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Saving and Re-building Lives: Determinants of Short-term and Long-term Disaster Relief

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Abstract

We analyse both theoretically and empirically, the factors that influence the amount of humanitarian aid received by countries which are struck by natural disasters, particularly distinguishing between immediate disaster relief and long term humanitarian aid. The theoretical model is able to make predictions as well as explain some of the peculiarities in the empirical results. We show that both short and long term humanitarian aid increases with number of people killed, financial loss and level of corruption, while GDP per capita had no effect. More populated countries receive more humanitarian aid. Earthquake, tsunami and drought attract more aid.

Keywords: *Humanitarian Aid, Disaster Relief, Natural Disaster*

JEL Code Classification*: C01, O12, Q54*

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1. Introduction

During the last few decades, there has been a heightened awareness of natural disasters around the world. Dilley et al. (2005) estimated that 3.4 billion people - which constitute more than half of the world's population - live in areas which are exposed to at least one significant hazard. In 2012 alone, natural disasters around the world resulted in nearly 107 million people being affected, 11548 people being killed and a financial loss of USD 156 million.[1] According to the annual report of the United Nations Office for the Coordination of Humanitarian Affairs (OCHA), humanitarian aid in 2012 was a massive USD 17.9 billion. The level of aid flow and the severity with which natural disasters affect people and economies have prompted researchers to study this issue from several angles.

Our paper contributes to the strand of literature which studies the determinants of disaster relief/ humanitarian aid (both terms are used interchangeably throughout this paper). This paper consists of a theoretical model as well as an empirical investigation which analyses how the various factors affect the amount of humanitarian aid disbursed by the donors, making a distinction between short term and long term aid. The determinants of these two types of aid could be different. To the best of our knowledge, there is no study which makes a distinction between immediate disaster relief and long term humanitarian aid, either in a theoretical framework or in an empirical analysis.[2] The theoretical model presented in our paper makes some predictions and provide an understanding on how the aid disbursement works. The results of the model help explain the outcomes of the empirical investigation including some apparent puzzles.

In this paper, *immediate disaster relief* is the assistance given to victims of natural disasters who require basic humanitarian assistance such as medical care, food, shelter etc. to help them survive in the aftermath of the disaster and alleviate their suffering; whereas *long term humanitarian aid* is the assistance given towards disaster reconstruction and rehabilitation to help rebuild the victims' personal assets, the communities' infrastructure or public services such as hospitals, schools, roads, bridges, shops, fishing boats, farms and personal financial losses that have been affected by the natural disasters.

In the empirical literature on disaster relief, there are few papers that study the determinants of humanitarian aid. Stromberg (2007) investigates the factors which determine the binary decision of the donors whether or not humanitarian aid is given (unlike our analysis where the dependent variable is the amount of humanitarian aid), using data on natural disasters that occurred between 1980-2004. He finds that colonial history, common language, trade relations and close proximity will increase the probability of receiving disaster relief.

[1] http://www.emdat.be/advanced_search/index.html

[2] Some papers discuss the long-term and short-term effects of natural disasters (Cavallo and Noy (2009), Raddatz (2007), Noy (2009), Loayza (2009), Raddatz (2009), Jaramillo (2009)).

Olsen et al. (2003) investigate the determinants of humanitarian aid based on a qualitative and quantitative analysis. They find that there are three key factors that determine the amount of humanitarian aid disbursed by the donors, namely the intensity of media coverage; the degree of donors' political and security interest and the strength of humanitarian NGOs and international organisations in the affected country. Fink and Redaelli (2009) show that bilateral humanitarian aid is determined by political and strategic interests of donors, captured by the close proximity between the donor and the recipient countries; the availability of crude oil in the recipient countries and whether the recipient countries are former colonies. Raschky and Schwindt (2009) also show that donors are influenced by strategic interests such as availability of oil and trade relationships. Becerra et al (2012) find that the severity of disasters influences the amount of aid received, as are the country size and foreign reserves, but they find no evidence of strategic behaviour.

Existing research has focused on bilateral aid, analysing the factors that have led a specific country to give aid to another specific country such as colonial past, language, distance, political strategy, trade opportunities etc. We are focusing on the total amount of disaster relief that is received in response to different disasters and seeing how these relate to not only some features of the country -- population, GDP per capita, measures of corruption, but more importantly to features of the disaster itself - its nature, scale and severity. Moreover, we also analyse separately the factors affecting immediate relief and long term aid. Does the international community as a whole end up giving more aid to those who are in greater need as a result of greater damage?

To analyse the determinants of humanitarian aid, a panel data analysis is performed, based on data on countries affected by natural disasters over the period of 1995 - 2008 and the humanitarian aid - both immediate relief and long term - that was received. Such an empirical investigation is possible because of two datasets that are available. The first is the Project-Level Aid (PLAID) dataset developed by William and Mary University and Brigham Young University. This dataset provides a detailed coding which gives information about when and why the aid was given, enabling us to select data only on disaster relief disbursed in response to natural disasters, as well as distinguish between short-term and long-term disaster reliefs. The second dataset, EM-DAT, is maintained by the Centre for Research on the Epidemiology of Disasters (CRED) at the University of Louvain, which gives information about the occurrences of all the natural disasters and the damages caused by them such as the amount of financial loss, the number of people killed and the number of people affected by the natural disasters.

In our analysis, we consider three natural disaster-specific characteristics which can affect the amount of aid it attracts: its *nature, scale and severity*. The nature of the disaster is related to whether it is a flood, earthquake, epidemic etc. The scale of disaster is the number of people affected. People can be affected in several ways:

loss inflicted on a person through injury, illness and potential or even actual loss of life; while loss of property refers to damage to homes and/or means of livelihood (e.g. boats). Some victims require immediate relief to save their lives while others require long term aid to rebuild their lives. Severity can be thought of as being measured in terms of the extent of loss to the person and property, so it could be reflected in factors such as the number of people killed and amount of financial loss.

The theoretical model we put forward is simple but quite powerful and capable of predicting our empirical findings. Once a country is hit by a natural disaster, the aid agency has to decide the type of humanitarian aid to be given to the affected country. The model also distinguishes between short term and long term humanitarian aid. In the model, we allow immediate relief to reduce the probability of death of those who face the risk of dying as a result of the natural disaster while the long term aid restores part of the financial loss that is suffered by the victims.

The theoretical model attempts to investigate first of all, whether there are any underlying determinants relating to both the scale and severity of the disaster and to the socioeconomic features of the country that help explain the different amount of short-term and long-term humanitarian aid that are given to different countries. Although we recognise that the amount of each type of aid given could well vary depending on the nature of the disaster (we include this in our empirical analysis), we will suppress any explicit reference to the nature of the disaster. First the theoretical framework investigates the effects of the scale and severity of the disaster. Then it goes on to relate both types of aid to the variables that we observe, i.e. number of people affected, number of deaths, the amount of financial loss, GDP per capita and the level of corruption.

Our empirical results show that both long term and short term humanitarian aid increase with the number of people killed and the amount of financial loss. Those who are dead cannot benefit from the increase in aid. Financial loss should attract long term aid to restore the damaged property, but why should it attract short term aid? The theoretical model shows that these outcomes are indeed possible. The reason is that financial losses signal the severity of the disaster and thus attract more short term aid as well. Long term aid also significantly increases with the total number of people affected according to the empirical analysis. The GDP per capita was found to be not statistically significant in determining either type of humanitarian aid, while the theoretical model shows the effect to be ambiguous. This result indicates that the donors are not influenced by how wealthy the affected country is, when it comes to humanitarian aid.

The level of corruption significantly increased both types of aid. Even though it is a surprising result, considering this is for humanitarian purposes, donors seem to care sufficiently about the victims that they increase the amount of aid in order to help them, even though much of it will be leaked. The theoretical model shows that if the donor is sufficiently inequality averse, and the level of corruption is not that high, there would be an increase in humanitarian aid when the level of corruption increases.

Empirical results show that countries with larger population receive significantly higher humanitarian aid, which reflect that donors should be more mindful of the needs of smaller countries. Disaster relief is significantly higher if the type of disaster that struck was earthquake, tsunami or drought, while it is lower if the country suffers extreme weather conditions. Long term aid is actually lower in response to a flood. Humanitarian aid in response to volcanos, avalanches, storm and wildfires is not significant. One of the contributions of this paper is to raise awareness to donors that the above mentioned disasters are not receiving as much aid compared with other types which cause damage of similar scale and severity.

Our paper is also related to a few other strands of literature. Poorer countries suffer more because they are less prepared to face natural disasters and poor people suffer more because they cannot afford to relocate to less disaster-prone areas (Kahn (2005), Toya and Skidmore (2006), Raddatz (2009), Stromberg (2007)). A few papers study the decision of donors whether to give cash or in-kind aid (Raschky and Schwindt (2009), Amegashie et al., (2007)).

The remainder of the paper is structured as follows. In Section 2, we present the theoretical framework. Section 3 is devoted for the empirical analysis, while section 4 concludes.

2. Theoretical Model

There are $K > 1$ countries that are hit by a particular type of natural disaster. An aid agency has a humanitarian aid budget, H, which has to be allocated to these different countries as both short-term and long-term aid. Consider a particular country k. The average income of this country before the disaster struck is $y_k > 0$, which indicates the level of development of this country. The degree of corruption in this country is χ_k, where $0 < \chi_k < 1$; thus for any given amount of humanitarian aid given as either short-term or long-term aid only a fraction $(1 - \chi_k)$ reaches the intended recipients. The two parameters, y_k and χ_k, capture the socioeconomic characteristics of this country. Now consider in turn the factors that might affect the amount of long-term and short-term aid to be given to each country.

Long-Term Humanitarian Aid: Let ${N_k}^L$ be the number of people who have survived the disaster but have suffered some financial loss. Long-term aid is needed for reconstruction and rehabilitation. The scale of the disaster in terms of the need for long-term aid is measured by ${N_k}^L$. Each person suffers, on average, a financial loss of $l_k = {\sigma_k}^L y_k$ where $0 \le {\sigma_k}^L < 1$, so that they are left with an average income of $(1 - {\sigma_k}^L) y_k$ after the disaster. The *severity* of the disaster in terms of the need for long-term aid is measured by ${\sigma_k}^L$. Therefore, the total financial loss in country k is

$$L_k = {N_k}^L l_k = {N_k}^L {\sigma_k}^L y_k. \qquad (1)$$

This measure reflects both the *scale* and *severity* of the long-term humanitarian problem facing country k. Let ${f_k}^L$, where $0 \leq {f_k}^L \leq 1$ denote the fraction of an individual's financial loss that is restored through long-term humanitarian aid. The restriction that no more than the whole loss is restored reflects the fact that this is humanitarian rather than general development aid. The total welfare from the long-term aid given to country k is measured by

$$ {W_k}^L = {N_k}^L u[y_k(1 - {\sigma_k}^L + {f_k}^L {\sigma_k}^L)], \quad (2) $$

where $u(c)$ is an individual welfare function that reflects the agency's views about how individual well-being relates to consumption, and is assumed not to vary across countries. The welfare function is assumed to satisfy the usual conditions $u' > 0, u" < 0$. We make the relatively standard assumption that the aid agency's individual welfare belongs to the class for which $u'(c) = c^{-\varepsilon}$, where $\varepsilon \geq 0$ is a measure of the agency's inequality aversion.

Taking into account the level of corruption in country k, the total amount of long-term humanitarian aid that would have to be given to country k by the aid agency to achieve the level of welfare, ${W_k}^L$, is given by:

$$ {H_k}^L = \frac{{N_k}^L {f_k}^L {\sigma_k}^L y_k}{(1-\chi_k)}. \quad (3) $$

Short-Term Aid: Let ${N_k}^S$ be the number of people in need of short-term humanitarian aid and so potentially at risk of dying if they do not receive such assistance. This measures the scale of the disaster in terms of the need for short-term humanitarian, and is fixed and independent of ${N_k}^L$. Donors consider the long term needs of victims irrespective of whether they are also in need of short term aid and vice versa.

Assume that a fraction ${f_k}^S$, where $0 \leq {f_k}^S \leq 1$, of these people will survive if, on average, each of them receives an amount $c({f_k}^S, {\sigma_k}^S) \geq 0$ where, as we will see, $0 \leq {\sigma_k}^S < 1$ is a parameter that will measure the severity of the disaster that has struck country k in terms of the need for short-term aid. In other words, $c(.)$ captures the cost of saving a victim requiring immediate relief.

Assume that the generic form of the function $c(f, \sigma)$ satisfies the following conditions for all σ, where $0 \leq \sigma < 1$ and for all f, where $0 < f \leq 1 - \sigma$:

(i) $c(0, \sigma) = 0$, which means if no aid is given then no one survives.

(ii) $c_f(f, \sigma) > 0, c_{ff}(f, \sigma) > 0$; $c_f(f, \sigma) \to \infty$ as $f \to 1 - \sigma$. The marginal cost of increasing the survival rate is positive, increasing and tends to infinity as the fraction of those who survive tends to the limit set by the severity of the disaster; the fraction of people who survive will be bounded above by a factor that depends on the severity of the disaster. The more severe the disaster, the smaller the fraction that will survive.

(iii). $c_f(f,\sigma) > 0$; $c_{\sigma f}(f,\sigma) > 0$, which captures the fact that an increase in the severity of the disaster increases both the total and the marginal cost of any survival fraction.

An example of a function that satisfies all these conditions is

$$c(f,\sigma) = \frac{\alpha}{\beta}\left[\left(1 - \frac{f}{1-\sigma}\right)^{-\beta} - 1\right], \quad (4)$$

where the parameters $\alpha > 0, \beta > 0$.

Notice that since $0 < f_k{}^S \leq 1 - \sigma_k{}^S$ it follows that the fraction of people who ultimately die as a result of the disaster, $1 - f_k{}^S$, is greater than $\sigma_k{}^S$, our measure of the severity of the disaster. Given this interpretation of the short term severity parameter, $\sigma_k{}^S$, it represents the fraction of the population at risk who cannot be saved because they are killed more or less outright. In this sense it provides a useful measure of the severity of the disaster. The number of people killed outright in country k is therefore

$$K_k = \sigma_k{}^S N_k{}^S, \quad (5)$$

which reflects both the severity and scale of the short-term disaster.

We assume that the perceived benefit to the aid agency of saving a life - i.e. increasing survival - is $b(\sigma_k{}^S), b' > 0$, which is independent of the scale and severity of the disaster as well as the affected country. This formulation reflects three key assumptions. First, we allow for the possibility that the value of saving a life may depend on the severity of the disaster, so the larger the number of people killed outright the greater is the imperative perceived by the agency to try to stop yet more people dying. Secondly, the value of saving a life is independent of $f_k{}^S$, the fraction of lives saved. In particular there is no diminishing marginal benefit. This reflects the assumption that the aid agency believes that each life that can be saved is just as valuable as every other life that is saved. Finally, conditioning on the severity of the disaster, the value of saving a life does not depend on the country struck by disaster or the nature of the disaster, which reflect the assumption that the value of saving a life is the same across countries and independent of the nature of the disaster. We introduce a two-parameter class of function as a specific functional form for the aid agency's benefit of saving a life, given by equation (6), which satisfies the above conditions and will be useful in our analysis later:

$$b(\sigma) = B\sigma^{\gamma}(1-\sigma)^{-\delta}, \quad (6)$$

where $B > 0, \gamma \geq 0, \delta \geq 0$ are constants. This formulation allows for the possibility that the severity of the disaster could affect the perceived benefit of saving a life in different ways. As we will see later, if $\gamma > 0$, then disasters that are very mild will receive no short-term funding. On the other hand if $\delta < 1$ then disasters that are extremely severe will also receive no short-term aid - reflecting the perception that it is so difficult to save anyone else, that it is not worth spending resources by attempting to do so. We realise that these are strong assumptions and draw attention to the fact that this specific functional form does allow $b(.)$ to be independent of the degree of severity when $\gamma = \delta = 0$.

The total welfare from the short-term humanitarian aid given to country k is

$$W_k{}^S = N_k{}^S f_k{}^S b(\sigma_k{}^S) \tag{7}$$

and, taking into account the effective aid that benefits the intended victims, the total amount of short-term humanitarian aid given by the agency to country k is

$$H_k{}^S = \frac{N_k{}^S c(f_k{}^S, \sigma_k{}^S)}{(1-\chi_k)} \tag{8}$$

2.1. The Aid Agency's Decision Problem

The aid agency's objective is to maximise the total welfare in equation (9), which is the summation of (2) and (7) which is ($W_k{}^S$+$W_k{}^L$). For each country, k, it takes as given the socioeconomic characteristics of that country, (y_k, χ_k), and both the scale and severity of the short-term and long-term characteristics of the disaster that has struck that country -- $(N_k{}^S, \sigma_k{}^S)$ and $(N_k{}^L, \sigma_k{}^L)$ respectively. The constraint faced by the aid agency given by (10) is that the total of aid given as the short term and long term aid should not exceed the aid budget of H, which is the summation of (3) and (8). The choice variables are the proportion of victims to save and the proportion of financial loss to replace, $f_k{}^S, f_k{}^L, k = 1, \dots K$.

$$\underset{f_k{}^S, f_k{}^L}{Maximise} \sum_{k=1}^{K} \{N_k{}^S f_k{}^S B + N_k{}^L u[y_k(1 - \sigma_k{}^L + \sigma_k{}^L f_k{}^L]\} \tag{9}$$

$$subject\ to \sum_{k=1}^{K} \frac{\{N_k{}^S f_k{}^S B + N_k{}^L u[y_k(1 - \sigma_k{}^L + \sigma_k{}^L f_k{}^L]\}}{(1-\chi_k)} \leq H \tag{10}$$

At an interior solution the first order conditions are given in (11) to (13):

$$b(\sigma_k{}^S) \leq \frac{\lambda c_f\left(\hat{f}_k{}^S, \sigma_k{}^S\right)}{(1-\chi_k)}, \quad \hat{f}_k{}^S \geq 0; \tag{11}$$

$$u'[y_k(1 - \sigma_k{}^L + \sigma_k{}^L f_k{}^L)] \leq \frac{\lambda}{(1-\chi_k)} + v_k, \qquad \hat{f}_k{}^L \geq 0; \tag{12}$$

$$v_k \geq 0, \qquad f_k{}^L \leq 1, \tag{13}$$

where v_k is the Lagrange multiplier on the constraint $\hat{f}_k{}^L \leq 1$ and each pair of inequalities holds with complementary slackness. Similar Lagrange multipliers are not needed for the short-term aid because of our assumption on the cost function $c(f_k{}^S, \sigma_k{}^S)$ that $\hat{f}_k{}^S < 1 - \sigma_k{}^S$. The Lagrange multiplier for constraint (10) is given by λ.

This paper aims to explain why, in a given allocation, some disasters get neither short term nor long term aid, and why, for those that do receive aid, some attract more short-term and/or long-term aid than others. In what follows, we treat λ as a constant and see how the amount of short-term and long-term aid given to each country is influenced by the socioeconomic factors and the *scale* and *severity* of the disaster. For notational simplicity, the sub-script, k for country is now dropped. Before proceeding to develop the cross-section implications of (11) and (12) for the determinants of aid there are two general points to note. The first point is that the optimal fractions $\hat{f}_k{}^S$, $\hat{f}_k{}^L$, and hence the amount of short-term and long-term aid *received by each individual* do not depend on the *scale* of the disaster in country k but only on the *severity* of the disaster and the socioeconomic characteristics of the country, which include the GDP per capita and the scale of corruption.

Secondly we note that in reality, the donors do not directly observe the theoretical constructs of the model - the scale and severity of the short-term and long-term humanitarian disaster facing a country. Rather what can be observed are some related variables: the number of people killed, the number of people affected and the financial loss. These are related to the *scale* and *severity* of the short and long-term aspects of natural disasters. Equation (1) tells us how financial loss is related. The total number of people affected by the disaster (defined as those suffering injury/illness, becoming homeless and losing their livelihood) in country k can be written as,

$$A_k = (1 - \sigma_k{}^S)N_k{}^S + N_k{}^L. \tag{14}$$

Notice that it follows from (5) and (14) that the number of people killed would be,

$$K_k = N_k{}^S + N_k{}^L - A_k. \tag{15}$$

However (1), (14) and (15) constitute just three equations in what are in principle four variables characterising the scale and severity of both the short-term and long-term humanitarian disaster that have hit a country. It is reasonable to assume that typically, the severity of these two aspects of natural disasters is related. In fact we make a rather strong assumption that they are identical, i.e. that $\sigma^L = \sigma^S$ and denote this common value by σ. We can rearrange (1), (14) and (15) to obtain functions for the scale and severity of the disaster as follows:

$$N^L = \frac{A + K}{1 + \frac{Ky}{L}} \tag{16}$$

$$N^S = \frac{A + K}{1 + \frac{L}{Ky}} \tag{17}$$

$$\sigma = \frac{\frac{L}{y} + K}{A + K} \tag{18}$$

Notice that in order for the severity of the disaster to satisfy the condition that $\sigma \leq 1$ it must be that case that

$$\frac{L}{y} \leq A \quad i.e. that \ \frac{L}{y} \leq y, \tag{19}$$

which states that the scale of the financial loss per person affected must be less than the average income. In what follows we assume that (19) always holds.

Proposition 1 predicts how the scale and severity of the disaster (number of people needing long term aid, number of people needing short term aid and the extent of both types of losses captured by σ) are affected by the variables that can be observed (total number of people who are affected, number of people who are killed outright, financial loss and average income).

The number of people needing long term aid increases with the total number of people affected and financial loss, while it decreases with the number of people killed and average income. Number of people in need of short term aid increases with total number of people affected, number of people killed and average income, but goes down with financial loss. As financial loss increases, it increases those needing long term aid, at the expense of those needing short term aid. Number of people killed indicates the severity of the disaster whereby people being in danger of losing lives - increasing those in need of short term aid at the expense of long term aid. Increase in the number of people killed and financial loss obviously indicates a higher level of severity of disaster, whereas a higher average income points towards a lower severity, as would the number of people affected (higher the scale, lower the severity). Having higher income will result in the country receiving less long term aid, so that it requires the agency to give it more short term aid to save its victims. It is straight forward to notice from (16) to (19) how $Proposition$ 1 follows.

Proposition 1 : $(i)\ \frac{\partial N^L}{\partial A} > 0,\ \frac{\partial N^L}{\partial K} < 0,\ \frac{\partial N^L}{\partial y} < 0,\ \frac{\partial N^L}{\partial L} > 0\ ;\ (ii)\ \frac{\partial N^S}{\partial A} > 0,\ \frac{\partial N^S}{\partial K} > 0,\ \frac{\partial N^S}{\partial y} > 0,\ \frac{\partial N^S}{\partial L} < 0\ ;\ (iii)\ \frac{\partial \sigma}{\partial A} < 0,\ \frac{\partial \sigma}{\partial K} > 0,\ \frac{\partial \sigma}{\partial y} < 0,\ \frac{\partial \sigma}{\partial L} > 0.$

2.1.1. Determinants of Long-Term Humanitarian Aid

We start developing the predictions of the theory in relation to the theoretical constructs of the model. Notice from (12) that the optimal fraction of property loss that is restored, $\hat{f}^L$ depends solely on (i) the severity of the disaster; (ii) the degree of corruption in the country in which the disaster has occurred; (iii) the level of per capita GDP in the country in which the disaster has occurred. It is independent of the long-term scale of the disaster.

Consider first the issue of how likely it is that no long term aid will be given - so $\hat{f}^L = 0$. According to (12) this will happen if

$$y \geq u'^{-1}\left(\frac{\frac{\lambda}{1-\chi}}{1-\sigma}\right). \tag{20}$$

This shows that it is more likely that no long term aid will be given when the severity of the disaster is lower and at higher levels of income and corruption of the country.

Next, consider the possibility that $\hat{f}^L = 1$ so that the financial loss that is suffered due to the disaster is fully restored. From (13) we see that this will happen if

$$y \leq u'^{-1}\left(\frac{\lambda}{1-\chi}\right). \tag{21}$$

Thus, it is more likely that the financial loss is fully restored by the aid agency, the poorer and lesser corrupt the country in which the disaster occurs. However this condition does not depend on the severity of the disaster.

Whenever long term aid is given, partially restoring the financial loss, $0 < \hat{f}^L < 1$, then it follows from (12) and (13) that $\hat{f}^L$ will be a strictly decreasing function of the levels of corruption and per capita GDP of the country in which the disaster occurs; and a strictly increasing function of the severity of the disaster. It follows from the above discussion that the total amount of long-term humanitarian aid decided by the aid agency is as given in (22).

$$\widehat{H}^L = \left\{\begin{array}{c} 0 \; if \; y \geq u'^{-1}\left(\frac{\frac{\lambda}{1-\chi}}{1-\sigma}\right) \\ \frac{N^L}{1-\chi}\left[u'^{-1}\left(\frac{\lambda}{1-\chi}\right) - y(1-\sigma)\right] \; if \; u'^{-1}\left(\frac{\lambda}{1-\chi}\right) < y < u'^{-1}\left(\frac{\frac{\lambda}{1-\chi}}{1-\sigma}\right) \\ \frac{N^L \sigma y}{1-\chi} \;\; if \; y \leq u'^{-1}\left(\frac{\lambda}{1-\chi}\right) \end{array}\right\} \tag{22}$$

The amount of long-term humanitarian aid depends on four factors: the scale of the disaster, N^L; the severity of the disaster, σ; the level of corruption, χ and the GDP per capita, y. It is straightforward to see that $\widehat{H}^L$ is directly proportional to N^L and that it is also increasing in σ. In the case of y, it is strictly increasing when income is below $u'^{-1}\left(\frac{\lambda}{1-\chi}\right)$ but strictly decreasing when income is above this level. So, the aid agency tends to focus aid on poorer countries, leaving richer ones to repair the consequences of the disaster from their own resources.

The impact of corruption is less clear cut. There is a direct effect through which aid increases in the level of corruption to benefit the victims, but there is also an indirect effect whereby the greater the corruption the smaller the fraction of damage restored, leading to the prediction that, if the level of corruption is sufficiently high no aid will be given. In what follows we will use the specific functional form that we introduced earlier, $u'(c) = c^{-\varepsilon}$. In which case,

$$u'^{-1}\left(\frac{\lambda}{1-\chi}\right) = \mu(1-\chi)^{\frac{1}{\varepsilon}} \tag{23}$$

where $\mu = \lambda^{\frac{1}{\varepsilon}}$. Substituting (23) into (22) we get the following:

$$\widehat{H}^L = \begin{cases} 0 \; if \; y \geq \dfrac{\mu(1-\chi)^{\frac{1}{\varepsilon}}}{1-\sigma} \\ \dfrac{N^L}{1-\chi}\left[\mu(1-\chi)^{\frac{1}{\varepsilon}} - y(1-\sigma)\right] \; if \; \mu(1-\chi)^{\frac{1}{\varepsilon}} < y < \dfrac{\mu(1-\chi)^{\frac{1}{\varepsilon}}}{1-\sigma} \\ \dfrac{N^L \sigma y}{1-\chi} \; if \; y \leq \mu(1-\chi)^{\frac{1}{\varepsilon}} \end{cases} \tag{24}$$

How long-term aid changes with corruption is shown by (25).

$$\frac{\partial \widehat{H}^L}{\partial \chi} = -\frac{N^L}{(1-\chi)^2}\left[\mu\frac{(1-\varepsilon)(1-\chi)^{\frac{1}{\varepsilon}}}{\varepsilon} + y(1-\sigma)\right] \tag{25}$$

It is clear that if $\varepsilon \leq 1$, then $\frac{\partial \widehat{H}^L}{\partial \chi} < 0$ - i.e. when the aid agency's inequality aversion is low, long-term aid is a decreasing function of corruption. What about the outcome when $\varepsilon > 1$? We can re-write (25) as follows.

$$\frac{\partial \widehat{H}^L}{\partial \chi} = -\frac{N^L}{(1-\chi)^2}\left[1 - \left(\frac{y(1-\sigma)\varepsilon}{\mu(1-\varepsilon)}\right)^{\varepsilon} - \chi\right] \tag{26}$$

Therefore $\frac{\partial \widehat{H}^L}{\partial \chi} \gtreqless 0 \; if \; \chi \lesseqgtr \left[1 - \left(\frac{y(1-\sigma)\varepsilon}{\mu(1-\varepsilon)}\right)^{\varepsilon}\right]$. When $\varepsilon > 1$, then $\left[1 - \left(\frac{y(1-\sigma)\varepsilon}{\mu(1-\varepsilon)}\right)^{\varepsilon}\right] > 1$. Since $\chi \leq 1$, we can only have a situation where $\chi < \left[1 - \left(\frac{y(1-\sigma)\varepsilon}{\mu(1-\varepsilon)}\right)^{\varepsilon}\right]$. So we can conclude that if $\varepsilon > 1$, $\frac{\partial \widehat{H}^L}{\partial \chi} > 0$ - i.e. when inequality aversion is sufficiently high, long-term aid is an increasing function of corruption.

Proposition 2 summarises the above analysis about how long term aid is affected.

Proposition *2:* *Long-term humanitarian aid is*

- *(i)* *an increasing function of the scale and severity of the disaster;*
- *(ii)* *not affected by per-capita GDP for both very poor and very rich countries, for other countries, an inverse U-shaped function of per-capita GDP;*
- *(iii)* *a decreasing function of the level of corruption if the aid agency is not too inequality averse,* $\varepsilon \leq 1$*;*
- *(iv)* *an increasing function of the level of corruption if the aid agency is sufficiently inequality averse,* $\varepsilon > 1$.

Now we move on to relate long-term humanitarian aid to factors that are observable, namely number of people killed, number of people who are affected and financial loss. We can re-write (22) as follows, by substituting out (1) and (16):

$$\widehat{H}^L = \begin{Bmatrix} 0 \; if \; y \geq \dfrac{\mu(1-\chi)^{\frac{1}{\varepsilon}}}{1-\sigma} \\ L - \left[\dfrac{A+K}{1+\frac{Ky}{L}}\right]\left[y - \mu(1-\chi)^{\frac{1}{\varepsilon}}\right] \; if \; \mu(1-\chi)^{\frac{1}{\varepsilon}} < y < \dfrac{\mu(1-\chi)^{\frac{1}{\varepsilon}}}{1-\sigma} \\ \dfrac{L}{1-\chi} \;\; if \; y \leq \mu(1-\chi)^{\frac{1}{\varepsilon}} \end{Bmatrix} \quad (27)$$

Using (27) and the predictions of Proposition 1 regarding the scale and severity of the long term aid requirement, we make the following analysis. It is straight forward to see that $\frac{d\widehat{H}^L}{dA} < 0$ when $\mu(1-\chi)^{\frac{1}{\varepsilon}} < y < \frac{\mu(1-\chi)^{\frac{1}{\varepsilon}}}{1-\sigma}$. This could be because the increase in the total scale indicates a reduction in the severity of the disaster with less people killed. It is also worth drawing attention to the fact that when $y \geq \frac{\mu(1-\chi)^{\frac{1}{\varepsilon}}}{1-\sigma}$, $\widehat{H}^L$ will fully restore what is lost and is not dependent on A. Similarly, when $y \leq \mu(1-\chi)^{\frac{1}{\varepsilon}}$, there will be no short term aid, and therefore will not be influenced by A.

When more people are killed, the affected country is given more long term aid,

$$\frac{d\widehat{H}^L}{dK} = -\frac{\left[y - \mu(1-\chi)^{\frac{1}{\varepsilon}}\right]\left(1 - \frac{Ay}{L}\right)}{\left(1+\frac{Ky}{L}\right)^2} > 0 \; because \; \frac{Ay}{L} > 1. \quad (28)$$

When financial loss increases, there is a positive direct impact on long term aid, which however, is counteracted by a negative indirect effect working via the impact of financial loss on the scale of the disaster. Therefore the effect is ambiguous.

$$\frac{d\widehat{H}^L}{dL} = 1 - \frac{Ky\left[y - \beta(1-\chi)^{\frac{1}{\varepsilon}}\right](A+K)}{\left(1+\frac{Ky}{L}\right)^2 L^2} \gtreqless 0. \quad (29)$$

Proposition 3 summarises how long term aid is affected by the observable features of the disaster.

Proposition 3: *Long-term humanitarian aid is a decreasing function of the number of people affected and an increasing function of the number of people killed, while the impact of financial loss on long-term humanitarian aid is ambiguous.*

2.1.2. Determinants of Short-Term Humanitarian Aid

Similar to the case of long-term aid, we begin by deriving predictions in terms of the constructs of the theory -- particularly the scale and severity of the disaster -- and then turn to the predictions in terms of observables. If we consider first the issue of how likely it is that no short term aid will be given - so $\hat{f}^S = 0$ - then we see from (11) that the greater the degree of corruption, the larger the right hand side of the equation and so the less likely that short-term aid be given. Turning to the impact of the severity of the disaster we see that this has two effects which go in opposite directions. The greater the severity of the disaster, the higher the marginal cost of saving a life and so the larger is the right hand side of (11), which means the more likely it is that no aid will be given. However, the greater the severity of the disaster the higher might be the perceived benefit of trying to save a life and so the less likely it is that no aid will be given.

In those cases where immediate relief is given - $\hat{f}^S > 0$ - then the same arguments indicate that $\hat{f}^S$ will be a strictly decreasing function of the degree of corruption but can be either an increasing or decreasing function of the scale of the disaster depending on which of the two effects identified above is greater.

Turning to the total amount of short-term aid given to a country struck by the disaster, we see from (8) that this is:

$$\hat{H}^S = N^S \frac{c\left[\hat{f}^S(\sigma,\chi),\sigma\right]}{(1-\chi)}. \tag{30}$$

So the amount of short-term humanitarian aid depends on just three factors: the scale of the disaster, N^S; the severity of the disaster, σ and level of corruption, χ. Total short-term humanitarian aid is directly proportional to the scale of the disaster, similar to long-term aid.

In relation to both the severity of the disaster and the level of corruption, there are two opposing effects. The direct effect implies that an increase in the severity of the disaster means that more aid has to be given to achieve any given survival fraction, while an increase in the level of corruption means that more has to be spent in any given country to ensure that a given amount of aid reaches the victims. However there is also the indirect effect that an increase in both severity and corruption reduces the optimal survival fraction which reduces the amount of aid that will be given.

At this level of generality it is difficult to say much about which of these two effects dominates. To make some progress, we consider the functional forms for $c(f,\sigma)$ and $b(\sigma_k{}^S)$ that we introduced in (4) and (6) respectively and substitute them into (11):

$$\hat{H}^S = \frac{N^S\alpha}{\beta(1-\chi)}\mathrm{Max}\left\{0,\left[\left(\frac{\mathrm{B}(1-\chi)\sigma^{\gamma}(1-\sigma)^{1-\delta}}{\lambda\alpha}\right)^{\frac{\beta}{1+\beta}}-1\right]\right\}. \tag{31}$$

Now consider the impact of the severity of the disaster on short-term aid. If $\gamma > 0$, there will be no short term aid given if the disaster is sufficiently mild (less severe) and if $\delta < 1$, then there will also be no short-term aid given if the disaster is extremely severe. If $\delta > 1$, then a positive amount of short-term aid will certainly be given if the disaster is severe and, if positive, the amount of short-term aid will be a strictly increasing function of the severity of disaster. More specifically,

$$\frac{\partial \widehat{H}^S}{\partial \sigma} = \left[\frac{N^S \alpha}{(1+\beta)(1-\chi)^{\frac{1}{1+\beta}}}\left(\frac{B}{\lambda}\right)\sigma^{\frac{\gamma+(1+\beta)(\gamma-1))}{1+\beta}}(1-\sigma)^{\frac{1-\delta(2+\beta)}{1+\beta}}\right](\gamma+\sigma\delta-\gamma\sigma-\sigma). \qquad (32)$$

From (32) we can see that the value inside the square brackets is positive, so $\frac{\partial \widehat{H}^S}{\partial \sigma} \gtreqless 0$ if $\sigma \lesseqgtr \frac{\gamma}{1+\gamma-\delta}$, which suggests an inverse U-shaped function.

Turning now to the impact of corruption on short-term aid, we can see from the term within the square brackets in (31) that if the degree of corruption is sufficiently large, then no short-term aid will be given. However if the degree of corruption is low and the amount of short-term aid is high then $\widehat{H}^S \approx \frac{N^S \alpha}{\beta(1-\chi)^{\frac{1}{1+\beta}}}\left(\frac{B\sigma^{\gamma}(1-\sigma)^{1-\delta}}{\lambda\alpha}\right)^{\frac{\beta}{1+\beta}}$. Thus, short-term aid will be a strictly increasing function of the degree of corruption. Taken together, this suggests an inverse U-shaped relation between short-term humanitarian aid and the degree of corruption. Finally we observe that short-term aid is not influenced by y. Proposition 4 summarises the above discussion.

Proposition 4: *Short-term humanitarian aid is an increasing function of the scale of the disaster; may either be a strictly increasing or an inverse U-shaped function of the severity of the disaster and an inverse U-shaped function of corruption. Short term aid is not affected by the per capita GDP.*

Next we turn to the predictions in terms of what can be observed, number of people killed, K; number of people affected, A and the amount of financial loss, L. Proposition 1 and Proposition 4 are used to conduct this analysis. We see that short-term humanitarian aid is certainly an increasing function of the severity of the disaster over an initial range of severity. To the extent that short-term humanitarian aid is an increasing function of the severity of the disaster (at least over a range of values of severity), we can come to the following conclusions, which is summarised in Proposition 5.

When K increases, it will increase N^S,which in turn increases $\widehat{H}^S$; while it increases σ, which will increases $\widehat{H}^S$. Therefore, an increase in the number of people killed will increase the amount of immediate relief that the affected country attracts. As far as the total number of people affected and the financial loss are concerned, there are opposing effects. When A increases, it will increase N^S,which in turn increases $\widehat{H}^S$ while it decreases σ, which will decreases $\widehat{H}^S$. So the effect is ambiguous. Likewise, when L increases, it will decrease N^S, which in turn decreases $\widehat{H}^S$ while it increases σ, which will increase $\widehat{H}^S$, causing the effect to be ambiguous.

Proposition 5: *So long as the short-term humanitarian aid is an increasing function of the severity of the disaster, short-term aid is an increasing function of the number of people killed, while the effects of the number affected and financial loss are ambiguous.*

3. Empirical Analysis

In this section we investigate whether the disaster-related factors and country-specific characteristics influence the amount of humanitarian aid - immediate and long-term relief - disbursed by the donors. The former refers to the type of disaster, scale and severity of disaster, while the latter is related to the level of development, corruption and the size of the country. The scale and severity of the disaster cannot be directly observed. We use variables that can be observed, detailed description of which follows in sub section 3.1.

Our empirical investigation seeks answers to questions such as the following. Is the amount of disaster relief received by the affected countries related to the scale of financial damage caused by the natural disaster? Do the donors tend to cluster the disaster relief where it will have the largest impact on the victims in terms of saving lives and reducing suffering? Do resource-poor countries receive more disaster relief? Does the level of corruption in the affected countries influence donors' aid disbursement? Does the type of disaster (earthquake, flood etc.) have an effect on the aid? Do these relationships differ between immediate relief and long-term humanitarian aid? For instance, does higher financial loss attract higher long term aid because of the need for reconstruction and number of people killed attract higher short term aid because it indicates the severity of the disaster in claiming lives.

3.1. Description and Sources of Data

We use the data on the effects of 5394 natural disasters that occurred during 1995 - 2008 in 186 countries and the humanitarian aid that was received towards these disasters. The impact of each disaster is different from another. Some disasters would have killed more people, but the financial loss could be less, and vice versa. There are disasters which have resulted in no reported deaths whereas there are others with no reported financial loss. Disasters do not occur in all countries in all the years, hence the panel is unbalanced.

Dependent variable: The dependent variable is the humanitarian aid that was received by the affected country as a response to the disasters, distinguishing between the short term disaster relief to enable survival and long term aid to assist the rebuilding and rehabilitating of victims.

There are several sources of data for humanitarian aid which are available. The two commonly known database include the Creditor Reporting System (CRS) maintained by the OECD and the Financial Tracking Service (FTS) maintained by the

UN. The CRS aid activity database collects information on official development assistance and other official flows to developing countries.

Another humanitarian aid database, the Project-Level Aid (PLAID), was developed by William and Mary University and Brigham Young University, which we have used for this analysis. The humanitarian aid data contained in this database comes from a number of sources, including the OECD's CRS, annual reports and project documents published by donors, web-accessible databases and project documents, spread sheets and data exports obtained directly from donor agencies. The majority of aid activities in this database are drawn from the OECD's CRS. For donors who are not members of the Development Assistance Committee (DAC) of the OECD or those who do not report to the OECD CRS, data were gathered through many different channels.

Few versions of the PLAID data existed, but the version which we used in our empirical analysis was the PLAID beta 1.9.2 which can be found on http://www.AidData.org. The coverage of this PLAID data set includes information on each individual project committed by both bilateral and multilateral aid donors. It also provides detailed coding for a variety of additional factors which makes it possible for us to obtain data on disaster relief given for emergencies caused only by natural disasters.

The descriptive information given for each entry in PLAID beta 1.9.2 enabled us to match the disaster relief with the specific disaster event. There are some cases where we could not match them perfectly because the aid could match more than one disaster which took place in that country and year. For the panel data analysis that we carry out, we only need the aid to be matched with the type of disaster, country and year the disaster took place as well as the damage it caused.

First of all, we find out the total humanitarian aid that is received towards each disaster. Then we went on to categorise it into two types: short-term and long-term disaster reliefs, based on the long descriptions provided by the database. The broad criteria used in our classification are as follows. The short-term disaster relief refers to the immediate assistance offered to the victims of natural disasters to ensure their survival, usually taking the form of distributions of food, water, medical supplies, and provision of temporary shelters etc., while the long-term disaster relief refers to the donors' supports in the reconstruction and rehabilitation programmes that take place in the countries affected by the natural disaster. It is important to highlight that the long-term disaster relief does not include investment in disaster mitigation nor does it include investment in disaster prevention and preparedness programmes.

According to the reported data that we use for this investigation, some disasters have attracted no humanitarian aid at all whereas others have attracted short term or long term aid, while there are some which have attracted both types. The objective of our empirical analysis is to find out what factors drive these differences.

Explanatory Variables: Data on the occurrences of natural disasters, the type of disaster and the damages caused by them are obtained from the Emergency Events Database (EM-DAT), maintained by the Centre for Research on the Epidemiology of Disasters (CRED) at the University of Louvain. The three explanatory variables that capture the damage caused by the disaster are the number of people killed, number of people affected (this includes those who are homeless, injured and those badly affected, in need of immediate relief) and the amount of financial loss. The type of disaster is included in the analysis as a dummy variable which could be one of earthquake, flood, drought, epidemic, landslide or avalanche, wildfires, volcano, storm, extreme temperature and tsunami. The URL for this database is http://www.emdat.be/.

The EM-DAT database provides updated information about the natural disasters that took place around the world and the consequences brought by them. For a disaster to be included in the EM-DAT database, it should meet at least one of the following criteria: at least ten people killed, at least hundred people affected, a state of emergency is called or international assistance is called for. The number of people killed refers to those who died as a direct consequence of the disaster (even though it includes those who are presumed dead, the figure is adjusted as and when the correct information is received). The financial loss is an estimate of the value of the assets that the country had lost due to a given disaster. When it comes to the total number of people affected, it is worth mentioning that the extent of the injuries to those who are injured, and the extent of damage to properties and houses of those who became homeless are not known. For the purpose of comparing with the theoretical framework, we do not know whether the people affected are in need of immediate relief or long term aid.

Other than these disaster related explanatory variables and the dummy variables for the type of disaster, we also have three variables that capture the socio economic characteristics of the affected country. These are the corruption perception index (CPI), GDP per capita, and the total population of the country. The CPI, as the term suggests, captures the level of corruption. The CPI index, which is between 0 and 10, assesses each country's perceived levels of corruption as determined by expert assessments and opinion surveys. The higher is the CPI, the less corrupt is the country. This data is publicly available at http://www.transparency.org/policy_research/surveys_indices/cpi. The GDP per capita (in current USD) indicates the average income of an individual in the country. The population variable does not feature in our theoretical model. We decided to control for it to see whether the size of the country has any influence on the donors. Data on GDP per capita and population size are made available by the United Nations Statistics Division. The URL for this database is http://unstats.un.org/unsd/snaama/dnllist.asp.

Table 1 gives the information according to the data we use for our analysis, about the number of disasters, the extent of damage that is caused by the disasters, captured by the number of people killed, affected and the amount of financial loss resulted from different types of disasters that occurred. Some people could be affected more than once because of disasters in the same region.

Table 1: Natural Disasters and Consequences during 1995 - 2008.

Type	**Number of disasters**	**Number of people killed**	**Number of people affected**	**Financial loss (million USD)**
Earthquake	359	503,659	185,795,103	424219.99
Flood	1,947	127,075	8,096,765,200	272634.90
Drought	250	6,406	1,110,003,220	41581.30
Epidemic	799	96,484	7,245,171	1.70
Landslide/Avalanche	244	12,017	3,611,713	5566.83
Wildfires	182	924	2,003,512,730	21007.31
Volcano	80	303	1,556,926	203.10
Storm	1,280	121,737	1,760,874,330	660268.69
Extreme temperature	232	94,545	84,404,594	45142.56
Tsunami	21	593,542	8,746,597	20004.40

3.2. Empirical methodology

We conducted a panel data analysis to find out the determinants of disaster relief. We considered the fact that the humanitarian aid that is received can never be negative. The regression model is described in equation (33). The subscript i denotes the 186 different countries and the subscript $t = 1995,\ldots,2008$ denotes the year. The dependent variable is the humanitarian aid given by ${H_{it}}^{\alpha}$ $(a = S, L, T)$ where ${H_{it}}^{S}, {H_{it}}^{L}$ and ${H_{it}}^{T}$ refer to the short-term disaster relief, long-term disaster and total disaster relief, respectively.

Table 2: Summary Statistics of Variables

Variable	Mean	Standard deviation	Minimum	Maximum
H^A $(million\ \$)$	7.20	61.98	0	1215.92
H^S $(million\ \$)$	1.19	12.02	0	261.75
H^L $(million\ \$)$	6.00	55.96	0	1208.66
$Population\ (million)$	49.40	154.53	0.03	1330.05
$Gdpcap$ (\$)	6,193.60	10,550.18	63.00	65566.00
CPI	3.68	1.98	0.4	10.00
$Finloss$ (million)	912.67	9,338.976	0	284,060.30
$Killed$ (000)	0.95	10.96	0	332.31
$Affected(000)$	14,140.59	409,063.8	0	1.64e+07

The explanatory variables, $Finloss, Killed, Affected$ denote the amount of financial loss, number of peopled killed and the number of people affected by natural disasters by respectively. The variables, $Population$, $Gdpcap$ and CPI denote the number of population, GDP per capita and the corruption perception index of the recipient country respectively.

There could be more than one disaster in one country in a particular year which could also determine the amount of aid that is received. The number of disasters that occurred in a particular year is captured by the variable, $Disasters$. The rest of the variables are dummy variables, which equal to one if that particular type of disaster occurred at least once in that country in that year and zero otherwise.

The dependent variable is the amount of humanitarian aid, which cannot be negative. If we use a panel data model without restrictions, the estimates will be inconsistent with the slopes being downward biased and the intercept being upward biased. Taking into account that $H^a \geq 0$: we estimate $E(H^{a*}/x) = Max(0, \boldsymbol{x\beta})$. A tobit model with the lowest level of the dependent variable being zero, would be consistent because it will give maximum likelihood estimates.[3] Since fixed effects Tobit models cannot be regressed, we have used dummy variables for countries, $\boldsymbol{\beta C_i}$, so that country-specific effects are controlled for. We consider this model to be the most suitable for this analysis even though the estimates may not be unbiased. Three separate regressions were run to find out how these three dependent variables (${H_{it}}^S, {H_{it}}^L$ and ${H_{it}}^T$) are influenced by the explanatory variables. We have also used the Tobit random effects model without controlling for the countries in order to check the effect of CPI because it does not vary within countries too much.

$$
{H_{it}}^{\alpha} = Max\left\{0, \left(\begin{array}{c} \beta_0 + \beta_1 Finloss_{it} + \beta_2 Killed_{it} + \beta_3 Affected_{it} + \\ \beta_4 Population_{it} + \beta_5 Gdpcap_{it} + \beta_6 CPI_{it} + \beta_7 Disasters_{it} + \\ \beta_8 Flood_{it} + \beta_9 Earthquake_{it} + \beta_{10} Tsunami_{it} + \beta_{11} Drought_{it} + \\ \beta_{12} Volcano_{it} + \beta_{13} Avalanch_{it} + \beta_{14} Extreme_{it} + \beta_{15} Epidemic_{it} + \\ \beta_{16} Storm_{it} + \beta_{17} Wildfires_{it} + \beta C_i + u_{it} \end{array}\right)\right\} \quad (33).
$$

3.3. Empirical Results

In this subsection, the results of the panel data regression using the Tobit model are presented. Countries are controlled for, but are not presented because there are too many. Table 3, Table 4 and Table 5 contain the results from our empirical investigation of the determinants of total humanitarian aid, short term disaster relief and long term disaster relief respectively. The standard errors are given within parentheses and *, ** and *** indicate that the variable are statistically significant at 10 percent, 5 percent and 1 percent respectively.

[3] It assumes that $H^{a*}/x \sim Normal(x\beta, s^2)$ and $s^2 = var(H^{a*}/x)$ and does not depend on x.

The coefficients indicate the change in humanitarian aid weighted by the probability of attracting positive amount of aid. The ${H_{it}}^{\alpha}$ and $Finloss$ are in millions of US dollars; $Killed$ and $Affected$ are in thousands; $Gdpcap$ is in current US dollars and CPI is given as an index which is between zero and ten where lower the value, higher the level of corruption.

Table 3: Determinants of Total Disaster Relief

H^T	I	II
$Population$	0.68838* (0.36962)	0.7881225** (0.3586174)
$Gdpcap$	0.000246* (0.00371)	0.000246* (0.00371)
CPI	−26.04295** (11.24409)	0.000246** (11.11835)
$Finloss$	0.0016027*** (0.0016027)	0.0014014*** (0.0005016)
$Killed$	4.194763*** (0.2719686)	4.357838*** (0.2389704)
$Affected$	0.00003466*** (0.00000601)	0.0000336*** (0.0000336)
$Disasters$	6.379708*** (2.012796)	6.066022*** (1.743004)
$Flood$	8.109651 (11.06593)	
$Earthquake$	39.78723*** (39.78723)	40.01094*** (13.2313)
$Tsunami$	43.33861 (31.80823)	
$Drought$	39.28206*** (10.88)	39.63541*** (39.63541)
$Volcano$	−9.358858 (2.47074)	
$Avalanch$	−1.607068 (13.80701)	
$Extremetemp$	−88.87203*** (19.46213)	−90.57443*** (19.27466)
$Epidemic$	−13.28513 (6.631624)	
$Storm$	8.33046 (11.62142)	
$Wildfires$	−17.95567 (20.34714)	

In all three regressions, the number killed and financial loss are highly significant (total and long term aid at 1%, while short term aid is at 5% significance level), suggesting that an increase in the number of people killed by the disaster and an increase in the amount of financial loss will result in an increase in the probability of receiving disaster relief and of the expected amount. Though people who are dead cannot benefit from the aid, number killed is an indicator of the severity of the disaster and assistance from the donors to minimise further suffering and restore the damage. It also could mean that many bread winners of families being dead, requiring financial assistance for the affected families in the long run.

The total aid and long term aid significantly increases (at 1%) with the number of people affected by the disasters, while its effect on short term aid was not significant. Recall that the number of people affected by natural disaster includes those who became homeless, injured and affected severely and in need of immediate assistance. However, according to our investigation, donors perceive this indicator to require long term assistance.

Table 4: Determinants of Short Term Disaster Relief

H^S	I	II
$Population$	0.4436216^{***} (0.1324854)	0.4002443^{***} (0.1245782)
$Gdpcap$	0.0004843 (0.0015404)	
CPI	-7.648553^{**} (3.794085)	-7.62367^{**} (3.794085)
$Finloss$	0.0002894^{**} (0.0001227)	0.0002818^{**} (0.0001186)
$Killed$	0.2735108^{***} (0.0809464)	0.2887515^{***} (0.0789501)
$Affected$	0.00000199 (0.00000188)	
$Disasters$	1.001273^{**} (0.6518507)	1.170689^{**} (0.5665288)
$Flood$	8.559362^{**} (3.699207)	7.996562^{**} (3.560856)
$Earthquake$	14.32392^{***} (4.43326)	13.61853^{***} (4.43326)
$Tsunami$	22.34297^{**} (10.23278)	20.94611^{**} (10.11857)
$Drought$	15.00415^{***} (3.581501)	14.52061^{***} (3.493365)
$Volcano$	1.757915 (6.768336)	
$Avalanch$	4.593298 (4.504904)	
$Extremetemp$	-15.82023^{***} (6.362575)	-16.73173^{***} (6.32152)
$Epidemic$	0.3275552 (3.439476)	
$Storm$	2.472262 (3.907754)	
$Wildfires$	2.929514 (6.631624)	

The level of development captured by the GDP per capita was found be significant in determining either the short term or long term aid (total aid was significant at 10% level, indicating that the donors do not place much emphasis on the level of development of the affected country when considering the allocation of humanitarian aid. Population level significantly increases total aid (at 10%) and short term aid (at 1%), which indicates that populated countries benefit more compared to smaller countries.

It is interesting to note that the level of corruption is significant at 5% level for total, long-term and short-term humanitarian aid, indicating that higher corruption attracts higher amount of aid. When it comes to humanitarian aid, the donors are so concerned about the victims that they give more aid to compensate for what might be leaked out due to corruption. The results of the random effects panel regression are presented in the Appendix. This model which does not control for the different countries, also confirm these results (Table A1-3).

Table 5: Determinants of Long Term Disaster Relief

H^L	I	II
$Population$	-0.1306048 (0.5025238)	
$Gdpcap$	-0.0023893 (0.005673)	
CPI	-39.3695^{**} (17.31166)	-42.38721^{***} (17.13034)
$Finloss$	0.0008357^{***} (0.0008357	0.0027407^{***} (0.0007988)
$Killed$	4.198412^{***} (0.3499186)	4.239634^{***} (0.3427376)
$Affected$	0.0000461^{***} (0.00000835)	0.0000436^{***} (0.00000804)
$Disasters$	11.0821^{***} (3.299867)	10.783232^{***} (3.129856)
$Flood$	-40.39658^{**} (17.8999)	-39.2034^{**} (17.50219)
$Earthquake$	53.58815^{***} (20.55906)	56.55222^{***} (20.08626)
$Tsunami$	94.94196^{**} (44.96548)	97.19509^{**} (44.96548)
$Drought$	32.49247^{***} (17.75344)	35.16121^{**} (17.45005)
$Volcano$	-11.48524 (32.82165)	
$Avalanch$	-16.9481 (22.42129)	
$Extremetemp$	-134.1715^{***} (30.89421)	-132.288^{***} (30.89421)
$Epidemic$	-37.86449^{**} (17.629)	-37.17531^{**} (17.3659)
$Storm$	13.41685 (18.34191)	
$Wildfires$	-39.7657 (33.59188)	

The number of disasters (given by the variable, $Disasters$) is a significant determinant in all three regressions. The more a country is prone to being hit by disasters, the more aid it attracts: short term aid (5% level of significance), long term aid (1% level of significance) and total aid (1% level of significance).

Short term aid is significantly increased because of flood, tsunami (at 5%), earthquake and drought (at 1%). Donors recognise that these types of disasters would require more immediate assistance. It also could be because these disasters attract more publicity about the hardship suffered by the victims. Long term aid statistically increases with earthquake, drought (at 1%) and tsunami (at 5%). These disasters would damage buildings and other assets, which require long term assistance to rebuild.

Some types of disasters - avalanches, volcanos, storm, extreme temperature and wildfires – do not attract as much humanitarian aid when compared to other types which cause damage of similar scale and severity. Extreme temperature results in significantly lower total, short term and long term aid (at 1%). Surprisingly, long term aid is negatively influenced by floods (at 5%).

4. Conclusion

We have analysed the factors that influence the amount of humanitarian aid received by countries which are struck by natural disasters, drawing a distinction between the amount of humanitarian aid received as immediate relief and what is received as long term humanitarian aid. The theoretical model shows how the humanitarian aid that is given depends on the scale and severity of the disaster which are not observable as well as factors that are observable - disaster-specific variables (number of people killed, affected and financial loss) and country-specific variables (GDP per capita and corruption). The predictions of the theoretical model are able to explain the empirical results that followed.

Our empirical results show that both the number of people killed and financial loss which indicate the severity of a disaster are statistically significant, while the number of people affected is significant only for the long term aid. If possible, it might be worth trying to break this down into long term and short term needs of those affected. Level of development is not statistically significant in determining the level of humanitarian aid. Corruption significantly increases humanitarian aid of either type, indicating the high inequality aversion of the donors, who care for the victims to such an extent.

Research about humanitarian aid can be taken forward in various ways. In particular, the factors affecting disaster relief given towards different types of mitigation, which includes the damage caused by different types of natural disasters, is worth studying. This problem can be analysed both from the donor's and the recipient's perspective. It is also worthwhile investigating the types of mitigation efforts that are effective, so that such projects could be promoted and financed.

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Appendix

The results of the random effects model of the panel data regression, which are the same for pooled regression, are given below along with the ones for 'fixed effects' for comparison. Tables A1, A2 and A3 give the results for total HA, long-term HA and short-term HA respectively. The results confirm the effect of CPI, which was the main concern when controlling for the countries. The other difference is that the in the random effects model indicate that the probability and the amount of humanitarian aid will decrease if $Gdpcap$ is higher. We can rely more on the model which controls for other country-specific effects.

Table A1: Determinants of Total Disaster Relief

HA^T	Pooled/ Random Effect		'Fixed Effect'	
	I	II	I	II
$Population$	-0.0418596 (0.0371189)		0.68838^{*} (0.36962)	0.7881225^{**} (0.3586174)
$Gdpcap$	-0.0044529^{***} (0.0012836)	-0.0043188^{***} (0.0012682)	0.000246^{*} (0.00371)	
CPI	-9.293034^{**} (4.676868)	-9.759294^{**} (4.686084)	-26.042955^{**} (11.24409)	-27.90781^{**} (11.11835)
$Finloss$	0.0012905^{***} (0.000336)	0.0012433^{***} (0.0003322)	0.0016027^{***} (0.000572)	0.0014014^{***} (0.0005016)
$Killed$	4.107991^{***} (0.2621469)	4.10641^{***} (0.2594929)	4.194763^{***} (0.2719686)	4.357838^{***} (0.2389704)
$Affected$	0.0000307^{***} (0.00000633)	0.0000296^{***} (0.00000619)	0.0000346^{***} (0.00000601)	0.0000336^{***} (0.00000584)
$Disasters$	5.484761^{***} (1.83201)	5.091394^{***} (1.405173)	6.379708^{***} (2.012796)	6.066022^{***} (1.743004)
$Flood$	10.64793 (9.769138)		8.109651 (11.06593)	
$Earthquake$	35.66524^{***} (12.28524)	34.11647^{***} (12.19996)	39.78723^{***} (13.62136)	40.01094^{***} (13.2313)
$Tsunami$	57.01677^{*} (31.15458)	54.52965^{*} (30.88297)	43.33861 (31.80823)	
$Drought$	36.84515^{***} (10.55835)	35.49165^{***} (10.25705)	39.28206^{***} (10.88)	39.63541^{***} (10.45472)
$Volcano$	-3.083733 (19.45383)		-9.358858 (2.47074)	
$Avalanch$	-2.279674 (13.46577)		-1.607068 (13.80701)	
$Extremetemp$	-66.63952^{***} (17.63648)	-68.48246^{***} (17.4827)	-88.87203^{***} (19.46213)	-90.57443^{***} (19.27466)
$Epidemic$	-17.9193^{*} (9.675328)	-18.70195^{**} (9.382569)	-13.28513 (10.52071)	
$Storm$	26.57633^{***} (10.12072))	24.125^{**} (9.693189)	8.33046 (11.62142)	
$Wildfires$	-39.88297^{**} (19.7276)	-39.61884^{**} (19.58719)	-17.95567 (20.34714)	

Table A2: Determinants of long term disaster relief

HA^L	Pooled/ Random Effect		'Fixed Effect'	
	I	II	I	II
$Population$	-0.0750245 (0.0608813)		-0.1306048 (0.5025238)	
$Gdpcap$	-0.0041137^{**} (0.0018886)	-0.0036676^{**} (0.0018333)	-0.0023893 (0.005673)	
CPI	-16.38574^{**} (7.866695)	-16.74401^{**} (7.820975)	-39.3695^{**} (17.31166)	-42.38721^{***} (17.13034)
$Finloss$	0.0018343^{***} (0.0004756)	0.0017485^{***} (0.0004711)	0.0028448^{***} (0.0008357)	0.0027407^{***} (0.0007988)
$Killed$	3.96316^{***} (0.3617722)	3.913192^{***} (0.3592756)	4.198412^{***} (0.3499186)	4.239634^{***} (0.3427376)
$Affected$	0.0000398^{***} (2.996452)	0.0000363^{***} (2.315031)	0.0000461^{***} (0.00000835)	0.0000436^{***} (0.00000804)
$Disasters$	10.31231^{***} (3.299867)	6.526464^{***} (3.299867)	11.0821^{***} (3.299867)	10.783232^{***} (3.129856)
$Flood$	-25.91719 (16.68052)		-40.39658^{**} (17.8999)	-39.2034^{**} (17.50219)
$Earthquake$	51.15077^{***} (19.8643)	53.99151^{***} (19.85456)	53.58815^{***} (20.55906)	56.55222^{***} (20.08626)
$Tsunami$	97.29056^{**} (45.90315)	107.7914^{**} (45.61624)	94.94196^{**} (44.96548)	97.19509^{**} (44.96548)
$Drought$	29.97084^{*} (17.94014)	35.92513^{**} (17.78109)	32.49247^{***} (17.75344)	35.16121^{**} (17.45005)
$Volcano$	-6.729559 (32.84008)		-11.48524 (32.82165)	
$Avalanch$	-15.34827 (23.38077)		-16.9481 (22.42129)	
$Extremetemp$	-96.19339^{***} (30.38778)	-93.43714^{***} (30.12581)	-134.1715^{***} (30.89421)	-132.288^{***} (30.57079)
$Epidemic$	-43.32823^{**} (17.05657)	-36.10109^{**} (16.61151)	-37.86449^{**} (17.629)	-37.17531^{**} (17.3659)
$Storm$	45.16899^{***} (17.23061)	54.03149^{***} (16.6043)	13.41685 (18.34191)	
$Wildfires$	-66.38844^{**} (35.34797)	-59.22872^{**} (34.83567)	-39.7657 (33.59188)	

Table A3: Determinants of Short Term Disaster Relief

HA^S	Pooled/ Random Effect		'Fixed Effect'	
	I	II	I	II
$Population$	-0.0069309 (0.0108734)		0.4436216^{***} (0.1324854)	0.4002443^{***} (0.1245782)
$Gdpcap$	-0.0019426^{**} (0.0005198)	-0.0019048^{***} (0.0005039)	-0.0004843 (0.0005039)	
CPI	-1.820946 (1.522106)	-1.908272 (1.511675)	-7.648553^{**} (3.820505	-7.62367^{**} (3.794085)
$Finloss$	0.0003857^{***} (0.0000109)	0.0003624^{***} (0.0001065)	0.0002894^{**} (0.0001227)	0.0002818^{**} (0.0001186)
$Killed$	0.2545535^{***} (0.0813737)	0.263458^{***} (0.0801282)	0.2735108^{***} (0.0809464)	0.2887515^{***} (0.0789501)
$Affected$	0.0000108 (0.00000195)		0.0000199 (0.00000188)	
$Disasters$	1.177205^{**} (0.5880165)	0.941451^{**} (0.4452636)	1.001273^{**} (0.6518507)	1.170689^{**} (0.5665288)
$Flood$	7.430482^{***} (3.12790)	7.884083^{***} (3.040933)	8.559362^{**} (3.699207)	7.996562^{**} (3.560856)
$Earthquake$	9.346277^{**} (3.910353)	9.720624^{**} (3.910353)	14.32392^{***} (4.533598)	13.61853^{***} (4.43326)
$Tsunami$	29.58473^{***} (9.742156)	29.77207^{***} (9.676018)	22.34297^{**} (10.23278)	20.94611^{**} (10.11857)
$Drought$	13.58754^{***} (3.362266)	13.64486^{***} (3.302922)	15.00415^{***} (3.581501)	14.52061^{***} (3.493365)
$Volcano$	6.768336 (6.163206)		1.757915 (6.768336)	
$Avalanch$	1.84092 (4.241369)		4.593298 (4.504904)	
$Extremetemp$	-13.1667^{**} (5.397098)	-13.74467^{***} (5.354032)	-15.82023^{***} (6.362575)	-16.73173^{***} (6.32152)
$Epidemic$	-1.968907 (3.055019)		0.3275552 (3.439476)	
$Storm$	6.852578^{**} (3.204247)	7.097234^{**} (7.097234)	2.472262 (3.907754)	
$Wildfires$	-7.586214 (6.139343)		2.929514 (6.631624)	