1. Creating a database of disaster donations.

1.1 Search Strategy and Coding Procedures

Our dataset comprises data on every sudden natural disaster recorded in the EM-DAT database. As detailed below, we used a combination of manual and automatic procedures to find data on disaster donations, and code their value and sources.

1. **Building the core of the dataset**

   We searched for news items related to each disaster in the Factiva and Lexis Nexis databases. The search window is one year after the official time of occurrence of the disaster according to EM-DAT. For example, the 2010 earthquake in Chile had the range 02/27/2010-02/27/2011. To identify relevant articles, we searched for combinations of 'affected country name', 'type of disaster', and (where applicable) 'disaster name'.

2. **Searching for information on the *type of disaster* and *corporate giving***

   We searched within each article for information on the type of disaster, and corporate aid donations.

   a. The disasters that passed the criterion of a sudden shock were identified as follows:
      i. Mass movement: "landslide" OR "avalanche" OR "rockfall" OR "subsidence"
      ii. Earthquake: "seismic" OR "quake" OR "earthquake" OR "tsunami"
      iii. Flood: "flood"
      iv. Storm: "storm" OR "typhoon" OR "cyclone
      v. " OR "hurricane" OR "tornado"
      vi. Volcano: "volcano" OR "volcanic" OR "eruption"

   b. Corporate giving was identified by searching for the following terms: "donation" OR "donate" OR "donated" OR "donating" OR "pledge" OR "pledged" OR "pledging" OR "give" OR "gave" OR "given" OR "giving." An example of the Boolean search is:

      [03/11/2011-03/11/2012]; ("Japan" OR "Japanese" OR "Japan's" OR "Japans"[1]) AND ("tsunami" OR "earthquake" OR "quake" OR "disaster") AND ("donation"

[1] There were spelling mistakes in some articles.

OR "donate" OR "pledge" OR "pledging" OR "give" OR "gave" OR "given" OR "giving").

3. Coding each corporate aid donation

In order to make over 2,310,000 electronic reports computationally tractable, we applied differential language analysis using *JavaScript Object Notation* (i.e., *JSON* and *AJAX*) to parse the data. For each article, we coded the following fields:

a. Entity making the donation

b. Actual donation.

i. In case of in-kind donations, the characteristics of the product or service were recorded (e.g., 1000 bottles of water, a team of nine technicians) and monetized using either current prices applicable in the affected country (e.g., the average price of one litter of bottled water, the daily man-power wage for a specific professional or technician) or an equivalent pecuniary value based on other firms' reporting of their donation to the same disaster.

ii. In case of donations reported in a currency different than the dollar, we converted using the currency exchange rate of the day of the donation.

c. To increase the relevance of the output (for example, some news reports were a series of articles with no relevance to the study but whose combination would make the report to be included in the outcome), the search was qualified with the following filtering process:

i. The name of the country had to be within 50 words of the type of the disaster or the word "disaster."

ii. Entities and the act of donating were parsed: The entities per article were extracted and grouped in three categories: organization (e.g., Tepco), location (e.g., Canada), and individual (e.g., Barack Obama).

iii. The verb identifying the act of donating had to be within 30 words of an entity

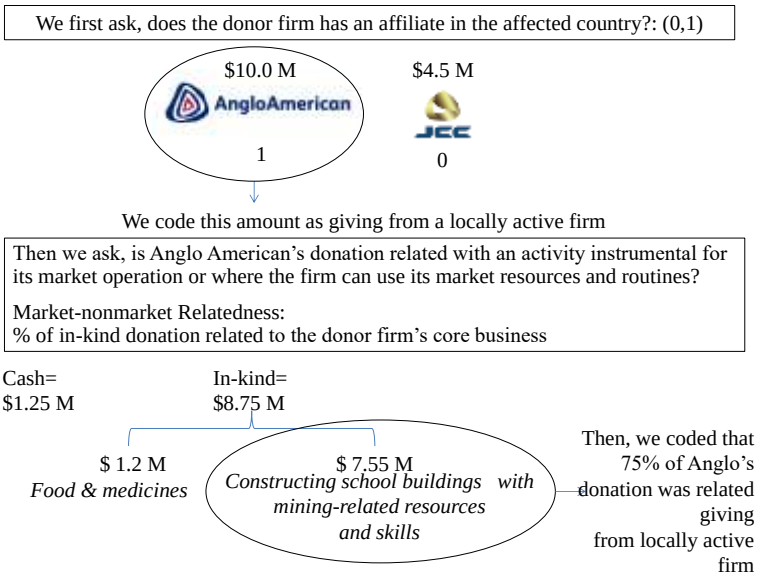
1.2 Coding for giving from locally active corporations and *related aid*

We used an automated coding process to search within each report for details about the type, financial value, date, and source of each donation. A group of researchers specifically hired for this task coded donations that were coming from corporations with local affiliates as reflected in

the Lexis Nexis Corporate Affiliations database. For each in-kind donation, we recorded the characteristics of the product or service in question and converted this to a monetary figure based on current prices in the affected nation (as reported in the Billion Prices Project[2]), the monetary value reported by the donor, or the reported value of similar donations from other organizations. Donations were converted into U.S. dollars using the exchange rate on the date the gift was made.

We developed a measure of *related giving* that reflects the degree to which disaster aid leverages firm-specific routines or resources. To calculate this, we began by using a firm's four-digit SIC code to identify its key business activities. We coded the dollar amount of in-kind donations that aligned with these activities as *related* [i.e., products, services, or activities that are relevant for the firm's market operation (e.g., Bayer providing medicines in response to Typhoon Haiyan)].

Once these two coding procedures have been completed, we randomly selected a sample of 5% of coded donations. A group of researchers not involved in the previous procedures checked for measurement error. This resulted in fewer than 5% of the selected sample that marked as inaccurate. About 60% of these errors were mainly associated with monetizing the in-kind value of donations, with less than 8% of the donations were incorrectly marked as related giving. The rest of sample of discrepancies were mainly associated with missing data on the nature of donor's business. The following figure illustrates an example of our coding:



[2] http://bpp.mit.edu/.

1.3 Assessing data quality

The following procedures were implemented to rule out measurement error:

1. Five percent of the events (156) for the period 2003-2013 were randomly selected and giving was manually searched using Google, Lexis Nexis, and Factiva. From this procedure, 5.128 percent of the selected events (8) had data inaccuracies, e.g., donation amount, date of donation.
2. We had access to exclusive information of donation for the 2010 tsunami and earthquake in Chile via the Chilean government. By comparing our database with the list of donors provided by the Chilean government, we found that our dataset comprised 68 percent of the official source. Our tracking did not include donating frequency of small- and medium-sized Chilean, non-multinational enterprises. In terms of magnitude, our dataset accounted for 92 percent of the total corporate aid for the event.
3. When available, the accuracy of the data was corroborated using external sources:
    a. The Financial Tracking System (FTS) of the United Nations Office for Coordination of Humanitarian Affairs (OCHA), which is a global database that records self-reported international humanitarian aid for different humanitarian crises.[3] The FTS has information on corporate donation for about 3 percent of the tracked events; and government and NGO donation for about 10 percent of the tracked events. In all cases, for corporate giving, the built dataset was larger than the FTS dataset.
    b. Disaster corporate aid trackers of the Corporate Citizenship Center (CCC) at the U.S. Chamber of Commerce Foundation.[4] This source provided information on corporate donation for 0.610 percent of the tracked events. In all cases, our database was larger than the CCC dataset.

[3] For information about the method of collection of FTS data and their verification, visit the following site: http://fts.unocha.org/pageloader.aspx?page=AboutFTS-Data.
[4] These data are available at http://www.uschamberfoundation.org/corporate-citizenship-center/disaster-corporate-aid-trackers.