Second*, disaster impact is negatively linked to a country's economy as reflected by its national income and its growth, which in turn are negatively linked to the vulnerability of its population (child mortality under age five and incidence of tuberculosis), thus creating reinforcing feedback. *Third*, time-series analysis shows exponentially increasing impact when impact is measured by the total number of people affected every year or property damage worldwide, even when we normalise the impact by population or income respectively. The results therefore provide initial evidence for a positive feedback loop at work. The implication is that we need to develop a strategic view of humanitarian operations encompassing both humanitarian relief and development to interrupt this vicious cycle of disasters.

This paper contributes to the humanitarian operations literature in at least two ways: (1) Analysis of country-level data in this paper sets the stage for a grounded "systems view" to "replace well-intended intuition" (Starr and Van Wassenhove 2014). This work provides the empirical basis for building *system dynamics* (SD) and other simulation-based models to look for longer-term solutions for intervention than those in place currently. It also provides a starting point for additionally incorporating hazards like climate change and its varied impact on different countries. (2) By building on the disaster-and-development literature, this work provides a foundation for building theory for strategic humanitarian operations allowing us "to harmonize short-term humanitarian and long-term development efforts in the same region" (Kovács and Spens 2011). The analysis complements the 'micro' context of specific cases and situations in the humanitarian literature (cf. Tomasini and Van Wassenhove 2009; Pedraza Martinez et al. 2011) with a 'macro' context at the country level across the globe. The paper and the feedback loop allow for links to be made with the development literature (cf. Shepherd et al. 2013; Fothergill and Peek 2004; Bankoff et al. 2004; Pelling 2003; Blakie et al. 1994).

The managerial significance of this work is that governments, international bodies like the World Bank and the International Federation of the Red Cross and Red Crescent Societies (IFRC) as well as regional NGOs can use SD models based on this paper to allocate resources more cost-effectively across response, reconstruction, preparedness and prevention than is currently being done.[1] Humanitarian organizations can use this work to seek support to "develop more sustainable solutions from social, ecological, and economical perspectives" (Kovács and Spens 2011) *beyond* response and preparedness. The existence of such feedback loops requires rethinking disaster management and development jointly as ways to interrupt feedback, whether by way of prevention, mitigation, development or reconstruction (Rodes et al 2008; LOG 2014). Both development efforts and humanitarian operations can align themselves around the same specific vulnerability metrics (Birkmann 2006; Cutter and Finch 2008), an example being *child mortality under age five* (UNICEF 2000) as a *lagging* indicator for development and as a *leading* indicator for disaster impact.

---

[1] The World Bank (2013) provides similar advice using a risk management perspective.

The rest of the paper is organized as follows: §2 provides the theoretical background on positive (i.e., reinforcing) feedback loops as well as existing research to support the relations within a reinforcing feedback loop structure. §3 presents the chosen measures, data sources and methods, and §4 provides the results. Finally, §5 discusses the implications and limitations of this work as well as opportunities for further research.

2. Theory

The literature (cf. Manuel-Navarrete et al. 2007; McEntire 2001; Barrett and Carter 2000; Vatsa 2004) generally suggests *natural disasters* and *poverty* to be intimately linked via vicious cycles. Other concepts entailed in posited vicious cycles include deforestation, poverty, urbanisation, vulnerability and other factors. However, there is dearth of empirical evidence in support of these vicious cycles.

Swedish economist Gunnar Myrdal furthered the development and use of *circular and cumulative causation* (CCC) with core variables and with multiple links to propose multiple causes in socio-economic settings. For instance, he studied Asian underdevelopment using CCC (cf. O'Hara 2008). However, the large number of concepts used in any such model and bidirectional links between them make it difficult to test these models.

To provide empirical evidence for a posited 'vicious cycle', we consider the *positive feedback loop* from control theory as used for instance in engineering, particularly in electronics. The forward part of this loop comprises an input that is transformed into an output. The feedback is the output, transformed by another function *B*, going back with the input – if it adds to the input, we get unlimited amplification over time, leading to ever-increasing output and we call this a *positive* feedback loop. In such a loop, the transformation function is itself transformed by the output. (If the feedback subtracts from the input, the output reduces over time and we call this a *negative* feedback loop.)

In particular, we are interested in *vulnerability* as the transformation function that converts hazards into disasters: a country with higher vulnerability would have a bigger disaster with more people affected than a country with lower vulnerability, all else being equal including the physical intensity of the hazard. Vulnerability is thus the propensity across different population segments to be affected by natural hazards and other shocks (LOG 2014; Blakie et al. 1994; Cannon 1994; Anderson 1995). Vulnerability studies were instrumental in the 1990s in changing the thinking that the impact of 'natural disasters' was manmade. The literature linking disasters and vulnerability is largely conceptual (cf. Cannon 1994) and with divergent understanding of vulnerability, which is sometimes conflated with *poverty* (cf. Rodriguez-Oreggia et al 2013). In this paper we view poverty separately as an attribute of a country or region.

Consider a country facing a constant hazard rate H as the exogenous input. The transformation function is the vulnerability $V(t)$, which converts the input into disaster impact $D(t)$ as output. This output also worsens the state of the economy $E(t)$, which in turn increases the vulnerability $V(t)$. With such an arrangement, the disaster impact would keep growing as feedback would keep increasing the amplifying effect of the transformation even with the hazard rate remaining constant (**Figure 1**).

Insert Figure 1 somewhere here

For some constants k_1, k_2, and k_3, we *propose* that vulnerability transforms hazards into disaster impact so that

$$D(t) = k_1 \, H \, V(t) \tag{1}$$

Consequently, $D'(t) = k_1 \, H \, V'(t)$, the prime symbol reflecting the first derivative with respect to time. The feedback function reflecting the economy $E(t)$ is such that the rate of change in the economy $E'(t)$ is proportional to the disaster impact at time t

$$E'(t) = k_2 \, D(t) \tag{2}$$

Moreover, vulnerability depends on the economy so that

$$V(t) = k_3 E(t) \tag{3}$$

so that $V'(t) = k_3 \, E'(t)$.

From (1) and (3), $D'(t) = k_1 \, H \, V'(t) = k_1 \, k_3 \, H \, E'(t)$. Substituting (2), we have

$$D'(t) = k_1\ k_2\ k_3\ H\ D(t)$$

Solving this differential equation, we obtain

$$D(t) = c_1.\ \exp(c_2\ t) \quad (4)$$

for some constants c_1 and c_2 as functions of k_1, k_2, k_3 and H. Equations (1)-(4) can be statistically tested by taking natural logarithms on both sides first to allow for the use of linear regression and time series

$$\log D(t) = a + \log H + \log V(t) \quad (5)$$

$$\log E'(t) = b + \log D(t) \quad (6)$$

$$\log V(t) = c + \log E(t) \quad (7)$$

$$\log D(t) = d + \mathrm{e}\ t \quad (8)$$

for some constants $a \ldots e$.

This parsimonious conceptualisation omits many other (meta) constructs of interest: climate change, conflict, corporate irresponsibility, government policy, growth path, urbanisation, or manmade causes such as fracking leading to earthquakes (cf. Corbyn 2011; Turner 2012). Nonetheless, future research can add these to the above conceptual model in empirical or SD models.

Support for equation (1) comes from Alexander's (1994) argument that vulnerability is a key determinant of disasters. As Rodriguez-Oreggia et al. (2013) put it, "While the occurrence of a natural hazard could be considered exogenous, its transformation into a disaster is not." Indeed, this is a tenet for vulnerability studies (cf. Blakie et al 1994). In line with this reasoning, we take *hazards* to be exogenous and expect *vulnerability* to determine the impact of any hazard: a more vulnerable population segment, or country as a whole, will suffer greater impact than a less vulnerable segment for a hazard of the same intensity. LOG (2014) describes this as

Hazard + Vulnerability = Disaster

which is the same as (5) when the measures in the above equation are the log-transformed values of the measures in (3).

As regards equation (2), hypothesizing that a disaster impacts a country's economy seems reasonable. However results in the past have been mixed depending on the measure of impact, people affected or killed (cf. Noy 2009), or damage to property (which assumes there is property to begin with). Toya and Skidmore (2007) link fatalities (and property damage) to socio-economic variables: educational attainment, openness, financial development, and size of government besides income. There is also empirical literature looking into specific measures of poverty and disaster impact *within* particular countries: Fothergill and Peek (2004) review the literature on disasters in the United States; Rodriguez-Oreggia et al (2013) link different types of poverty to different types of disasters at the municipal level in Mexico and Carter et al (2007) focus on Ethiopia and Honduras.

Finally, regarding equation (3), links between *poverty* as an aspect of the social economy and *vulnerability* have also been investigated. Fothergill and Peek (2004) review US-based studies of people living in highly susceptible areas owing to poverty, thus becoming highly vulnerable. Even within the same country, measures for socio-economic status such as education, income, and even ethnicity indicate a strong link to earthquake preparedness – and thus to vulnerability – in the earthquake-prone state of California (cf. Turner et al, 1986).

3. Material and methods

We need appropriate measures as well as sources for data for *disaster impact*, the *economy*, *population vulnerability* and *hazards* to test the posited relationships (5)-(8).

3.1 Disaster impact, the economy and population vulnerability

The Centre for Research on the Epidemiology of Disasters (CRED) at the Université Catholique de Louvain compiles and publicises data on both natural and manmade disasters in their database, EM-DAT, at the university's Brussels campus. The centre compiles data from UN agencies, non-governmental organizations, insurance companies, research institutes and press agencies and are continually reviewed for accuracy and consistency (Guha-Sapir, et al, 2004; 2013). The resulting database categorizes natural disasters – the subject of this paper – as follows: (1) *biological*: epidemics and insect infestations; (2) *climatological*: droughts, extreme temperature and wildfires; (3) *geophysical*: earthquakes, mass movement (dry) and volcanoes; (4) *hydrological*: floods and mass movement (wet); and (5) *meteorological*: storms.

Although EM-DAT has data starting with year 1900, we focused on the 50-year period from Jan. 1963 to Dec. 2012.[2] This is because better information is available 1963 onwards: missing information is coded as '0' in the EM-DAT data and there are many zeros prior to 1963 in the time series for numbers of people affected, injured or rendered homeless. Additionally, reliable economic data at the country level from earlier (< 1960) or later years (> 2012) were hard to find for many countries at the time of this writing.

CRED includes a 'disaster' in their database if it results in: (a) 10 or more people killed, (b) 100 or more people *affected*, (c) the declaration of a state of emergency, or (d) a call for international assistance. '*Affected*' in turn is defined as "people requiring immediate assistance during a period of emergency, i.e., requiring basic survival needs such as food, water, shelter, sanitation and immediate medical assistance or the appearance of a significant number of cases of an infectious disease introduced in a region or a population that is usually free from that disease."

We choose as measures of disaster impact *total affected* as the sum of those affected, injured, or rendered homeless as used by CRED as well as *total property damage*. We also look at the *number of fatalities* (cf. Kahn 2005). In the five decades from 1963 to 2012, natural disasters have killed more than 5 million people and have affected nearly 7 billion in total with nearly $2.5 trillion of property damage. Only four disaster types – floods, drought, storms and earthquakes – were responsible for nearly 98% of the *total affected* globally during 1963-2012; Rodriguez-Oreggia et al (2013) used only these four in their Mexican study (**Table 1**).

---

[2] For an older period, see Degg's (1992) analysis of disasters between WWII and 1990 across the globe contrasting developed and developing countries.

Table 1: Data summary showing the percentage of total number of occurrences and total impact from 1963-2012 for different types of disasters (highest numbers in a column in bold) worldwide. *Source*: EM-DAT: International Disaster Database – www.emdat.be – Université Catholique de Louvain – Brussels – Belgium.

Type	Occu-rrence	Deaths	Affected	Injured	Homeless	**Total affected**	**Property damage**
Epidemic	10.93%	4.43%	0.37%	6.60%	-	0.36%	-
Insect infestation	0.69%	-	0.01%	-	-	0.01%	0.01%
Drought	5.08%	**42.31%**	31.97%	-	0.01%	31.17%	4.95%
Extreme temp.	3.96%	3.23%	1.43%	25.70%	0.15%	1.42%	2.28%
Wildfire	3.03%	0.04%	0.09%	0.07%	0.10%	0.09%	2.13%
Earthquake	8.43%	25.61%	2.18%	**31.49%**	13.67%	2.48%	30.00%
Mass mvmt. dry	0.39%	0.05%	-	0.01%	-	-	-
Volcano	1.61%	0.57%	0.07%	0.16%	0.22%	0.08%	0.12%
Flood	**33.69%**	5.54%	**50.92%**	17.97%	**51.61%**	**50.90%**	23.21%
Mass mvmt. wet	4.83%	0.74%	0.14%	0.14%	2.58%	0.20%	0.34%
Storm	27.35%	17.48%	12.83%	17.86%	31.65%	13.29%	**36.97%**
Total %	*100.00%*	*100.00%*	*100.00%*	*100.00%*	*100.00%*	*100.00%*	*100.00%*
Total (1963-2012)	11,839	5.179 m	6,693 m	7.327 m	163.7 m	6,864 m	$2,497 b
Average/year	237	103,589	134 m	146,557	3.27 m	137.3 m	$50 b

In this paper, we use economic and disaster data on 179 countries. Starting with 212 countries for which the World Bank provided economic data for 2012, we had to drop 15 for which no disaster data was available and 2 more for which most data were missing. Of the countries remaining in our sample, 14 had little economic information available and were therefore dropped. Of the remaining 181 countries, 72 did not have economic data going back to 1962 but of these, 70 had economic data at least for the 1990-2012 period. Rather than drop all these 72 countries, we took a shorter time period of 1990-2012 for analysis, taking care that all measures were on a per year basis and dropped only 2. The 179 countries left in our sample are a mix of 'developed' and 'developing' countries across the world and not just those in Asia or Africa. This diversity is reflected in the list of ten countries with the most *occurrences* of disasters: United States (664), China (574), Philippines (436), India (394), Indonesia (270), Bangladesh (239), Japan (186), Mexico (172), Australia (171), and Iran (167).

The variable *total affected* during 1963-2012 was normalised by the country's population in 1990 and the total *property damage* by the country's national income in 1990. We took 1990 as the 'base' year for normalizing the total impact over the 1963-2012 period for each country (or 1990-2012 for the newer countries in the sample as discussed earlier). This is because the average global population during the five decades was the same as the population in 1989 and the average global per capita income during this period was the same as that in 1991.

Although the *economy* of a country is a broad concept that should ideally be captured as complex multi-dimensional constructs, our focus in this paper is on narrow sets of measures that governments (or transnational NGOs) already collect at the country-level every year. Having comparable data across nearly all countries is important for analysis. As such, we narrowed the economy of a country to commonly reported metrics such as *per capita income* in current US dollars for any given year, say 2012, and its *growth* over a specified period, say 1963-2012.[3] For countries that were not in existence or had merged or split in the first half of this period, we took the narrower window of 1990-2012 to avoid dropping them from the sample altogether as discussed earlier. The World Bank estimates per capita income based on Gross National Income (GNI) using the so-called Atlas method and the mid-year population of the country. We took the *per capita income* in 1962, (or 1990 for the countries in existence for the shorter period 1990-2012) as a control variable. For adjusting for population growth and GDP growth, we also took 1990 population and GDP (or rather GNI in current dollars) for each country in the dataset.

Similarly, this study focuses on only two mainstream measures for population *vulnerability*: (1) *child mortality* under age 5 per 1,000 live births, and (2) *incidence of tuberculosis* (TB) per 10,000 people for any given year (in this paper, 2012). The reasoning is that a high child mortality or high incidence of TB for a country reflects

---

[3] As we shall see later, even with only these few variables, we find that regression models have high adjusted-R^2. This shows there is some value in measuring economy and vulnerability narrowly as we have done.

its inability to take care of its most vulnerable: a natural hazard would likely have a much bigger impact than in a country with low values of these indicators. These indicators vary widely even in the same geographical region of the world: in 2012, India's child mortality was 4 times China's, which in turn was 3 times Singapore's.

From the data compiled from EM-DAT and the World Bank, we derived the variables used in our statistical analysis by taking logarithm and/or normalizing the data for the countries' population or GDP (**Table 2**).

Table 2: Variables for studying the relationship between disaster impact, poverty and vulnerability, obtained by transforming compiled data.

Variable	Description	N	Mean	Min	Max
Country Code	ISO code of country as identifier	179			
Region	One of five regions in which the country lies – (1) Africa, (2) America, (3) Asia, (4) Europe and (5) Oceania	179			
Log-Pop-1990	Log of 1990 population in tens of thousands	179	6.165034	-.1049162	11.63972
Log-Num-Occ	Log of number of occurrences of disasters per year	179	-.2743332	-3.912023	2.725235
Log-Num-Dead	Log of no. fatalities per 10,000 of population per year	174	-3.316065	-8.352666	2.725235
Log-Tot-Aff-Norm	Log of total no. affected normalized per 10,000 of population per year	179	3.501901	-4.672693	6.689991
Log-Damage-Norm	Log of total damage normalized per $10,000 of 1990 GDP of country per year	150	2.553999	-7.256135	7.877024
Log-PCI-1	Log of per capita income at the beginning of the period (1962 or 1990)	168	6.140636	3.555348	10.00873
Log-PCI-2	Log of per capita income at the end of the period (2012)	179	8.502949	4.812184	11.55799
Log-PCI-Growth	Log of PCI growth in percent over the period	167	1.693961	.0870739	2.548252
Log-Child-Mortality-5	Log of child mortality under age 5 per 1000 live births in 2012	175	3.044246	.7884573	5.150977
Log-TB-Incidence	Log of TB incidence per 10,000 population in 2012	179	3.935249	.3364722	7.205635

3.2 Hazards

For a *hazard*, the focus is on *potential* impact as anticipated from its physical attributes – say, the magnitude of an earthquake or the height of the water level of a river. In contrast, the CRED working definition reflects the understanding of a *disaster* in terms of *actual* impact. One definition of a natural hazard is "any natural process or phenomena that *may* cause loss of life, injury or other health impacts, social or economic disruption or environmental damage" (UNISDR, 2009: p.20). An earthquake in a region known to have earthquakes is a *hazard* of potential destructiveness, given its magnitude. It becomes a *disaster* only if its occurrence leads to an impact that crosses the CRED or similar thresholds. The impact of a hazard can vary by country and by magnitude: the 1994 Northridge earthquake (experienced by the author) with magnitude 6.7 in California killed 57 people while the 2001 Gujarat earthquake with magnitude of 7.7 in India killed more than 20,000 people.

We focus on earthquakes as hazards to study the link between vulnerability and disasters for three reasons. *First*, we have to be careful in choosing a hazard type that had a more-or-less constant rate (e.g., a constant rate for Poisson arrivals) so that the increase in disasters cannot be attributed to the increase in hazard rate. Of the four leading types of hazards by impact, only earthquakes qualify: the other three – floods, droughts and storms – have an increasing rate possibly due to climate change as argued by the Intergovernmental Panel on Climate Change (IPCC 2014:p.7-8). For instance, there were 749 earthquakes of size 7 and above during 1963-2012 worldwide (5,863 earthquakes of size 6 and above) as per the United States Geological Survey (USGS) database with a stable rate over time. In contrast, earthquake-related *disasters* increased over the same period as indicated by the EM-DAT database (**Figure 2**).

Insert Figure 2 somewhere here

Second, we need to control for the physical characteristics of the hazard. It is only for earthquakes that we have the availability and comparability of the physical characteristics across countries. In contrast, the river crest height (relate to 'normal') is neither comparable across rivers nor readily available for flood disasters. And while wind speed is available, it is not straightforward to compare storms in different countries or even in the same country at different times. For comparison, the hazard should be present in many countries so we could rule out, for instance, volcanic eruptions. For earthquakes, we have comparable data on both the physical attributes and the impact.

Finally, we need to consider the onset time of disasters (LOG 2014). For relatively slow or moderate onset-speed disaster occurrences by way of floods and storms, governments have been able to reduce the death rate over the five-decade period by being able to move people immediately before and during the disaster. This would complicate our testing by additionally requiring different countries' respective ability to move people to safety. On the other hand, earthquakes have rapid onset and being able to move large numbers of people during that time is not relevant so we do not need to take ability to move into consideration.

Data were obtained from Denver-based National Geophysical Data Center on all earthquakes *with at least one fatality* during the period 1963 to 2012 so as to allow study with disaster impact being *number of fatalities*. Having one fatality at least has the potential to bias the data by excluding earthquakes in countries like Japan or the US with high levels of preparedness; however, this is offset by the exclusion of earthquakes in regions where the number of fatalities could not be reliably determined and reported also as 0 (missing value). We dropped a small number of observations of earthquakes with depth that was unknown or was more than 200 km. Earthquake magnitude is measured with any of a subset of six different magnitude metrics, with values quite close to each other. One of these is the *surface wave magnitude* (M_s), the base 10 logarithm of intensity -- therefore, we do not need to take the logarithm of this number. We chose M_s where it was available – this was true for a large majority of the earthquakes – while the maximum of the other metrics was chosen for the others. This is to give 'benefit of doubt' – equally, we could have taken the median. Observations with magnitude less than 4 were deleted; the earthquakes in the remaining sample have surface magnitude between 4 and 8.

For each earthquake in the sample, data on *child mortality under 5* and *population density* for the particular country and year of occurrence were obtained. Given the 50-year span, it was difficult to get this country information for all earthquakes and some observations had to be dropped from the sample. The eventual sample has 629 earthquakes from 78 countries, led by Iran with 78 earthquakes, China with 71, Indonesia with 54, and Turkey with 47 over the 1963-2012 period. Summary statistics for the variables show that the average earthquake size in the sample of 629 earthquakes was of magnitude 6 with an average depth of about 30 km (**Table 3**).

Table 3. Summary statistics of 631 earthquakes for: (1) logarithm of the *fatalities in the earthquake*, (2) logarithm of the *child mortality under age 5* for the year and country of the occurrence, (3) logarithm of *population density* for the year and country of the occurrence, (4) magnitude of the earthquake, and (5) depth of the earthquake. *Source*: NGDC database for earthquake data and World Bank for country data.

Variable	N	Mean	SD	Min	Max
Log (Number dead)	631	2.359927	2.383193	0	12.34
Log (Child mortality)	629	3.939234	.9655368	1.22	5.70
Log (Population density)	631	4.071176	1.026192	-0.1	6.97
Earthquake magnitude	631	5.991759	.8520164	4	8
Earthquake depth	631	29.45483	31.91781	0	236

*p <0.05, **p < 0.01, ***p < 0.001

3.3 Pooled disaster impact time series

Disaster impact is pooled worldwide to obtain two annual time series, *total affected* and *property damage* from 1963 to 2012 (**Figure 3**) along with the annual number of disaster occurrences.

Insert Figure 3 somewhere here

Could the increasing trend be attributed to population and income growth over these 50 years? Cutter and Emrich (2005) attribute growing economic losses in the US to growing population and migration within the country. Therefore, we *normalised* the impact variables of interest – *total affected* and *property damage* – by the global population and the global income respectively for the year in consideration.[4] The normalised variables are logarithms of (a) *total affected per* 100,000 *of global population* and (b) *property damage per* $1 billion *of global income* for the respective years.

3.4 Methods

To test all the statistical links in a loop, we need more than one test. Also, it may not be possible to use the same unit of analysis for all tests. As such, we seek to perform three tests using the statistical package Stata 12.1: *First*, for the forward part of the loop, we use a model linking hazards and vulnerability to disaster impact with hazard as the unit of analysis. *Second*, for the feedback loop, we use an integrated model linking disasters to the economy, and the economy to population vulnerability with country as the unit of analysis. *Finally*, we study disaster impact over time (posited as exponential growth) using a time-series model with disaster impact over 1963-2012 with year as the unit of analysis.

For the first test, we used regression to link the hazard rate of earthquakes and vulnerability to the disaster impact as per equation (5) in Section 2. The impact of the earthquake is captured here as the *number of fatalities* for this earthquake as the dependent variable for regression. The independent variables are the *magnitude* of the earthquake (with its *depth* as a control variable) and, as a measure of *population vulnerability*, *child mortality* under age 5. *Population density* of the country in the year of the earthquake was additionally used as a control variable.

For the second test linking the different measures of disaster impact, the economy and population vulnerability (**Figure 4**), structural equation modelling (SEM) is the method of choice. (Separately, we also ran individual regression models to obtain such familiar metrics as adjusted-R^2.) Measures of disaster impact include *number of*

---

[4] Another way would have been to normalize the data prior to pooling, for instance, China, Indonesia and Turkey had quite a few major earthquakes but also grew at a faster pace than many other countries.

deaths (per year) besides the *total affected* (per year, normalized by 1990 population) and *total damage* (per year, normalized by 1990 GDP). There are three *control variables* at this base level: the *1990 population*, the *number of occurrences* of disasters (per year), and the *per capita income at the beginning* of the period for which disaster data has been accumulated (1963-2012 or 1990-2012). At the next level, for the economy, we have *per capita income* and *its growth*. Finally, for population vulnerability, we have two measures: *child mortality under age 5* and *TB incidence per 10,000 people*. Taking natural logarithms as per equations (6)-(7) in Section 2 also takes care of the extremely skewed distributions of these measures.

Three things were taken into account when doing the SEM analysis. *First*, countries in the same region can have within-region 'correlation' in disaster impact so we alternatively analysed data to ensure that the standard error is 'robust' to cluster-correlation (cf. Williams 2000). For this alternative analysis, we used 'region' as the clustering variable and employed the method provided in Stata software by Rogers (1993). *Second*, there are a few missing values in our dataset, so maximum likelihood estimation has to be cognizant of missing values; we did so in Stata by using the option *mlmv*. *Finally*, the two population vulnerability variables may be 'explained' in the same way so we allowed covariance in their residuals (**Figure 4**).

Insert Figure 4 somewhere here

For the third test as per equation (8) in §2, the annual time series we used comprised annual worldwide disaster data. By pooling all the countries' data we do not have to worry about geographical boundaries that changed during this period or the highly sporadic nature of disasters in any particular country. We seek to test whether or not disaster impact has grown exponentially over the 1963-2012 period, i.e., to test whether or not the natural logarithm of disaster impact has grown linearly in time. The Dicky-Fuller test was used to test stationarity of the trending time series with one time lag.

4. Results

Below we provide the detailed results of the three tests.

4.1 Vulnerability transforming hazards into disasters

Four models were run to understand the relative contribution of the different variables. These models indicate that the *number of fatalities* from the earthquake is significantly explained by *child mortality under age 5* in the country of the occurrence, while controlling for *earthquake magnitude* and *earthquake depth* as well as the *population density* of the country in the year in which the earthquake occurred. The magnitude of the earthquake and the depth of the earthquake are significant – bigger earthquakes at shallower depths do kill more people as we would expect. However, the marginal contribution of *population density* in explaining the *number of fatalities* is significant only at 10% and not even that in some robust variants of the model – the scatter plot of deaths (log-transformed) does not show any discernible link (**Table 4**).

Table 4. Regression results: Logarithm of *deaths in the earthquake* explained by (1) logarithm of the *child mortality under age 5* for the year and country of the occurrence, (2) logarithm of *population density* for the year and country of the occurrence, (3) surface magnitude of the earthquake, and (4) depth of the earthquake. *Sources:* NGDC database for earthquakes and the World Bank for country data.

	Log (Deaths in the earthquake) – coefficients (standard error)			
Log (Child mortality)		.5965041*** (0.0874)	.6928144*** (0.0873)	.7389756 *** (0.0904)
Log (Pop density)				.1624118^{0} (0.0840)
Earthquake magnitude M_s	1.198285*** (.1030575)	1.080329*** (.0989)	1.177709*** (.0984)	1.192354*** (0.0990)
Earthquake depth	-.0100594*** (.002751)		-.0144547*** (0.0027)	-.0141361*** (.0027)
Const	-4.523608*** (.6131313)	-6.458744*** (.6701)	-6.995506*** (0.6639193)	-7.935542*** (0.8216)
Adj. R-sq	0.1794	0.2174	0.2509	0.2541
N	631	629	629	629

$^{0}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Regression diagnostics were carried out using the guidelines provided by Chen et al. (2003: Chapter 2) in Stata and no particular concerns were noted as regards the values of the coefficients or their significance. We did not see non-linearity in the scatter plots of log-transformed fatalities against the independent variables. Variance inflation factors were all just above 1 so well below the threshold of 10. While the collinearity test yielded condition numbers that were a little high for each of the four models, the regression coefficients are quite stable across the four models. Some 35 data points (earthquakes) had Cook's value higher than the recommended threshold but dropping these observations did not change the values of the coefficients or their significance level much. The Durbin-Watson statistic for all models was between 0.52 and 0.56 so residuals are not auto-correlated. Although the residuals in the models were not normally distributed (Shapiro-Wilk test), no particular pattern was discernible in the residual plots in any of these models and robust regression gave results that are nearly identical to those from those from OLS as reported in Table 4. While the scatter plot of magnitude shows that earthquakes at depths larger than 100 km have only high magnitudes, dropping the 24 earthquakes with these depths from our sample of 631 did not change the regression results. Although the scatter plot of residuals against fitted values shows variance to be growing with fitted values and a number of tests confirm heteroskedasticity, regression with robust standard errors (as opposed to robust regression) gives results that were nearly identical to those of OLS. Still, further work is indicated by tests of model specification, with the Ramsey specification error test suggesting the need to look for omitted variables even in the fourth model.

4.2 Disaster impact, the economy, and population vulnerability as feedback

For the period 1963 to 2012 (or 1990 to 2012 for some of the countries), per capita income at the start of the period is significantly related to that at the end of the period. Both per capita income at the end of the period and its growth are negatively linked to the number of total affected (normalised) but positively to the (normalised) damage to property. (This suggests damage to property is higher in richer countries but more people are affected in poorer countries.) Per capita income at the end of the period is not linked significantly to any of the control variables – the total number of disasters, the country's population in 1990, or the total number of fatalities. The *growth of per capita income* shows a slight positive link with the country's population in 1990 but is not linked significantly to the per capita income at the beginning of the period (**Figure 5, Table 5**).

As expected, both *child mortality* and *TB incidence* are negatively linked to the (ending) *per capita income*. Worryingly, both are *positively* linked to *PCI growth*, hinting that emphasis on growth in countries like India and China is contributing to vulnerability for large sections of these countries' populations (**Figure 5, Table 5**).[5]

Although the chi-squared value of the model we used versus the saturated model may seem high at 152, it is much lower than the baseline model vis-à-vis the saturated model, which has chi-squared value of 763 (**Table 5**). As such, this model provides much better fit than the baseline model.

Insert Figure 5 somewhere here

Table 5: SEM results with standardised coefficients (standard error): dependent variables are (1) logarithm of per capital income at end of period in 2012; (2) logarithm of growth of per capita income over period; (3) logarithm of child mortality under age 5 in 2012; and (4) logarithm of tuberculosis incidence per 10,000 people in 2012.

	Dependent variable			
Variable	**Log (PCI at end of period)**	**Log (PCI growth)**	**Log (child mortality < age 5)**	**Log (TB incidence)**
Log (population in 1990)	-.009712 (.1060)	.0595114 (.1507)		

[5] The same independent variables turn out to be significant with high explanatory power in independent regressions for the four separate models with per capita income, its growth, child mortality and TB incidence as dependent variables respectively. Adjusted R^2 values were 59%, 17%, 76%, and 52% respectively, potentially justifying our choice of measures.

Log (number of disaster occurrences)	.0817197 (.1183)	-.018555 (.1682)		
Log (number dead)	-.0784552 (.0721)	-.155171 (.1091)		
Log (normalised total affected)	-.523497*** (.0736)	-.4572079*** (.1050)		
Log (normalised damage)	.1837299* (.0621)	.3255755*** (.0844)		
Log (PCI beginning of period)	.3800214*** (.0655)	-.1535069 (.0942)		
Log (PCI end of period)			-.9069457*** (.0221)	-.7919325*** (.0386)
Log (PCI growth)			.1161852* (.0485)	.2281426*** (.0615)
Const	4.364965*** (0.6698)	4.508663*** (.8775)	7.299124*** (.3556)	6.191273*** (.3188)
Std error variance	.4015062 (.0474)	.7798083 (.0589)	.22034 (.0314)	.4174792 (.0544)
Std error covariance			.4510379** (.0618)	
Chi-square (13 dof): Model vs. saturated	152.01***	p > chi-sq = 0.0000		
Chi-square (30 dof): Baseline vs. saturated	763.242***	p > chi-sq = 0.0000		

$^{0}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p<0.001$

As mentioned earlier, we have to consider that there may be cluster correlation for the countries in the same region (Asia, Africa, etc.). To make the standard error 'robust' to cluster-correlation, we used the procedure of Rogers (1993) in Stata. The results have the same coefficients and in all but one case – and even that one being marginal to begin with – the same significance levels as well (**Appendix: Table A2**). Therefore we can discount the impact of within-cluster correlation of the region as regards the values or significance of the coefficients.

4.3 Exponential growth of disaster impact over time

The time series of disaster impact over time, normalized and log-transformed, show a positive linear trend indicating exponential growth. However, there is some tapering off in the number of occurrences starting with the late 1990s possibly following the initiatives during the International Decade for Natural Disaster Reduction (IDNDR) programme (cf. Lechat, 1990) (refer back to **Figure 3**). The trend is significantly positive for all three time-series as tested using the Dicky-Fuller test with one lag term and trend as in

$$y_t = \text{const} + L_1\, y_{t-1} + (\text{trend})\, t + \text{error}$$

Both the time series *total affected* and *total damage* (both log-transformed and normalised) are stationary with a positive trend suggesting exponential growth if the series were not log-transformed. The time series *number of occurrences* (log-transformed) is not stationary however so analysis in further research could separate the periods 1963-2000 and 2001-2012, with 2000 being the end of the IDNDR programme (**Table 6**).

Table 6. Results of Dicky-Fuller test with one lag term on annual time series from 1963 to 2012 showing a positive time trend for (1) logarithm of *occurrence of disasters*, (2) logarithm of *total affected* (absolute values), (3) logarithm of *property damage* (absolute values), (4) logarithm of *total affected* (normalised by the global population of the year), and (5) logarithm of *property damage* (normalised by global income of the respective year)

		Time series with absolute numbers		Time series with normalised values	
	Log (Occurrence of disasters)	Log (Total Affected)	Log (Property Damage, $'000)	Log (Total Affected per 100,000 global population of the year)	Log (Total Damage $ per $1b of global income of the year)
L1 (p-value)	-0.2780* (0.015)	-1.1336*** (0.000)	-0.8184*** (0.000)	-1.1338*** (0.000)	-.8184*** (0.000)
Trend (p-value)	0.01174* (0.044)	0.0666*** (0.000)	0.0803*** (0.000)	.04853*** (0.000)	.01637* (0.018)
Constant (p-value)	1.201** (0.009)	19.0406*** (0.000)	11.774*** (0.000)	7.2762*** (0.000)	5.74452*** (0.000)
Z(t) (McKinnon approximate p-value)	-2.518 (0.319)	-7.713*** (0.000)	-5.625*** (0.000)	-7.715*** (0.000)	-5.625*** (0.000)

*p < 0.05, **p < 0.01, ***p < 0.001

Consider the normalised *impact* as in the previous sub-section and divide by the *number of disaster occurrences* in the respective year. We thus get (a) *total number of* *people affected/100,000 population* per occurrence and (b) *total damage/$1 billion of income* per occurrence. There is no tapering off here starting in the late 1990s so the normalized impact on the world as a whole per occurrence of a disaster is pretty much the same throughout the 50 years despite arguably better response systems over this time! It could also be argued that the definition of a disaster has been consistent over the 50 years (**Figure 6**).

Insert Figure 6 somewhere here

Using the Dicky-Fuller test again on impact per occurrence for both *total affected* and the *property damage*, the resulting time series are stationary and the respective trends are not significantly different from zero (**Table 7**).

Table 7. Results of Dicky-Fuller test showing a flat trend for the annual time series with normalised values per disaster – (1) total affected/100,000 global population *per occurrence* and (2) for total damage/$1b income *per occurrence* – from 1963 to 2012 and especially over the more recent period from 1983 to 2012.

	1963-2012		1983-2012	
	Total Affected/ 100k population/ occurrence	Total Damage, $/ $1b of income/ occurrence	Total Affected/ 100k population/ occurrence	Total Damage, $/ $1b of income/ occurrence
L1 (p-value)	-1.2066*** (0.000)	-0.7713*** (0.000)	-1.080*** (0.000)	-0.8905*** (0.000)
Trend (p-value)	-0.2673 (0.076)	-0.1517* (0.015)	-0.2934 (0.074)	-0.316 (0.700)
Constant (p-value)	22.2347*** (0.000)	10.5047*** (0.000)	16.116*** (0.000)	6.314** (0.003)
Z(t) (McKinnon approx. p-value)	-8.439*** (0.000)	-5.615*** (0.000)	-5.690*** (0.000)	-4.660** (0.001)

*p < 0.05, **p < 0.01, ***p < 0.001

This time series analysis allows governments and transnational non-government organizations to compute the long-term 'cost of a disaster'. At the global level, the long-term mean impact per occurrence (as calculated for an autoregressive process of order 1) is 16.116/(1+1.08)=7.74 people affected per 100,000 of the global population and 6.314/(1+0.8905)=$3.33 of property damage per $1 billion of global annual income for the period 1983-2012 in current US$ (**Table 7**).[6] The specific numbers for year 2014 are that the world had 240 natural disasters according to EM-DAT, each disaster affecting 5.57 people per 100,000 of global population and causing $4.56 in property damage per $1 billion of global income.[7]

5. Discussion

We now consider the possible implications for the initial evidence we have provided for the posited model in equations (5)-(8) in Section 2 for the existence of a positive feedback loop comprising the economy, population vulnerability and disaster impact, given a constant exogenous hazard rate.

5.1 A strategic view of humanitarian operations

The most important implication is that policy makers in government and transnational non-government organizations need to look beyond preparedness and response against disasters towards prevention of disasters and towards rebuilding the economy following disasters. The positive feedback loop indicated by this paper offers a rationale for holistic intervention comprising response, reconstruction, preparedness and prevention to counter the vicious cycle of disasters. The greater the impact mitigated through response, the lesser the reconstruction needed and the greater the prosperity. Greater prosperity leads to higher preparedness and more resilience for the country's population in a virtuous cycle countering the vicious one this paper has investigated (**Figure 7**).

---

[6] The calculation for long-term mean is based on a one-period lag time or AR(1) stochastic process and is equal to const/(1 – L1).

[7] The numbers are 93.5 million affected in total in 2014 out of a global population of 7 billion and $82.6 billion property damage with a global income of $75,400 billion.

Insert Figure 7 somewhere here

This virtuous cycle has implications for the participants to collaborate in this picture that is larger than humanitarian operations or development alone. Active **c**ollaboration among partners (LOG 2014[8]) is extremely important as operational objectives for humanitarian operations are different from those for development efforts. Our work provides a rationale as to *why* and *how* governments, NGOs and international agencies need to work together on matters of development and humanitarian preparedness and response. The Logistics Emergency Teams (LET) partnership comprises three large global logistics and transportation companies, Agility, UPS and Maersk, working together to support the Logistics Cluster pro bono.[9] We need to add other companies and even small entrepreneurs to help with humanitarian relief as doing so aids development (Sodhi and Tang 2014a).

5.2 Funding humanitarian operations and development

There is need for improving resource allocation. Despite the dramatic increase in the occurrence and impact of disasters over the past decades (cf. Guha-Sapir et al, 2004; 2013; Economist 2012), funds are often too late, too little and specified too narrowly to be effective (cf. Toyasaki and Walkobinger 2011; Walkobinger and Toyasaki 2011; Walker and Pepper 2007). Humanitarian operations on an international scale appear to be funded mainly in response to 'CNN' disasters as these unfold on television screens around the world (Tomasini and Van Wassenhove 2009). Response-based funding does not help non-governmental organisations (NGOs) invest in preparation, say, in logistics – warehouses, trucks, etc. (Gustavsson 2003). Indeed, "the main issue holding back many humanitarian organizations is finding the funds to finance the

[8] See http://log.logcluster.org/operational-environment/partnership/index.html.

[9] See www.logcluster.org/logistics-emergency-teams.

training and procedures that will lead to better preparedness and therefore more effective logistical operations" (Van Wassenhove 2006).

At the same time, on the development side, donor countries are shifting funds from development aid to humanitarian relief (Krause 2014: 3). This shift renders the beneficiary countries even more vulnerable to future disasters than before. Moreover, with strings attached to foreign aid, governments of affected countries have to decide when (and where) they should spend their own resources and when to accept 'aid'.

It is sobering to note however that many developing countries justify defence spending for development by way of technology transfer. Over the decade from 2004 to 2013, defense spending in Asia grew by 60% and in Africa by 65% in contrast to 10% in Europe (Economist 2014). As already noted, Asia and Africa are the two most disaster-ridden regions in the world.

5.3 The importance of monitoring child mortality for development and humanitarian relief

In the positive feedback loop studied in this project, a vulnerability metric like child mortality (under age 5 per 1,000 live births) plays two roles: (1) For development efforts targeting the economy, it is a *lagging* indicator. (2) In predicting disasters, child mortality is also a *leading* indicator that humanitarian agencies need to watch carefully. The same reasoning applies to other vulnerability metrics.

Countries that keep child mortality low also do other things that make themselves resilient to shocks such as disasters. Therefore, the focus for developing countries should be on such specific indicators as child mortality as measure of progress for both development and for disaster response and preparedness.. Development research on improving children's wellbeing through school feeding programmes (Kretschmer et al. 2014) or even through teaching basic hygiene is indirectly important for humanitarian operations as well. For *strategic* humanitarian operations therefore, bellwether metrics should include child mortality, improving which would require a mix of development initiatives as well as preparedness against disasters in disaster-prone countries.

5.4 Implications for humanitarian supply-chain research

Apte (2010, p. 86) provides a comprehensive list of areas of research mentioned in the humanitarian operations literature: prepositioning; supply chain characteristics; material flows; people flows (evacuation); objectives; performance measures; information management; and collaboration. The top three disaster categories responsible for the largest number of total affected – droughts, floods and storms – have slow-to-moderate onset time and last for the medium-to-long-term. This blurs the difference between humanitarian and development efforts, and therefore supply chains, as regards many of the topics in Apte's (2010) list for these disaster types. The difference between short-term humanitarian objectives and long-term development objectives is also reduced, as for instance with deprivation cost (Holguín-Veras et al. 2013). In any case, this paper allows both sets of objectives for any type of disasters to be viewed as being part of the connected interventions to counteract the vicious cycle.

5.5 Areas for further research

Our work provides evidence only to indicate, not conclusively prove, the presence of a positive feedback loop entailing disasters. As such, it provides a rich vein of opportunities to be mined for further research for digging deeper into the evidence for the positive feedback loop investigated in this paper and extensions and for exploiting this research by developing system dynamics (SD) models for resource allocation decisions. Here are some specific opportunities:

Extending the feedback loop: There are many opportunities to extend the parsimonious feedback loop we presented with other concepts and other measures pertaining to climate change, government policy, and maturity of institutions, possibly using SD models grounded in statistical investigations of the type in this paper. Of these, climate change should be a top priority for further research (cf. Ibarrarán et 2009; IPCC 2012) especially because the top three disaster types in terms of total people affected – droughts, floods, and storms – have been linked to climate change (Shepherd et al. 2013; IPCC 2014). Climate change can be viewed as adding to the climate-related hazards of floods, droughts and storms exogenously so its omission in this paper is not problematic at least to a first order of approximation; see World Bank (2014) for different climate change scenarios – but the work in this paper can be extended with drivers of climate change feeding to hazards. Urbanization and migration too can be thought of as increasing vulnerability exogenously. Conflict, whether between or within countries, is yet another cause for disasters stemming from a high level of vulnerability to any natural hazard so that could be added too for extending the core feedback loop proposed in this paper.

Studying past interventions: We can study past interventions and compare different periods in the 50 years for which we analysed data. In particular, we need to study how (or whether) the International Decade for Natural Disaster Reduction efforts over 1990-2000 slowed the hitherto exponential increase in the number of disaster occurrences and the numbers of people affected in total. A natural question is whether exponential growth in the period prior to 1990 implies that humanitarian interventions were ineffective earlier and if so why. SD modelling based on empirical quantification as in this paper can also help in understanding the net disaster impact over time with the positive feedback loop of disaster, poverty and vulnerability on one hand and the virtuous cycle of interventions by way of negative feedback on the other.

Region- and disaster-specific research: We need to separately research different types of disasters in different regions, possibly using panel regressions.[10] Africa is affected most by droughts, the Americas and Asia by floods, and Europe and Oceania by storms. Asia, with populous nations like Bangladesh, China, India, Indonesia and Pakistan has borne the brunt of disaster impact over these 50 years with 89% of the 6.9 billion people affected in total, primarily because of floods and drought. Africa comes next with nearly 7% of all the people affected by drought and floods over the 50-year period we investigated. A distant third are the Americas – EM-DAT combines North and South America – with 3.7% of all the people affected by floods,

[10] Recall that the SEM modeling used in this paper takes cluster-correlation into account using the Africa, Americas, Asia, Europe and Oceania as five regions as clusters.

drought, and storms. Also, floods, droughts and storms together affected more than 95% of the people in total (**Table A1 in Appendix**).

Region-specific studies are also important on account of the concentration of the *total affected* in only a few countries. Of the total affected worldwide over 1963-2012, nearly 80% were in just three countries: China (44%), India (29%) and Bangladesh (6%). Property damage is somewhat less concentrated with more than 60% being incurred in just three countries, the US (29%), Japan (17%) and China (15%), that were also the three largest economies in the world by national income in 2012. The concentration in the number of occurrences is somewhere between that of the total affected and property damage.

As an example of region-specific research, we need research into improving 'people flow', i.e., evacuation of people needed for floods, droughts and storms in the countries that are most vulnerable to these types of disasters. These three disaster categories have (usually) slow onset, which means evacuation is (usually) possible. Such research would need to ask questions such as how to convince people to move along with their livestock and belongings before it is too late and how to actually carry out evacuation after disaster has struck. These questions entail decisions on the prepositioning of shelters. The ability to move people has been pointed out as the reason why fatalities have decreased (Economist 2012) but we need to understand why the number of people affected in total has continued to increase.

Overall, the above ideas are only some of the building blocks for *strategic humanitarian operations* – developing any link between development and humanitarian logistics for preparedness and response is a necessary and good avenue for further research.

Acknowledgement: The author would like to thank Luk Van Wassenhove, Alfonso Pedraza-Martinez, an anonymous associate editor and three referees for their thoughtful comments that have greatly helped in shaping the final version of this paper. I would also like to thank James Knuckles for his suggestions. I should add that any mistakes are mine alone.

References

Alexander, D. (1997). The study of natural disasters, 1977–97: Some reflections on a changing field of knowledge. *Disasters*, *21*(4), 284-304.

Anderson, M. B. (1995). Vulnerability to disaster and sustainable development: A general framework for assessing vulnerability, in Munasinghe M. and C. Clarke (eds.), *Disaster Prevention for Sustainable Development: Economic and Policy Issues. Washington, DC: IBRD/World Bank*, 41-59.

Apte, A. (2009). Humanitarian logistics: A new field of research and action. *Foundations and Trends in Technology, Information and Operations Management*, 3 (1): 1–100. DOI: 10.1561/0200000014

Bankoff, G., Frerks, G., & Hilhorst, D. (Eds.). (2004). *Mapping vulnerability: disasters, development, and people*. Routledge, London.

Barrett, C. B., and Carter, M. R. (2000). Can't get ahead for falling behind: new directions for development policy to escape relief and poverty traps. *Choices Magazine*, No. 2, 1-8.

Birkmann, J. (2006). *Measuring vulnerability to natural hazards: Towards disaster resilient societies*, 2nd Edition. United Nations University Press, New York, USA.

Blakie, P., Cannon, T., Davis, I., and Wisner, B. 1994. At risk: Natural hazards, people's vulnerability, and disasters. Routledge, London.

Bouwer, L. M. (2011). Have disaster losses increased due to anthropogenic climate change? *Bulletin of the American Meteorological Society*, *92*(1), 39-46.

Cannon, T. (1994). Vulnerability analysis and the explanation of 'natural'disasters, in Varley, A. (ed.) *Disasters, development and environment*, John Wiley & Sons, New York, 13-30.

Carter, M. R., Little, P. D., Mogues, T., & Negatu, W. (2007). Poverty traps and natural disasters in Ethiopia and Honduras. *World development*, *35*(5), 835-856.

Chen, X., Ender, P., Mitchell, M. and Wells, C. (2003). *Regression with Stata*, from http://www.ats.ucla.edu/stat/stata/webbooks/reg/default.htm (downloaded Feb. 20, 2016).

Corbyn, Z. (2011). Method predicts size of fracking earthquakes. Nature, 9th December, downloaded from http://www.nature.com/news/method-predicts-size-of-fracking-earthquakes-1.9608 on Aug 25, 2014.

Cutter, S. L., & Emrich, C. (2005). Are natural hazards and disaster losses in the US increasing? *Eos, Transactions American Geophysical Union*, *86*(41), 381-389.

Cutter, S. L., & Finch, C. (2008). Temporal and spatial changes in social vulnerability to natural hazards. *Proceedings of the National Academy of Sciences*, *105*(7), 2301-2306.

Degg, M. (1992). Natural disasters: recent trends and future prospects. *Geography*, 77(3), 198-209.

Economist (2012). Counting the cost of calamities. The Economist, Jan. 14, downloaded from http://www.economist.com/node/21542755 on Nov. 25, 2014.

Economist (2014). Arms and the African. *The Economist*, Nov 22, 413 (8914): 59-60.

Fothergill, A., & Peek, L. A. (2004). Poverty and disasters in the United States: A review of recent sociological findings. *Natural hazards*, *32*(1), 89-110.

Guha-Sapir D, Hoyois P., and Below. R. (2013). *Annual Disaster Statistical Review 2012: The Numbers and Trends*. CRED, Brussels. Available at http://www.cred.be/sites/default/files/ADSR_2012.pdf.

Guha-Sapir, D., Hargitt, D., & Hoyois, P. (2004). *Thirty years of natural disasters 1974-2003: The numbers*. Presses Univ. de Louvain, Belgium.

Gustavsson, L. (2003). Humanitarian logistics: context and challenges. *Forced Migration Review*, 18: 6-8.

Holguín-Veras, J., Jaller, M., Van Wassenhove, L. N., Pérez, N., & Wachtendorf, T. (2012). On the unique features of post-disaster humanitarian logistics. *Journal of Operations Management*, *30*(7), 494-506.

Holguín-Veras, J., Pérez, N., Jaller, M., Van Wassenhove, L. N., & Aros-Vera, F. (2013). On the appropriate objective function for post-disaster humanitarian logistics models. *Journal of Operations Management*, *31*(5), 262-280.

Ibarrarán, M. E., Ruth, M., Ahmad, S., & London, M. (2009). Climate change and natural disasters: macroeconomic performance and distributional impacts. *Environment, development and sustainability*, *11*(3), 549-569.

IPCC. (2012). *Managing the risks of extreme events and disasters to advance climate change adaptation: Special report of the intergovernmental panel on climate change*. Cambridge University Press, Cambridge, UK.

IPCC. (2014). Climate Change 2014 Synthesis Report: Summary for Policymakers, IPCC, Geneva, available at http://www.ipcc.ch/pdf/assessment-report/ar5/syr/AR5_SYR_FINAL_SPM.pdf, downloaded 17 July 2015.

Kahn, M. E. (2005). The death toll from natural disasters: the role of income, geography, and institutions. *Review of Economics and Statistics*, *87*(2), 271-284.

Kovács, G., & Spens, K. M. (2011). Trends and developments in humanitarian logistics–a gap analysis. *International Journal of Physical Distribution & Logistics Management*, *41*(1), 32-45.

Krause, M. (2014). *The Good Project: Humanitarian Relief NGOs and the Fragmentation of Reason*. University of Chicago Press, Chicago.

Kretschmer, A., Spinler, S., & Van Wassenhove, L. N. (2014). A school feeding supply chain framework: Critical factors for sustainable program design. *Production and Operations Management*, 23(6), 990-1001.

Lechat, M. F. (1990). The international decade for natural disaster reduction: background and objectives. *Disasters*, 14(1), 1-6.

LOG (2014). *Logistics operational guide*, Logistics Cluster. Downloaded from log.logcluster.org on 1st Oct. 2014.

Manuel-Navarrete, D., Gomez, J. J., & Gallopín, G. (2007). Syndromes of sustainability of development for assessing the vulnerability of coupled human–environmental systems. The case of hydrometeorological disasters in Central America and the Caribbean. *Global Environmental Change*, *17*(2), 207-217.

McEntire, D. A. (2001). Triggering agents, vulnerabilities and disaster reduction: towards a holistic paradigm. *Disaster Prevention and Management: An International Journal*, *10*(3), 189-196.

Noy, I. (2009). The macroeconomic consequences of disasters. *Journal of Development Economics*, *88*(2), 221-231.

O'Hara, P. A. (2008). Principle of circular and cumulative causation: Fusing Myrdalian and Kaldorian growth and development dynamics. *Journal of Economic Issues*, 42(2): 375-387.

Pearl, J. (2009). Causal inference in statistics: An overview. *Statistics Surveys*, *3*, 96-146.

Pedraza Martinez, A. J., Stapleton, O., & Van Wassenhove, L. N. (2011). Field vehicle fleet management in humanitarian operations: A case-based approach. *Journal of Operations Management*, 29(5), 404-421.

Peduzzi, P., Chatenoux, B., Dao, H., De Bono, A., Herold, C., Kossin, J., Mouton, F., and Nordbeck, O. (2012). Global trends in tropical cyclone risk. *Nature Climate Change*, 2(4), 289-294.

Pelling, M. (2003). *Natural disaster and development in a globalizing world*. Routledge, London.

Rodes, C. E., E. D. Pellizzari, M. J. Dellarco, M. D. Erickson, D. A. Vallero, D. B. Reissman, P. J. Lioy, M. Lippmann, T. A. Burke, and B. D. Goldstein (2008). ISEA2007 panel: Integration of better exposure characterizations into disaster preparedness for responders and the public. *Journal of Exposure Science and Environmental Epidemiology* 18 (6): 541-550.

Rodriguez-Oreggia, E., De La Fuente, A., De La Torre, R., & Moreno Moreno, H. A. (2013). Natural disasters, human development and poverty at the municipal level in Mexico. *The Journal of Development Studies*, *49*(3), 442-455.

Rogers, W. H. (1993). Regression standard errors in clustered samples. *Stata Technical Bulletin* 13: 19–23. Downloaded from http://www.stata.com/support/faqs/statistics/stb13_rogers.pdf on 1st June 2015.

Shepherd, A., Mitchell, T., Lewis, K., Lenhardt, A., Jones, L., Scott, L., and Muir-Wood, R. (2013). *The geography of poverty, disasters and climate extremes in 2030*, Overseas Development Institute, London. Downloaded from http://www.odi.org/sites/odi.org.uk/files/odi-assets/publications-opinion-files/8633.pdf on Dec. 5, 2014.

Sodhi, M. S. and Tang, C. S. (2014a). Buttressing supply chains against floods in Asia for humanitarian relief and economic recovery. *Production and Operations Management*, *23*(6), 938-950.

Sodhi, M. S. and Tang, C. S. (2014b). Supply-chain research opportunities with the poor as suppliers or distributors in developing countries. Production and Operations Management (online). DOI: 10.1111/poms.12161

Starr, M. K., & Van Wassenhove, L. N. (2014). Introduction to the special on humanitarian operations and crisis management. *Production and Operations Management*, *23*(6), 925-937.

Sudling, K.N. 2013. Ecology: A leak in the loop. *Nature*, **503**, 472-473.

Tomasini, R. M., & Van Wassenhove, L. N. (2009). From preparedness to partnerships: case study research on humanitarian logistics. *International Transactions in Operational Research*, 16(5), 549-559.

Toya, H., & Skidmore, M. (2007). Economic development and the impacts of natural disasters. *Economics Letters*, *94*(1), 20-25.

Toyasaki, F. & Wakolbinger, T. (2011). Impacts of earmarked private donations for disaster fundraising. *Annals of Operations Research*, 221:427-447.

Turner, D. (2012). Is that a fracking earthquake? LA Times, March 9. Downloaded from http://opinion.latimes.com/opinionla/2012/03/fracking-ohio.html on Aug 26, 2014.

Turner, R. H., Nigg, J. M., & Paz, D. H. (1986). *Waiting for disaster: Earthquake watch in California*. Univ of California Press, Los Angeles.

UNICEF (2000). *Poverty reduction begins with children*. Division of Evaluation, Policy and Planning, UNICEF, New York, USA.

UNISDR (2009). *2009 UNISDR terminology on disaster risk reduction*. United Nations International Strategy for Disaster Reduction, Geneva. Downloaded from unisdr.org/publications on Dec. 6, 2014.

Van Wassenhove, L. N. (2006). Humanitarian aid logistics: supply chain management in high gear. *Journal of the Operational Research Society*, *57*(5), 475-489.

Vatsa, K. S. (2004). Risk, vulnerability, and asset-based approach to disaster risk management. *International Journal of Sociology and Social Policy*, *24*(10/11), 1-48.

Wakolbinger, T. and Toyasaki, F. (2011). Impacts of funding systems on humanitarian operations. In M. Christopher, & P. Tatham (Eds.), *Humanitarian logistics: meeting the challenge of preparing for and responding to disasters* (pp. 33-46).

Walker, P., & Pepper, K. (2007). *Follow the Money: A review and analysis of the state of humanitarian funding*. Feinstein International Center Tufts University, Medford MA. Downloaded from http://fic.tufts.edu/ on Nov. 4, 2014.

Williams, R. L. (2000). A note on robust variance estimation for cluster-correlated data. *Biometrics*, 56(2), 645-646.

World Bank (2013). *World Development Report 2014: Risk and Opportunity—Managing Risk for Development.* Washington, DC: World Bank. doi: 10.1596/978-0-8213-9903–3.

World Bank Group (2014). *Turn Down the Heat*: *Confronting the New Climate Normal.* Washington, DC: World Bank. https://openknowledge.worldbank.org/handle/10986/20595 License: CC BY 3.0 IGO.

Appendix

Table A1: Data summary showing the percentage of number of people affected out of 6.865 billion affected in total over 1963-2012 for different types of disasters by continent, top three row and column totals in bold.

	Africa	Americas	Asia	Europe	Oceania	***Row total***
Drought	5.31%	1.01%	24.59%	0.15%	0.12%	***31.17%***
Earthquake	0.02%	0.45%	1.92%	0.08%	0.01%	*2.48%*
Epidemic	0.18%	0.06%	0.12%	-	-	*0.36%*
Extreme temperature	0.01%	0.08%	1.24%	0.02%	0.07%	*1.42%*
Flood	0.96%	1.25%	48.48%	0.20%	0.02%	***50.90%***
Insect infestation	0.01%	-	-	-	-	*0.01%*
Mass movement dry	-	-	-	-	-	-
Mass movement wet	-	0.08%	0.12%	-	-	*0.20%*
Storm	0.23%	0.77%	12.07%	0.13%	0.09%	***13.29%***
Volcano	0.01%	0.02%	0.04%	-	-	*0.08%*
Wildfire	-	0.02%	0.05%	0.02%	-	*0.09%*
Column total	***6.73%***	***3.74%***	***88.62%***	*0.59%*	*0.31%*	*100.00%*

Table A2: SEM results with standardised coefficients (standard error) and cluster-robust standard errors with the five *regions* as clusters (Rogers 1993; Williams 2000): dependent variables are (1) logarithm of per capital income at end of period in 2012; (2) logarithm of growth of per capita income over period; (3) logarithm of child mortality under age 5 in 2012; and (4) logarithm of tuberculosis incidence per 10,000 people in 2012.

	Dependent variable			
Variable	**Log (PCI ending)**	**Log (PCI growth)**	**Log (child mortality < age 5)**	**Log (TB incidence)**
Log (population in 1990)	-.009712 (.1189068)	.0595114* (.0237082)		
Log (number of occurrences)	.0817197 (.2073832)	-.018555 (.104715)		
Log (number dead)	-.0784552 (.1107042)	-.155171^{0} (.0895313)		
Log (normalised total affected)	-.523497*** (.0948412)	-.4572079*** (.1252112)		
Log (normalised damage)	.1837299* (.0753468)	.3255755*** (.0735818)		
Log (PCI at beginning of period)	.3800214*** (.0609709)	-.1535069 (.1372586)		
Log (PCI at end of period)			-.9069457*** (.0284447)	-.7919325*** (.0516703)
Log (PCI growth over period)			.1161852^{0} (.0625961)	.2281426*** (.0536243)
Const	4.364965*** (1.280136)	4.508663*** (1.517393)	7.299124*** (.8652251)	6.191273*** (.4114955)
Std error variance	4015062 (.0536943)	.7798083 (.0248836)	.22034 (.0337358)	.4174792 (.0641194)
Std error covariance			.4510379** (.1437534)	

$^{0}p < 0.1$, $*p < 0.05$, $**p < 0.01$, $***p<0.001$