

## ESTIMATING THE DIRECT ECONOMIC DAMAGES OF THE EARTHQUAKE IN HAITI\*

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This article makes an initial assessment of the monetary damages caused by the 2010 earthquake in Haiti. Damages are estimated for a disaster with both 200,000 and 250,000 total dead and missing, using Haiti's economic and demographic data. The base estimate is US\$8.1bn, but for several reasons this may be a lower-bound estimate. While the results are subject to many caveats, including possibly high forecast error, the implications of such an estimate are significant. Raising such a figure will require many donors. Hence excellent coordination of funding and execution will be key to ensuring the efficient use of funds.

We use simple regression techniques to assess the estimated direct cost of the catastrophic earthquake that struck Haiti on January 12, 2010. The earthquake, which hit about 15km (10 miles) southwest of the capital city Port-au-Prince, was followed by several strong aftershocks and has caused significant loss of human life, the displacement of hundreds of thousands and severe damage to the country's economic infrastructure.

In order to estimate the monetary damages caused by this event, we combine worldwide data from about 2,000 natural catastrophic events between 1970 and 2008. We model the dollar amount of damage of each event as a function of the number of dead or missing, the level of economic development (real GDP per capita), country size (alternatively measured as population size, real GDP or land area), regional dummies and a linear trend. Using these regression results we make out-of-sample predictions regarding the estimated dollar amount of damages that can be expected for a country with Haiti's economic and demographic characteristics in the aftermath of the catastrophic earthquake of January 12.

The unit of observation is an event as recorded in the Emergency Events Database (EM-DAT) maintained by the Centre for Research on the Epidemiology of Disasters (CRED) at the Catholic University of Louvain, Belgium (<http://www.emdat.be/>). The database is compiled from various sources, including various UN agencies, non-governmental organisations, insurance companies, research institutions and press agencies. Disasters can be hydro-meteorological, including floods, wave surges, storms, droughts, landslides and avalanches; geophysical, including earthquakes, tsunamis and volcanic eruptions; and biological, including epidemics and insect infestations (these are much more infrequent in this database). There are approximately 2,000 such events recorded in the dataset in the 1970–2008 period, for which we also have all the necessary information to conduct the empirical analysis.<sup>1</sup> The direct damage reported

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<sup>1</sup> We focus primarily on the three types of disasters which are more common and for which there is more reliable data available in the dataset: earthquakes (including tsunamis), floods and windstorms.

in EM-DAT is damage to fixed assets and capital (including inventories), damages to raw materials and extractable natural resources, and mortality and morbidity that are a direct consequence of the natural phenomenon recorded.

The nature of the exercise we perform is simple. It uses historical data on catastrophic events and econometric techniques to answer the following question: what are the expected costs of rebuilding Haiti's infrastructure?<sup>2</sup> Damages are estimated for a disaster with both 200,000 and 250,000 total dead and missing (i.e., the range of mortality that is estimated to have caused the earthquake) and using Haiti's economic and demographic data. The bottom line is that for a disaster with 200,000 total dead and missing, in a country with Haiti's observable characteristics, damages are expected to be about US\$7.2bn (2009 dollars). For a death toll of 250,000 the estimate would be US\$8.1bn. Intermediate numbers give intermediate results. Unfortunately, recent estimates place the actual death toll at the top of this range. Nonetheless, the errors attached to these estimates (obtained via bootstrapping) remain quite large, in part because there are relatively few disasters of this size: while the base estimate may be as high as US\$8.1bn for 250,000 deaths, an estimate of US\$13.9bn is within statistical error.

These estimates are useful for putting this event into perspective and informing the international community of the enormity of the challenge that lies ahead in the task of reconstructing Haiti. However, several caveats are in order. Given the nature of the exercise, the results should be interpreted with caution. First, there are conceivably measurement errors in the data<sup>3</sup> and the model we postulate may be incorrectly specified. Other problems with the empirics may also exist. Second, we cannot know if the experience of past episodes around the world will be relevant for Haiti. Every event is different and, although we control for country- and regional-specific characteristics in the regressions, we could have missed one or more important issues. This concern is compounded by the fact that the characteristics of this particular event are quite special: it is the most destructive event a country has ever experienced when measured in terms of the number of people killed as a share of the country's population<sup>4</sup> (see Table 1), and it has affected the capital city of the country: the centre of commerce, government and communication. Moreover, while many priceless buildings were destroyed or severely damaged, including the Presidential Palace, the National Cathedral, churches and Government Buildings, it has not been possible to control for this in the estimation. Finally, as with any empirical exercise of this nature, the estimates are subject to statistical uncertainty and, as detailed, there are few events of such ferocity as the Haiti 2010 earthquake.

The structure of this article is as follows: Section 1 discusses the empirical model and other methodological issues. Section 2 presents the regression results and Section 3

<sup>2</sup> Note that this assumes infrastructure is rebuilt – i.e., this is not then a Needs Assessment which may contemplate building different infrastructure or infrastructure in different places according to a revised development strategy – and we focus here on the more traditional damage assessment.

<sup>3</sup> Guha-Sapir (2006) discusses the main shortcomings of the disaster data. A key problem is lack of standardised collection methodologies and definitions.

<sup>4</sup> For example, while the ballpark estimates of the number of people killed or missing are similar to the 2004 tsunami in Indonesia, the population of Haiti is only a small fraction of the one of the Asian country, making this particular event more damaging in relative terms than that infamous tsunami.

Table 1  
*Large Natural Disasters*

Rank	Country	Year	Description	People killed	People killed per million inhabitants	Damages (US\$ Millions, 2009)
1	Haiti	2010	Earthquake	200,000–250,000	20,000–25,000	7,200–8,100
2	Nicaragua	1972	Earthquake	10,000	4,046	4,325
3	Guatemala	1976	Earthquake	23,000	3,707	3,725
4	Myanmar	2008	Cyclone Nargis	138,366	2,836	4,113
5	Honduras	1974	Cyclone Fifi	8,000	2,733	2,263
6	Honduras	1998	Cyclone Mitch	14,600	2,506	5,020
7	Sri Lanka	2004	Tsunami*	35,405	1,839	1,494
8	Venezuela	1999	Flood	30,005	1,282	4,072
9	Bangladesh	1991	Cyclone Gorki	139,252	1,232	3,038
10	Solomon Is	1975	Tsunami	200	1,076	n.a.
11	Indonesia	2004	Tsunami*	165,825	772	5,197

\*Indian Ocean Tsunami caused a total of 226,000 deaths over 12 countries.  
n.a. Not available.

Source. Authors' calculations based on EM-DAT and WDI databases.

presents the out-of-sample predictions for Haiti. Section 4 provides a policy discussion, and Section 5 concludes.

## 1. Model Specification and Methodology

Following the literature<sup>5</sup> we estimate a model of the form:

$$DIS_{it} = \alpha + \beta \mathbf{X}_{it} + \varepsilon_{it} \quad (1)$$

where  $DIS_{it}$  is a measure of dollar amount of direct damages caused by the immediate impact of a disaster in country  $i$  at time  $t$ . The economic impact of a disaster usually consists of direct consequences on the local economy (e.g., damage to infrastructure, crops, housing) and indirect consequences (e.g. loss of revenues, unemployment, market destabilisation) when the information is available. In EM-DAT database, the registered figure corresponds to the value of the immediate damage at the time of the event and usually only to the direct damage, expressed in US dollars (current value).<sup>6</sup>

For comparability purposes, all data are converted into 2009 US dollars using the United States' Consumer Price Index (CPI).  $\mathbf{X}_{it}$  is a vector of control variables of interest that capture the 'vulnerability' of the country to disasters (i.e., the conditions which increase the susceptibility of a country to the impact of natural hazards) and countries' demographic characteristics.  $\varepsilon_{it}$  is an independent and identically distributed (iid) error term. A Table with summary statistics for all the variables included in the various regressions is in the Appendix.

We first estimate the model for the full sample of events available in the dataset over the timeframe 1970–2008. Next, we use the coefficient estimates  $\hat{\alpha}$  and  $\hat{\beta}$  to

<sup>5</sup> See, for example, Kahn (2005), Skidmore and Toya (2007), Cavallo and Noy (2009) and references therein.

<sup>6</sup> See Scheuren *et al.* (2008).

predict out of sample the dollar amount of direct damages for the recent earthquake in Haiti. In other words, we replace  $\mathbf{X}_{i,t}$  in (1) with  $\mathbf{X}_{\text{Haiti},2010}$  and use the coefficient estimates from the model to provide an estimate for  $DIS_{\text{Haiti},2010}$ . Finally, we use bootstrapping simulation methods to determine the confidence intervals around these predictions.

We initially pool all types of events (approximately 2,000 events with full data) and compute pooled regressions. However, we alternatively compute the model for three different types of events separately: earthquakes, windstorms and floods. When we do so, we augment the set of controls to include measures of the physical intensities of events (i.e., Richter scale for earthquakes or wind speed for hurricanes).

One problem with the disaster data in the EM-DAT database should be noted at this point. As the threshold used to assess what events constitute a natural disaster is quite lenient, there are many events recorded in the dataset that are not conceivably catastrophic.<sup>7</sup> To avoid overrepresentation of small events in the sample (which may not be relevant for the case of Haiti) and to obtain a parsimonious representation, we exclude approximately 250 very small events, defined as those with fewer than 10 people reported dead or missing and for which reported damages are less than US\$10 million.<sup>8</sup>

As robustness checks, we also consider what may be thought of a 'more comparable' set of events to contrast Haiti earthquake by: estimating regressions on a subsample of developing countries only; and follow the approach proposed by King and Zeng (2006) consisting of first, pre-processing the sample in order to identify a subset of observations which are closer, in terms of their Euclidean distance, to Haiti's event mortality, the country's stage of development and size, and then running the same regressions on the more homogeneous subsample.

Another problem with the data is potential measurement error, particularly with the dependant variable (economic damage). Several institutions have developed methodologies to quantify economic losses in their specific domain. However, there is no standard procedure to determine a global figure for economic impact of natural disasters.<sup>9</sup> Furthermore, ambiguities exist regarding the intent behind the reporting of the data by different institutions. For example, while affected countries may have an incentive to inflate the impact in order to promote aid flows, the insurance industry may want to minimise the losses. The EM-DAT database is compiled from various sources, including UN agencies, non-governmental organisations, insurance companies, research institutes and press agencies. In order to partially overcome the misreporting problem, priority is given to data from UN agencies, governments and the International Federation of Red Cross and Red Crescent Societies. Moreover, the data is reviewed and validated by the academic institution that maintains the database.<sup>10</sup>

<sup>7</sup> EM-DAT defines a disaster as a natural situation or event which overwhelms local capacity and/or necessitates a request for external assistance. For a disaster to be entered into the EM-DAT database, at least one of the following criteria must be met: (1) 10 or more people are reported killed; (2) 100 people are reported affected; (3) a state of emergency is declared; or (4) a call for international assistance is issued. See Cavallo and Noy (2009) for a discussion.

<sup>8</sup> Including these events, we obtain even higher estimates of the damage.

<sup>9</sup> See Guha-Sapir (2006).

<sup>10</sup> The Centre for Research on the Epidemiology of Disasters (CRED) based at the Catholic University of Louvain, Brussels. However, the quality of the data can only be as good as the reporting system that feeds it.

Overall, the EM-DAT database is the most comprehensive and systematic publicly available cross-country database on natural disasters and it is particularly useful for regression-based analysis.<sup>11</sup>

## 2. Regression Results

The regression results for the pooled model are presented in Table 2. The estimation method is OLS and the preferred regression is in logarithms. The dependent variable is direct damage in 2009 US\$. The baseline specification includes a control for the intensity of the event in terms of mortality (number of people killed or missing), the stage of economic development (lagged real GDP per capita) and country size. For the latter we use either population size (column 1), land area in km<sup>2</sup> (column 2) or lagged real GDP

Table 2

*Baseline Regressions*

[Disasters regression model. Dependent variable: Log of Damages (2009 US\$ bn)  
Sample: 1971–2008]

Variables	Model				
	(1.1)	(1.2)	(1.3)	(1.4)	(1.5)
Number of people killed (in logs)	0.529 (20.78)***	0.537 (21.08)***	0.533 (20.93)***	0.527 (20.71)***	0.526 (20.63)***
Real GDP per capita (first lag, in logs)	0.501 (10.54)***	0.499 (11.54)***	0.356 (6.72)***	0.496 (10.36)***	0.485 (10.25)***
Population (in logs)	0.147 (4.85)***			0.184 (5.41)***	0.155 (5.18)***
Land area (in logs)		0.0855 (3.93)***			
Real GDP level (first lag, in logs)			0.146 (5.08)***		
Number of previous events				-0.00293 (-2.34)**	
Storm dummy					0.0455 (0.32)
Flood dummy					-0.268 (-1.87)*
linear trend	0.003 (0.68)	0.006 (1.29)	0.003 (0.72)	0.010 (1.72)*	0.005 (0.97)
Constant	-11.050 (-18.45)***	-9.823 (-21.95)***	-11.070 (-19.65)***	-11.770 (-17.65)***	-10.980 (-18.00)***
R-squared	0.388	0.388	0.394	0.390	0.392
Adjusted R-squared	0.383	0.383	0.389	0.385	0.387
Observations	1,760	1,774	1,773	1,760	1,760

*Notes.* For all regressions, regional dummies were included (not shown). Included regions are Asia (South Asia, East Asia and South East Asia), America (North and South America), Africa and Middle East (North Africa and Middle East and Sub Saharan Africa), Europe (Central and Eastern Europe and Western Europe) and Australia and Pacific Islands. *t* statistics in parenthesis. \*, \*\* and \*\*\* denote significance at the 10%, 5% and 1% level, respectively.

*Source.* Authors' calculations based on EM-DAT and WDI datasets.

<sup>11</sup> For an analytical review of selected data sets on natural disasters see Tschöegl *et al.* (2006).

(column 3).<sup>12</sup> In column 4 we include the number of previous natural events. Finally, in column 5 we also include a dummy for the type of event (earthquakes is the excluded variable).<sup>13</sup> All regressions include a linear trend, as some of the increases in reported damages over time may be due to improvements in recording capacity or data availability, as well as regional dummies (coefficient estimates not reported) to account for possible heterogeneity across regions in the incidence of the various events.

The fit of the regressions is good with an adjusted R-squared of approximately 0.4. The estimated damages increase significantly with the intensity of the event, with the level of economic development (in richer countries there is more wealth exposed to the disasters), with country size (bigger countries also have more wealth exposed) and decrease with the number of previous events (countries that have experience with events may have as a result stricter building and zoning codes, or may decide to locate wealth away from exposed areas). In terms of the type of events (column 5), earthquakes appear to be more destructive than floods but not more destructive than storms. The linear trend is usually not statistically significant.<sup>14</sup> The results are intuitive, with the possible exception of the positive sign of real GDP per capita, which appears to be at odds with previous results by Kahn (2005) and Skidmore and Toya (2007). Both of these papers use similar methods to examine the relationship between human and economic losses from natural disasters and economic development; both find that countries with higher income per capita experience fewer losses. This in turn is interpreted as meaning that economic development provides implicit insurance against natural disasters. The results are not directly comparable, however, because – in contrast with the papers cited – we use the number of people killed as a right-hand side (explanatory) variable. In other words, in this article, rather than focusing on the relationship between human mortality and economic development, we look at the relationship between mortality and economic development with monetary losses.

These results are also robust to the exclusion of events in industrialised countries. This is shown in Table 3. The coefficient estimates remain virtually unchanged, with the sole exception of the dummy for floods in column (4), suggesting that for the sample of developing countries only there is no statistically significant difference in the damage caused by earthquakes and floods.

Next, we recomputed the regressions separating by event types. When doing so, we can also control for the physical intensity of earthquakes (Richter scale) and windstorms (wind speed). The results are presented in Table 4.<sup>15</sup>

The results are also consistent with the baseline. The only exceptions are that the linear trend is positive and significant in the case of earthquakes (suggesting that earthquakes have become more damaging over time) and negative and significant for

<sup>12</sup> GDP measures are lagged to reduce possible endogeneity problems.

<sup>13</sup> The inclusion of additional control variables, such as level of educational attainment, openness to trade, financial development and the size of government do not significantly change the baseline results (details available upon request). The most likely reason is that some of these variables are known to be highly correlated with economic development.

<sup>14</sup> Its exclusion from the regressions does not change the results.

<sup>15</sup> We include the Richter scale in levels as, by definition, it is expressed in a logarithmic scale. For instance, an earthquake of 7.0 on the scale releases about 31 times more energy than an earthquake of 6.0. However, magnitude itself may not explain the damages caused by an earthquake. For example, earthquakes with lower magnitudes could be more destructive if they are located near densely populated areas.

Table 3

*Baseline Regressions with Developing Countries Only*

[Disasters regression model. Dependent variable: Log of Damages (2009 US\$ bn)  
Sample: 1971–2008]

Variables	Model				
	(2.1)	(2.2)	(2.3)	(2.4)	(2.5)
Number of people killed (in logs)	0.493 (17.31)***	0.503 (17.54)***	0.501 (17.42)***	0.490 (17.25)***	0.495 (17.26)***
Real GDP per capita (first lag, in logs)	0.444 (7.19)***	0.441 (7.75)***	0.280 (4.22)***	0.434 (6.97)***	0.436 (7.07)***
Population (in logs)	0.167 (4.55)***			0.187 (4.89)***	0.173 (4.72)***
Land area (in logs)		0.107 (4.05)***			
Real GDP level (first lag, in logs)			0.166 (4.76)***		
Number of previous events				-0.00264 (-1.84)*	
Storm dummy					0.162 (0.96)
Flood dummy					-0.0689 (-0.42)
linear trend	-0.003 (-0.45)	0.001 (0.22)	-0.002 (-0.41)	0.002 (0.33)	-0.001 (-0.24)
Constant	-10.720 (-14.71)***	-9.457 (-17.41)***	-10.740 (-15.65)***	-11.080 (-14.69)***	-10.830 (-14.40)***
R-squared	0.323	0.329	0.333	0.325	0.326
Adjusted R-squared	0.317	0.322	0.327	0.318	0.318
Observations	1,344	1,357	1,357	1,344	1,344

*Notes.* For all regressions, regional dummies were included (not shown). Included regions are Asia (South Asia, East Asia and South East Asia), America (North and South America), Africa and Middle East (North Africa and Middle East and Sub Saharan Africa), Europe (Central and Eastern Europe and Western Europe) and Australia and Pacific Islands. t statistics in brackets. \*, \*\* and \*\*\* denote significance at the 10%, 5% and 1% level, respectively.

*Source.* Authors' calculations based on EM-DAT and WDI datasets.

storms (suggesting that storms have become less damaging). These results may not be surprising, as earthquakes are by their nature less predictable and the exact location where they may strike is usually unknowable. Therefore, while it is possible to implement building codes and standards that better prepare infrastructure to resist possible earthquakes, it is not easy to locate wealth in 'safer' areas. In contrast, climatologic events like hurricanes disproportionately affect certain regions, particularly coastal locations in tropical areas. Vulnerable countries may therefore choose to locate their wealth away from the most exposed areas.<sup>16</sup>

<sup>16</sup> However, this does is not always the case. For example, Kellenberg and Mobarak (2008) suggest a nuanced, nonlinear relationship between economic development and vulnerability to natural disasters, with risk initially increasing with higher incomes as a result of changing behaviours, such as residents locating to more desirable but more dangerous sites near coasts and floodplains. Sadowski and Sutter (2005) provide some confirmation for this view by examining hurricanes in the US and the ways in which better preparedness leads to higher residential coastal concentrations (where the risk from hurricane-associated wave surges is higher).

Table 4

*Baseline Regressions by Event Type Disasters Regression Model*

[Dependent variable: Log of Damages (2009 US\$ bn) Sample: 1971–2008]

Variables	Model			
	Baseline regression	(3.1) Earthquakes	(3.2) Storms	(3.3) Floods
Richter magnitude scale		−0.104 (−0.54)		
Wind speed (in logs)			0.759 (2.10)**	
Number of people killed (in logs)	0.529 (20.78)***	0.657 (11.27)***	0.473 (6.74)***	0.597 (11.98)***
Real GDP per capita (first lag, in logs)	0.501 (10.54)***	0.572 (3.95)***	0.493 (4.36)***	0.527 (5.99)***
Population (in logs)	0.147 (4.85)***	−0.143 (−0.95)	0.150 (2.47)**	0.279 (4.95)***
linear trend	0.003 (0.68)	0.043 (2.62)***	−0.032 (−1.90)*	0.003 (0.43)
Constant	−11.050 (−18.45)***	−5.673 (−1.84)*	−13.210 (−5.71)***	−14.450 (−12.89)***
R-squared	0.388	0.569	0.521	0.339
Adjusted R-squared	0.383	0.531	0.485	0.327
Observations	1,760	1,71	201	753

*Notes.* For all regressions, regional dummies were included (not shown). Included regions are Asia (South Asia, East Asia and South East Asia), America (North and South America), Africa and Middle East (North Africa and Middle East and Sub Saharan Africa), Europe (Central and Eastern Europe and Western Europe) and Australia and Pacific Islands. t statistics in brackets. \*, \*\* and \*\*\* denote significance at the 10%, 5% and 1% level, respectively.

*Source.* Authors' calculations based on EM-DAT and WDI datasets.

Interestingly, the results in Table 4 suggest that the physical intensity of earthquakes does not affect the amount of damages (controlling for the number of people killed), while in the case of storms, wind speed has a significant independent effect on damages. This suggests that the number of people killed in earthquakes may be more correlated to the physical intensity of the event than in the case of windstorms.

### 3. Out-of-Sample Prediction for Haiti

The next step is to use the regression results to predict the damages caused by the devastating earthquake that hit in Haiti on January 12, 2010. The earthquake, which registered 7.0 on the Richter scale, struck very close to the capital city of Port-au-Prince, causing extensive casualties and huge damages to private and public assets. It should be noted that Haiti is already the poorest country in the Latin America and the Caribbean region and ranks in the bottom quartile of the United Nations Development Programme Human Development Index.

To estimate the overall damages caused by the earthquake in a country with Haiti's economic and demographic characteristics, we use the coefficient estimates from the baseline regressions, replacing matrix  $\mathbf{X}_{i,t}$  in (1) with  $\mathbf{X}_{\text{Haiti},2010}$ . Table 5 summarises the elements of  $\mathbf{X}_{\text{Haiti},2010}$  that are relevant for the estimation.

Table 5  
*Haiti's Data Matrix*  
 Estimated Damages for Haiti – Basic Assumptions

Explanatory variable	Value
Richter scale measure	7.0
Number of people killed	200,000
	250,000
GDP per capita (2000 US\$, 2008)	410.29
Population (2009)	9,951,529
Land Area (sq km)	27,560
GDP level (2000 US\$, 2008)	4,012,627,061
Number of previous events	9

Source: Authors' calculations and WDI dataset.

The estimates of the number of people killed are still subject to extensive discussion and revision. At the time of writing, estimates range anywhere between 200,000 and 250,000, including missing persons. As of February 10, 2010, the official estimate of the government of Haiti was a total of 230,000 people dead (not including missing). Figure 1 shows the estimated damage (*y*-axis) plotted against the death toll (*x*-axis) with confidence intervals computed using bootstrapping (1,000 replications).<sup>17</sup>

The results of the estimates indicate that, for an earthquake that causes 200,000 deaths in a country with Haiti's observable characteristics, the estimated damage is US\$7.2bn, with 90% confidence intervals between US\$4.1bn and US\$12.2bn. If the death toll were to reach 250,000, the estimated damage is US\$8.1bn, with 90% confi-

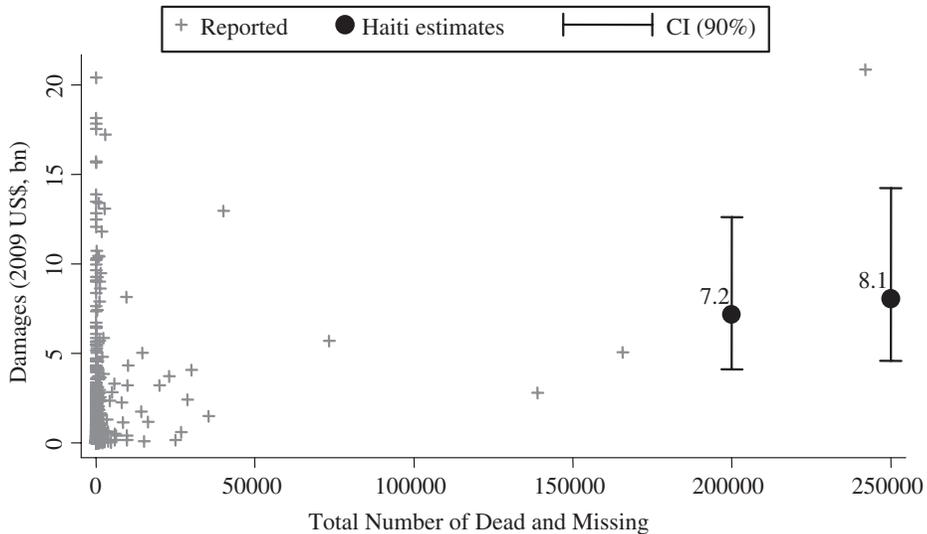


Fig. 1. *Estimated Damages for Natural Disasters*

Source. Author's calculation based on EM-DAT and WDI datasets.

<sup>17</sup> To perform the bootstrapping, we draw 1,000 random samples based on the observed data  $(DIS_{it}, \mathbf{X}_{it})'$  and estimate the economic damages for each sample. After that, we estimate the confidence intervals as the percentile 5 and 95 of the estimated damages distribution (Efron and Tibshirani, 1986).

dence intervals between US\$4.6bn and US\$13.9bn. Intermediate numbers give intermediate results. For example, using the official death toll of 230,000 as of February 10, the estimated damage is US\$7.7bn, with 90% confidence intervals between US\$4.4bn and US\$13.2bn.

These estimates are based on the regression results using model (1.1) in Table 2. Table 6 summarises the results we obtain using all the regressions reported in Table 2.

Figure 2 shows the *partial* correlation scatter plot between the log of US\$ damages (*y*-axis) and the log of total number of people killed (*x*-axis). This Figure (based on model 1.1 in Table 2) illustrates the strength of the relationship between the two variables after conditioning on the other explanatory variables included in the regression. Furthermore, it shows that while the event in Haiti is indeed very large, even after accounting for the observable characteristics we control for in the regressions, the results do not appear to be driven by outliers.<sup>18</sup>

Finally, given the heterogeneous feature of the disasters in the database, one possible concern is that the Haiti earthquake is not really comparable to the other events in the sample. This is because mortality is very high and the country is very small and poor (i.e., Haiti is the poorest country in the Western Hemisphere). Therefore the predictions based on regressions on a sample that do not match accurately to Haiti's event mortality, stage of development and country size may be biased. Whilst some of this is already accounted for by eliminating very small events from the sample and by checking the robustness of the results in a subsample of developing countries only, we further check the validity of the results using a more homogeneous sample. In particular, following the methodology proposed by King and Zeng (2006), we re-estimate damages using regressions that match more accurately Haiti's event mortality, stage of development and country size.<sup>19</sup> The procedure is implemented in two steps. In the

Table 6  
*Confidence Intervals*  
[Estimated damages for Haiti (2009 US\$ billions)]

Model	Estimate of people killed in Haiti					
	200,000			250,000		
	Point estimate	Lower CI	Upper CI	Point estimate	Lower CI	Upper CI
Regression (1.1)	7.2	4.1	12.2	8.1	4.6	13.9
Regression (1.2)	7.7	4.3	13.2	8.6	4.8	14.7
Regression (1.3)	7.5	4.3	12.2	8.4	4.8	13.9
Regression (1.4)	7.7	4.3	14.2	8.7	4.8	16.0
Regression (1.5)	8.8	5.0	16.2	9.9	5.6	18.4

*Note.* The confidence intervals (90%) were computed by bootstrapping (1,000 replications)

*Source:* Authors' calculations based on EM-DAT and WDI datasets.

<sup>18</sup> Moreover, it can be observed from Figure 2 that once we condition on the other explanatory variables included in the regressions, the relationship between economic damages and the number of people killed is much more parsimonious than what can be inferred from the unconditioned correlation (Figure 1).

<sup>19</sup> We have also made estimates based on matching on each dimension separately. The results are very similar and available from the authors upon request.

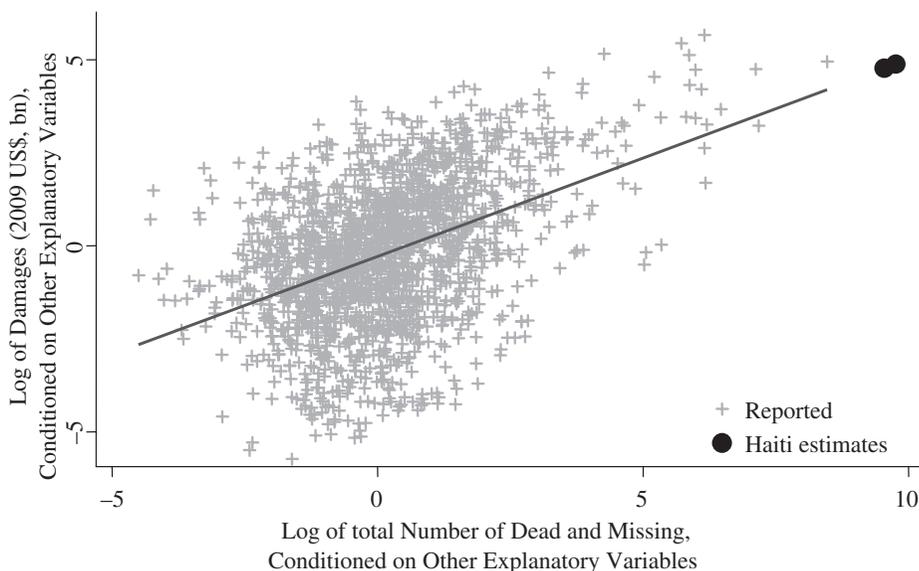


Fig. 2. *Estimated Damages for Natural Disasters*

Source. Author's calculation based on EM-DAT and WDI datasets.

first stage, we identify a subset of observations which are 'closer', in terms of their Euclidean distance, to the figures presented in Table 5 (Haiti's characteristics). For concreteness we use two alternative cutoffs for the maximum number of events that are 'closer' to the event of interest: 500 and 700 events.<sup>20</sup> These represent approximately 25% and 40% of the original sample size respectively. In the second stage, we estimate (1) on these subsamples and compute the out-of-sample predictions and confidence intervals as before using  $\mathbf{X}_{\text{Haiti},2010}$ .<sup>21</sup> The regression results are reported in Table 7 and the corresponding predictions in Table 8. The point estimates are reassuringly similar to the baseline. The only noticeable difference is that the confidence intervals in the regressions' coefficients estimates (Table 7) and the out-of-sample predictions (Table 8) are bigger. However, this is not surprising as it is the consequence of the reduced sample size.<sup>22</sup> Moreover, it is reassuring that when we account for the heterogeneous feature of the sample the baseline point estimates remain almost unchanged.

#### 4. Implications of the Results

These results hold significant implications for both Haiti and the international community. While a detailed assessment of needs will come from the so-called Post Disaster Needs Assessment that will be conducted in the coming months, the estimates above

<sup>20</sup> The results reported below are not very sensitive to the selected cutoff values.

<sup>21</sup> Possible sample selection bias is accounted for in the bootstrapping procedure.

<sup>22</sup> This underscores the inevitable trade-off imposed by the procedure: although it contributes to reduce the potential influence of irrelevant observations in the predictions, it also implies larger variance for the estimated coefficients and wider confidence bands for the out-of-sample predictions.

Table 7

*Baseline Regressions with Subsamples*

[Disasters regression model. Dependent variable: Log of Damages (2009 US\$ bn)  
Sample: 1971–2008]

Variables	Model		
	Baseline Regression	(4.1) Subsample 1 (500 obs)	(4.2) Subsample 2 (700 obs)
Number of people killed (in logs)	0.529 (20.78)***	0.739 (16.09)***	0.714 (18.07)***
Real GDP per capita (first lag, in logs)	0.501 (10.54)***	0.275 (2.07)**	0.274 (2.60)***
Population (in logs)	0.147 (4.85)***	0.061 (0.60)	0.147 (1.96)*
linear trend	0.003 (0.68)	-0.004 (-0.53)	-0.002 (-0.25)
Constant	-11.050 (-18.45)***	-9.413 (-5.57)***	-10.730 (-8.06)***
R-squared	0.388	0.424	0.435
Adjusted R-squared	0.383	0.410	0.426
Observations	1,760	500	700

*Notes.* For all regressions, regional dummies were included (not shown). Included regions are Asia (South Asia, East Asia and South East Asia), America (North and South America), Africa and Middle East (North Africa and Middle East and Sub Saharan Africa), Europe (Central and Eastern Europe and Western Europe) and Australia and Pacific Islands. *t* statistics in brackets. \*, \*\* and \*\*\* denote significance at the 10%, 5% and 1% level, respectively.

*Source.* Authors' calculations based on EM-DAT and WDI datasets.

Table 8

*Confidence Intervals for Subsamples*

[Estimated damages for Haiti (2009 US\$ billions)]

Model	Estimate of people killed in Haiti					
	200,000			250,000		
	Point estimate	Lower CI	Upper CI	Point estimate	Lower CI	Upper CI
Regression (4.1)	7.9	3.7	17.3	9.3	4.3	20.6
Regression (4.2)	6.9	3.5	13.9	8.1	4.0	16.4

*Note.* The confidence intervals (90%) were computed by bootstrapping (1,000 replications).

*Source.* Authors' calculations based on EM-DAT and WDI datasets.

indicate that Haiti's needs will total several billion dollars. This sum, moreover, will be beyond the scope of any one agency or bilateral donor, making donor coordination key in any reconstruction effort. Bobba and Powell (2006), for example, argue that aid is more effective when fewer donors are present, and multilateral organisations may thus be seen as a coordinating tool. Among possible approaches to coordination, one extreme is an all-encompassing, general-purpose and multi-donor trust fund managed by a single agency. It may be more feasible, though, to have several 'aggregator' funds, perhaps organised on thematic lines. However the coordination of the funding is achieved, it will be critical to ensure donors are coordinated on the ground. A single executing agency with appropriate powers, transparency and accountability to the Haitian Government

and donors would be helpful in this regard. While one view is that aid will be constrained by the capacity of institutions in Haiti to manage and execute the projects to be financed, this constraint may be endogenous to the architecture of funding and execution that donors and the Haitian Government find acceptable. Moreover, coordination and execution structures may also serve to ensure that aid is used most efficiently for Haiti rather than favouring particular projects favoured by donors or tied in any way, such as conditions to employ firms from any particular donor country.

Economic theory offers competing hypotheses as to the possible long-run impact of natural disasters on output dynamics. Traditional neoclassical growth models would predict lower growth at the time of a disaster that reduces the stock of capital, followed by higher growth rates as the economy reverts to its trend. By contrast, some endogenous growth theories would support the view that natural disasters induce a permanent fall in the level of output, particularly through its effects on human capital accumulation.<sup>23</sup> Similarly, the theory discussing the short-run effects of natural disasters does not help to disentangle output dynamics. For example: fiscal reconstruction stimulus; the additional demand for investment to replace destroyed capital; and the potential upgrading of production networks can lead to economic booms. However, fiscal sustainability problems and investment relocation decisions triggered by increased perception of future disasters can lead to stagnation.<sup>24</sup> This suggests that whether output losses are fully recovered in the aftermath of natural disasters is ultimately an empirical question. Recent work suggests that the impact of disasters such as the Haitian earthquake is very persistent. Cavallo *et al.* (2010) estimate, using a comparative case studies approach, that for very large disasters – whereby ‘large’ is defined in relation to the world mean of human casualties caused by natural events – ten years after a major disaster, the affected country’s output per capita may be some 30% lower than it would have been otherwise.<sup>25</sup> This is the case even given the significant increases in aid flows that tend to occur after a major disaster. Of course, this does not necessarily mean that aid does not work, as the negative growth effect would have been even worse if aid had not increased. However, this does underline the challenge ahead for Haiti and for the international community in its attempt to support the country.

One concern is that large aid inflows may provoke cost increases, real appreciation and the Dutch Disease, increasing aid-dependence and damaging private sector activity not directly related to reconstruction, including the export sector. In the case of Haiti, exports are small (some 10% of GDP) but they were growing (at an annual rate of 12% in 2009) and are highly concentrated in assembly industries including garments (some 90% of exports are assembly goods). The US Hope II legislation gives Haiti unparalleled access to US markets with generous ‘origin rules’ for garments and other selected activities, and there has been increasing interest from foreign firms in employing workers in Haiti for assembly and other activities. Given the growth effects of

<sup>23</sup> For example, Martin and Rogers (1997) show that if future benefits of learning by doing are not fully internalised by economic agents, then output slumps are periods in which opportunities for acquiring experience are forgone with permanent effects on output dynamics.

<sup>24</sup> See Cavallo and Noy (2009) for a recent review of the literature.

<sup>25</sup> The Haiti earthquake fits into the category of very large events for which the authors find these persistent effects as they use the number of people killed as a share of population as the benchmark to assess direct damages. For milder events they do not find evidence of any significant impact on GDP growth either in the short or long run.

natural disasters and the macroeconomic management issues of large aid flows, it appears important to ensure that the potential for job creation and growth in these sectors is not put at risk. Other potential growth areas for exports include high-value agricultural goods such as mangos (also useful for reforestation to resist soil degradation) and tourism, sectors whose support merits serious consideration.

## 5. Conclusions

In this short article we have attempted to give a preliminary estimate of the potential damages resulting from the tragedy of the January 12 Haiti earthquake. Our estimate derives from simple regression techniques employing data on past natural disasters and their damages estimates. Our base estimate is US\$8.1bn for a 250,000 death toll. We suspect for several reasons that this is a lower-bound estimate and an estimate of US\$13.9bn for the same death toll is within statistical error.

The implications of such an estimate are significant. Raising such a figure will require many donors, bilateral, multilateral and private. Hence excellent coordination of funding and of execution will be the key to ensuring the efficient use of funds. This is likely to imply that individual donors will have to relinquish control of their donations in terms of which projects they fund and the precise execution conditions, which in turn implies that appropriate mechanisms of transparency and accountability will be very important. Unfortunately, past experience suggests that, despite higher aid inflows after disasters, the growth impact of major disasters remains highly persistent. Apart from potential inefficiencies of the management of aid flows, microeconomic bottlenecks and a macroeconomic Dutch Disease-type phenomenon may hurt private activity not directly related to reconstruction. While Haiti's export sector is very small, it does have significant growth potential. The international community will need to consider how best to support private activities to ensure the negative growth impact is minimised and to ensure sustainable growth once reconstruction activities start to diminish.

## Appendix

Table A.1  
*Summary Statistics*

Variable	Observations	Mean	Std. Dev.	Minimum	Maximum
Damages (2009 US\$, bn)	1,760	1.03	5.54	0.00	141.35
Number of people killed	1,760	721	8,223	1	242,000
GDP per capita (2000 US\$, millions)	1,760	8,340	11,561	112	39,824
Population (thousands)	1,760	270,144	415,147	40	1,319,983
Land area (sq. km)	1,760	3,301,102	4,091,495	260	16,400,000
GDP (2000 US\$, millions)	1,760	1,349,238	2,676,706	96	11,300,000
Earthquake dummy	1,760	0.113	0.316	0.000	1.000
Storm dummy	1,760	0.460	0.499	0.000	1.000
Flood dummy	1,760	0.428	0.495	0.000	1.000
Number of previous events	1,760	85	83	1	222
Richter scale (units)	171	6.5	0.9	4.3	8.3
Wind speed measure for storms (kph)	201	178.3	65.2	45.0	418.0

*Source:* Authors' calculations based on EM-DAT and WDI datasets.

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