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# Predicting International Aid in the Face of Natural Disaster: A Study of Inequality and Corruption

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# PREDICTING INTERNATIONAL AID IN THE FACE OF NATURAL DISASTER:

# A STUDY OF INEQUALITY AND CORRUPTION

By

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A thesis submitted in partial fulfillment of the requirements of graduation with

WHARTON RESEARCH SCHOLARS

From the departments of

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## I. Introduction

A report from the New England Journal of Medicine reported a steady increase in the number of natural disasters[1] in the past few decades with over two million people reported killed between 1980 and 2004 according to the Centre for Research on the Epidemiology of Disaster (CRED). This problem has been compounded by the number of climate-related incidents such as storms and floods. In addition to the increasing frequency, the expanding scope of damage of natural disasters has been concerning for the international community at large[2]. It becomes more pressing, then, to further explore and understand the drivers of recovery and any political-economic factors that may contribute to this goal.

Inequality and corruption as some of these facets have received much attention from institutional scholars and economists alike but have not yet been studied in the context of post-disaster recovery. This paper, then, will examine inequality and corruption, specifically in its ability to predict international aid that flows into a country in the aftermath of a natural disaster to meet the immediate and long-term goals of the affected country. The paper find corruption, measured through Transparency Internationals' Corruption Perception Index, controlled for estimated damage and number of people killed has a coefficient of -0.48 in predicting the log of total international donations, significant at a five percent level. The Gini coefficient, on the other hand, as a proxy for inequality was found to have a significant coefficient of -0.057 at the 10 percent level.  The two results are seemly contradictory: while higher inequality is correlated with lower donation, higher corruption is correlated to higher

[1] Leaning, J., & Guha-Sapir, D. (2013). Natural disasters, armed conflict, and public health. *N Engl J Med*, *369*(19), 1836-1842.

[2] Riebeek, H. (2005, March 25). The Rising Cost of Natural Hazards : Feature Articles. Retrieved April 25, 2016, from http://earthobservatory.nasa.gov/Features/RisingCost/

donations. The implication behind this finding appears to be that though corruption and inequality are loosely related, they have different relationship with donations. While the result cannot speak to the casual relationship of inequality and corruption with international donations, it provides fertile ground for future research.

## II. Literature Review

Due to the increasing number and scope of natural disaster, there is a rich body of literature to better understand factors that drive resilience, or the ability to “bounce back” from natural disasters. Researchers have found that countries with higher income, educational attainment, and greater openness, more complete financial systems and smaller governments experience fewer losses[3]. Others note that social capital,[4] or networks, are key determinants of recovery, especially at a community level. Moreover, as most victims of natural disasters live in low-income countries with limited resources, donations from “richer countries could play a key role” in meeting immediate needs and working towards long-term recovery, according to Stromberg[5]. A study by Becerra and his colleagues found that the median increase in Official Development Assistance in the aftermath of large natural disasters was 18 percent[6], showing that the international community does respond to the needs of the affected country in its assistance for development. While some scholars argue that international disaster assistance, especially U.S. foreign aid is shown to be the most

[3] Toya, H., & Skidmore, M. (2007). Economic development and the impacts of natural disasters. *Economics Letters*, *94*(1), 20-25.
[4] Aldrich, D. P. (2011). The power of people: Social capital's role in recovery from the 1995 kobe earthquake. *Natural Hazards, 56*(3), 595-611.
[5] Strömberg, D.. (2007). Natural Disasters, Economic Development, and Humanitarian Aid. *The Journal of Economic Perspectives*,*21*(3), 199–222.
[6] Becerra, O., Cavallo, E., & Noy, I. (2014). Foreign aid in the aftermath of large natural disasters. *Review of Development Economics*, *18*(3), 445-460

prominently determined by foreign policy and domestic consideration,[7] international aid in the face of natural disaster plays a key role in funding the needs of the affected country. Of interest is how inequality and corruption, which has economic, political and societal implications on the standing of a nation in the international community.

First, we examine the body of literature surrounding inequality. While inequality can refer to disparities in consumption, income or wealth, this paper will focus on income disparity, as measured by the Gini coefficient for consistency of data. In the context of development, perhaps the most renowned theory is known as the Kuznet's curve, proposed by Simon Kuznet in the 1950s. His groundbreaking theory proposed an inverted "U" relationship between inequality and per capita income[8]. The rationale behind this proposal was that with rapid industrialization, and accordingly, the centralization of wealth in cities, the benefits will not be evenly distributed among citizens. While his theory has been criticized by the existence of counterexamples, most notable, the economic development of East Asian countries, including Japan, South Korea, Hong Kong, Taiwan and Singapore[9], Kuznet provides an interesting framework in which to understand level of development and inequality.

Inequality, on a societal level, is shown to have significant effects, including increased mortality rates for the poor and reduction in social cohesion.[10] While both have alarming

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[7] Drury, A. C., Olson, R. S., & Belle, D. A. V. (2005). The politics of humanitarian aid: U.S. foreign disaster assistance, 1964?1995. *Journal of Politics,67*(2), 454-473.
[8] Kuznets, S.. (1955). Economic Growth and Income Inequality.*The American Economic Review*, *45*(1), 1–28.
[9] Stiglitz, J. E. (1996). Some lessons from the east asian miracle. *The World Bank Research Observer*, *11*(2), 151-177
[10] Kawachi, Ichiro, et al. "Social capital, income inequality, and mortality."*American journal of public health* 87.9 (1997): 1491-1498.

considerations, reduction in social cohesion, otherwise known and social capital have wide-stretching ramifications for the economic growth of a nation. Knack and Keefer[11] were some of the first to provide evidence that "social capital" matters for measurable economic performance. Many institutionalists agree that this link is perhaps due to the link between social capital and generalized trust[12] and since higher generalized trust is shown to lower the cost of doing business, inequality is a noteworthy factor in rebuilding of an economy post-disaster. Furthermore, Robert Barro from the National Bureau of Economic Research found that higher inequality tends to retard growth in poor countries and encourage growth in richer places[13], which is reminiscent of Kuznet's theory discussed previously.

Corruption, like inequality, has multiple definitions. One of the definitions, which this paper will focus on for this paper, is "perversion or destruction of integrity in the discharge of public duties by bribery or favor.[14]" Most common form of measurement is through Transparency International's Corruption Perception Index, which through expert opinion attempts to capture the perceived level so public sector corruption worldwide. While some researchers have found that in the face of deficient institution frameworks, corruption increases efficiency[15], many have also found that corruption lower investments, thereby lowering economy growth[16]. The interplay between corruption and income inequality has been previously examined by Gupta, Davoodi and Alonso-Terme at the International

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[11] Knack, S., & Keefer, P. (1997). Does social capital have an economic payoff? A cross-country investigation. *The Quarterly Journal of Economics,112*(4), 1251-1288.
[12] Rothstein, B., & Stolle, D. (2008). The state and social capital: An institutional theory of generalized trust. *Comparative politics*, 441-459.
[13] Barro, R. J. (1999). *Inequality, growth, and investment* (No. w7038). National Bureau of Economic Research.
[14] Theobald, R. (1990). What is Corruption?. In *Corruption, Development and Underdevelopment* (pp. 1-18). Palgrave Macmillan UK.
[15] Méon, P. G., & Weill, L. (2010). Is corruption an efficient grease?. *World development*, *38*(3), 244-259.
[16] Mauro, P. (1995). Corruption and growth. *The quarterly journal of economics*, 681-712.

Monetary Fund in 2001, who found there is evidence of high and rising corruption increasing income inequality and poverty in a country[17]. Moreover, they note that the relationship may be explained by the fact that corruption interferes with one of the core functions of government, namely, the redistribution of income from the rich to the poor.

Overall, the literature review of inequality and corruption exemplify effect of inequality and corruption for growth, which is a crucial question in the sense that natural disasters are supposed to set back growth for a decade in the affected country. Donations, help bridge that gap, so if corruption and inequality affect donations, too, could provide policy implications that further emphasize the importance of improving transparency and equity in countries that are prone to natural disasters.

# I. Methodology

## *A. Data Set*

The dataset covers all major natural disasters worldwide from 2003 and 2013. The variable of interest, grand total of international aid was tracked taken from publicly available data from Office of Coordination of Humanitarian Affairs (OCHA) Financial Tracking Service (FTS), which "records all reported humanitarian aid contributions," according to its website.

Then, total affected, fatalities, estimated damage (in millions of USD) information was obtained from EM-DAT, the International Disaster Database, maintained by the Centre for

[17] Gupta, S., Davoodi, H., & Alonso-Terme, R. (2002). Does corruption affect income inequality and poverty?. *Economics of governance*, *3*(1), 23-45.

Research on the Epidemiology of Disaster and matched with information gathered through FTS. Gini Coefficient, Population and GDP information was taken from the World Bank's Database and also recorded. Finally, the Corruption Perception Index (CPI), a measure of corruption within the affected country, was accessed from Transparency International's database.

If the data was missing any of the listed variables, the entry was dropped for incomplete information. The data was then narrowed to focus on storms, earthquakes and floods, the predominant natural disaster type in the data set. Explicitly, the removal of mass movement and volcano activity removed 17 observations from the data set.  This resulted in a sample size of 1101 with a mean of around 86 MM USD of grand total in international donation. The model was fitted using JMP, a statistical software.

*B. Independent Variable*

The metric of interest is the dollar amount of donations, labeled "grand total" in the data set. The FTS database, from which the independent variable was recorded, does provide a reliable and comprehensive tracking of international aid by natural disaster. There are, however, a few things to note about the dataset. First, the data set is heavily skewed by a few data points including (Table 1), Earthquake in Japan 2010, Typhoon in the Philippines in 2013 and Indian Earthquake in 2005, which are outliers in the amount of donations that it has received.

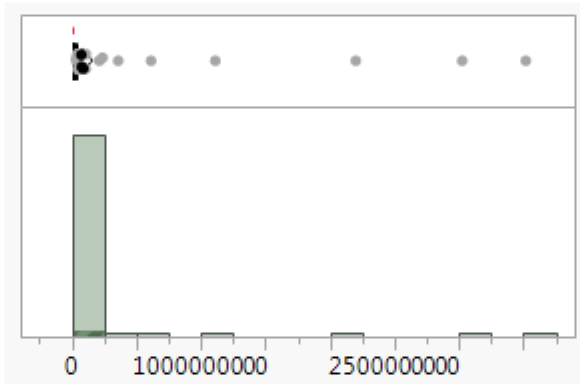


*Figure 1 Distribution of Grand Total of International Aid*

To temper the effect of these outliers, the logarithm of the independent (Table 2) is fitted against dependent variables. The transformed independent variable provides a relatively normal distribution. Second, the donations are a combination of aid from countries, organizations, corporations, foundations and religious groups. The donation was donated either directly to the bilateral, meaning the affected government, or to an external party, often the Red Cross or other UN-affiliated organizations.

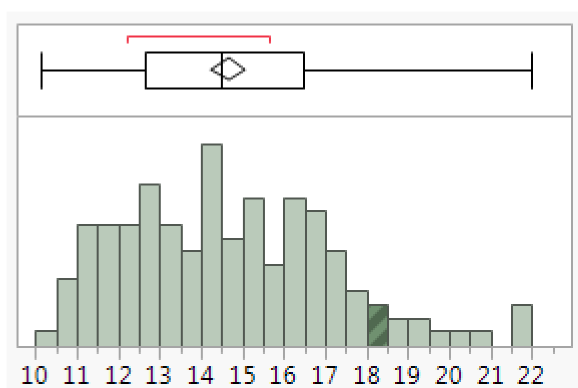


*Figure 2 Distribution of Log Grand Total of International Aid*

### *C. Dependent Variables*

All variables that were initially collected as part of the data set were analyzed for correlation. The top indicators were picked based on independence from each other. In particular, total affected was dropped due to its correlation with killed and GDP/ capita was dropped due to its high correlation with estimated damages. At the end the following four variables were chosen for the base model.

i) Estimated Damages: measured in millions of dollars, estimated damages, for the purposes of consistency were based off an external estimate done by the EM-DAT.

ii) Fatalities: similar to estimated damages, in order to ensure integrity of the data, the measurements were taken by EM-DAT, an external source that measured the casualties of each disaster. The units are in number of persons that was killed the disaster.

iii) Gini: measured from zero to 100, the Gini coefficient is regularly measured by a variety of organizations. The data was again taken from the World Bank to mediate potential biases that may arise from self-reported Gini coefficients. A higher Gini indicates a more unequal distribution of income.

iv) CPI: Measured on a scale of zero to ten, measured to the first decimal point, CPI is recorded by Transparency International, an independent organization.

## II. Results and Discussion

### *A. Base Model*

Based on literature and previous work, a few preliminary analysis was done to identify dependent variables, along with interaction variables that were promising candidates. Finding that the number of people killed, disaster type and estimated damages have significant coefficients. The basic model came with a relatively weak R-square of .225 with 141 observations analyzed. The results of effects test and parameter estimates are outlined below in Table 1 and 2 respectively.

TABLE 1— EFFECTS TEST OF BASE MODEL

| **Source** | **Nparm** | **DF** | **Sum of Sq.** | **F Ratio** | **Prob > F** |
|---|---|---|---|---|---|
| Disaster Type | 2 | 2 | 39.663235 | 3.8981 | 0.0226* |
| Killed | 1 | 1 | 76.092259 | 14.9566 | 0.0002* |
| Est. Damage (US$ Million) | 1 | 1 | 27.883615 | 5.4808 | 0.0207* |

TABLE 2— PARAMETER ESTIMATES OF BASE MODEL

| **Term** | **Estimate** | **Std Error** | **t Ratio** | **Prob>\|t\|** |
|---|---|---|---|---|
| Intercept | 14.661137 | 0.20779 | 70.56 | <.0001* |
| Disaster Type[Earthquake (seismic | 0.4566157 | 0.324334 | 1.41 | 0.1615 |
| Disaster Type[Flood] | -0.733836 | 0.263693 | -2.78 | 0.0062* |
| Killed | 3.2859e-5 | 8.496e-6 | 3.87 | 0.0002* |
| Est. Damage (US$ Million) | 0.0000243 | 1.038e-5 | 2.34 | 0.0207* |

The results signify that the variables Killed and Est. Damages has a positive relationship with log of total donations, while the categorical variable of disaster flood has a different effect on the independent variable based on if the disaster is an earthquake or a flood. The addition of an interaction variable, Disaster Type*Killed create a model that has a higher R-squared of 0.27. The findings are summarized in Table 3 and 4 below.

TABLE 3— EFFECTS TEST OF BASE MODEL W/ INTERACTION VARIABLE

| **Source** | **Nparm** | **DF** | **Sum of Sq.** | **F Ratio** | **Prob > F** |
|---|---|---|---|---|---|
| Disaster Type | 2 | 2 | 36.249091 | 3.7719 | 0.0255* |
| Killed | 1 | 1 | 50.645312 | 10.5398 | 0.0015* |

| | | | | | |
|---|---|---|---|---|---|
| Est. Damage (US$ Million) | 1 | 1 | 26.113653 | 5.4345 | 0.0212* |
| Disaster Type*Killed | 2 | 2 | 48.011674 | 4.9958 | 0.0081* |

TABLE 4— PARAMETER ESTIMATES OF BASE MODEL W/ INTERACTION VARIABLE

| **Term** | **Estimate** | **Std Error** | **t Ratio** | **Prob>\|t\|** |
|---|---|---|---|---|
| Intercept | 14.534236 | 0.206018 | 70.55 | <.0001* |
| Disaster Type[Earthquake (seismic | -2.506358 | 1.002297 | -2.50 | 0.0136* |
| Disaster Type[Flood] | 5.2174961 | 1.924216 | 2.71 | 0.0076* |
| Killed | 0.0008953 | 0.000276 | 3.25 | 0.0015* |
| Est. Damage (US$ Million) | 0.0000236 | 1.013e-5 | 2.33 | 0.0212* |
| Disaster Type[Earthquake (seismic | -0.000865 | 0.000276 | -3.14 | 0.0021* |
| Disaster Type[Flood]*(Killed-3616.27) | 0.0017209 | 0.000551 | 3.12 | 0.0022* |

The summary shows us that while the former directional relationship holds, the percentage change of donations based on changes in number of people killed depends on the type of disaster. We will look at both of the base models in examining the fit of the model with the addition of the Gini coefficient and the Corruption Perception Index.

### *B. Effect of inequality on international aid amount*

Adding Gini coefficient to the model, the logarithm of the grand total of international donations is fitted against disaster type, killed, estimated damage and Gini coefficient. The effects test is summarized below in Table 5.

TABLE 5— EFFECTS TEST OF MODEL W/GINI

| **Source** | **Nparm** | **DF** | **Sum of Sq.** | **F Ratio** | **Prob > F** |
|---|---|---|---|---|---|
| Disaster Type | 2 | 2 | 45.610931 | 4.3890 | 0.0145* |
| Killed | 1 | 1 | 63.552220 | 12.2310 | 0.0007* |
| Est. Damage (US$ Million) | 1 | 1 | 25.907353 | 4.9860 | 0.0275* |
| Gini | 1 | 1 | 22.578063 | 4.3453 | 0.0393* |

The R-squared for this model is 0.24, higher than the R-squared of the base model without interaction. The interaction variable was then fitted to understand if the interaction variable would help explain more of the noise in the model. The findings are summarized in Table 6.

TABLE 5— EFFECTS TEST OF MODEL W/GINI AND INTERACTION VARIABLE

| **Source** | **Nparm** | **DF** | **Sum of Sq.** | **F Ratio** | **Prob > F** |
|---|---|---|---|---|---|
| Disaster Type | 2 | 2 | 39.100171 | 4.1054 | 0.0190* |
| Killed | 1 | 1 | 62.862825 | 13.2009 | 0.0004* |
| Est. Damage (US$ Million) | 1 | 1 | 24.356357 | 5.1147 | 0.0256* |
| Gini | 1 | 1 | 10.038624 | 2.1081 | 0.1492 |
| Disaster Type*Killed | 2 | 2 | 60.301565 | 6.3315 | 0.0025* |

The R-squared for this model is 0.323. Like what we found in the base model, the interaction variable accounts for much more of the data and is found to have a significant coefficient. What is unexpected, however, is how the Gini coefficient became an insignificant variable at both the five and ten percent confidence level with the addition of the interaction variable. This points to the fact that the interaction variable has an interaction with the disaster type*killed variable. Based on the higher p-value shown in the disaster type F-test in the model with Gini and Interaction Variable, it is likely that the disaster type is related to the Gini. A potential explanation for this finding is the idea that certain disasters are more likely to happen to a set number of countries. For example, the Philippines is more likely to experience storms and typhoons, rather than earthquakes. Since the Philippines has a set Gini for every year, the disaster type may help indirectly tell the same story the Gini is telling in predicting percentage change in total donations. The parameter estimates of the base model with Gini is summarized below in

Table 6 for an understanding about the nature of the relationship between Gini and log of grand total of international donation.

TABLE 6— PARAMETER ESTIMATES OF BASE MODEL W/ GINI

| **Term** | **Estimate** | **Std Error** | **t Ratio** | **Prob>\|t\|** |
|---|---|---|---|---|
| Intercept | 16.894684 | 1.130068 | 14.95 | <.0001* |
| Disaster Type[Earthquake (seismic | 0.4676741 | 0.350672 | 1.33 | 0.1849 |
| Disaster Type[Flood] | -0.83167 | 0.281636 | -2.95 | 0.0038* |
| Killed | 3.6127e-5 | 1.033e-5 | 3.50 | 0.0007* |
| Est. Damage (US$ Million) | 2.358e-5 | 1.056e-5 | 2.23 | 0.0275* |
| Gini | -0.056867 | 0.02728 | -2.08 | 0.0393* |

The table shows us that the Gini and the log of the independent variable have a significant coefficient estimate of -.0569. A negative relationship implies that the increase of inequality leads to a decrease in the percentage change in international donations.

### C. *Effect of corruption on international aid amount*

In a similar fashion to the exploration of Gini, the CPI is added to the base model, fitted with estimated damages, number of people killed and disaster type. The findings of the effects test are summarized in Table 6 below. The R-squared of this model was .285, a higher fit than both the base model and the base model with the addition of the Gini.

Table 6— Effects test of model w/CPI

| Source | Nparm | DF | Sum of Sq. | F Ratio | Prob > F |
|---|---|---|---|---|---|
| Disaster Type | 2 | 2 | 45.781633 | 4.6596 | 0.0112* |
| Killed | 1 | 1 | 53.429486 | 10.8761 | 0.0013* |
| Est. Damage (US$ Million) | 1 | 1 | 55.349760 | 11.2670 | 0.0010* |
| CPI | 1 | 1 | 38.578112 | 7.8529 | 0.0059* |

The CPI is highly significant in this model. The parameters test summarized in Table 7 reveals more about the nature of the relationship between CPI and donation amount.

Table 7— Parameter Estimates of base model w/ CPI

| Term | Estimate | Std Error | t Ratio | Prob>\|t\| |
|---|---|---|---|---|
| Intercept | 16.111165 | 0.579098 | 27.82 | <.0001* |
| Disaster Type[Earthquake (seismic | 0.5887066 | 0.33233 | 1.77 | 0.0789 |
| Disaster Type[Flood] | -0.818444 | 0.268202 | -3.05 | 0.0028* |
| Killed | 2.817e-5 | 8.542e-6 | 3.30 | 0.0013* |
| Est. Damage (US$ Million) | 3.7381e-5 | 1.114e-5 | 3.36 | 0.0010* |
| CPI | -0.480505 | 0.171468 | -2.80 | 0.0059* |

The parameter estimate noted above for the CPI is -.0.48, which indicates an inverse relationship between CPI and the log of grand total of donations. While both the coefficient is negative, the result of this model gives us a puzzling result: the more corrupt the nation, the higher the log of grand total of international aid.

We now examine the effect of the addition of the interaction variable on the result of the model. The effects test of the base model with CPI and interaction variable are summarized below in Table 8.

Table 8— Effects test of model w/CPI and Interaction variable

| Source | Nparm | DF | Sum of Sq. | F Ratio | Prob > F |
|---|---|---|---|---|---|
| Disaster Type | 2 | 2 | 27.103965 | 2.8788 | 0.0600 |

| | | | | | |
|---|---|---|---|---|---|
| Killed | 1 | 1 | 37.061992 | 7.8729 | 0.0058* |
| Est. Damage (US$ Million) | 1 | 1 | 49.453672 | 10.5051 | 0.0015* |
| CPI | 1 | 1 | 30.918673 | 6.5679 | 0.0116* |
| Disaster Type*Killed | 2 | 2 | 35.041427 | 3.7218 | 0.0270* |

The R-square of this variable is 0.326, showing a similar fit to the addition of the interaction variable for the Gini coefficient. Though CPI seems to be a more robust indicator, it is clear that CPI and Gini are related in some way, which takes away from each other. A quick scatterplot shows us that the two are weakly related with an R factor of 0.112. This seems to align with findings by Gupta et al. which notes that higher corruption is positively correlated with higher inequality and poverty rates[18].

### D. *Effect of both inequality and corruption on aid amount*

A fit of the model with both CPI and Gini variables confirm that this relationship does in fact disperse the effect of the CPI and Gini. The combination, does however, produce a slightly higher R-squared factor of 0.291, pointing to the fact that while the two are related, they do in fact measure disparate aspect of society that cannot be substituted for each other. The effects test for the base model with Gini and CPI are summarized in Table 9 below.

TABLE 9— EFFECTS TEST OF MODEL W/GINI AND CPI

| **Source** | **Nparm** | **DF** | **Sum of Sq.** | **F Ratio** | **Prob > F** |
|---|---|---|---|---|---|
| Disaster Type | 2 | 2 | 48.699582 | 4.7828 | 0.0102* |
| Killed | 1 | 1 | 45.976590 | 9.0308 | 0.0033* |

[18] Gupta, S., Davoodi, H., & Alonso-Terme, R. (2002). Does corruption affect income inequality and poverty?. *Economics of governance*, *3*(1), 23-45.

| | | | | | |
|---|---|---|---|---|---|
| Est. Damage (US$ Million) | 1 | 1 | 45.458721 | 8.9290 | 0.0035* |
| Gini | 1 | 1 | 15.612705 | 3.0667 | 0.0827 |
| CPI | 1 | 1 | 21.635360 | 4.2496 | 0.0416* |

While there is definitely a dispersion of effect with the combination of Gini and CPI to the model, at the 10 percent level both Gini and CPI seems to have an effect on the log of grand total of aid. As we have done in the models previously, the disaster*killed interaction variable is added for comparison purposes. The effects test is summarized in Table 10 below.

TABLE 10— EFFECTS TEST OF MODEL W/GINI, CPI AND INTERACTION VARIABLE

| **Source** | **Nparm** | **DF** | **Sum of Sq.** | **F Ratio** | **Prob > F** |
|---|---|---|---|---|---|
| Disaster Type | 2 | 2 | 31.914883 | 3.3961 | 0.0371* |
| Killed | 1 | 1 | 54.989636 | 11.7031 | 0.0009* |
| Est. Damage (US$ Million) | 1 | 1 | 39.158273 | 8.3338 | 0.0047* |
| Gini | 1 | 1 | 7.488542 | 1.5937 | 0.2095 |
| CPI | 1 | 1 | 15.024206 | 3.1975 | 0.0766 |
| Disaster Type*Killed | 2 | 2 | 52.561016 | 5.5931 | 0.0049* |

R square of 0.357 for the model shown in Table 10 show that the best fit among all the models seen in this paper is one in which the Gini, CPI and Disaster Type*Killed variable are all included. However, the F-ratio for the Gini Coefficient is less than one with the p-value being extremely high. CPI, on the other hand seems to withstand the dispersion effect and remains significant at the 10 percent confidence level.

TABLE 11— PARAMETER ESTIMATES OF BASE MODEL W/ CPI AND GINI

| Term | Estimate | Std Error | t Ratio | Prob>\|t\| |
|---|---|---|---|---|
| Intercept | 17.879669 | 1.179818 | 15.15 | <.0001* |
| Disaster Type[Earthquake (seismic | 0.5516388 | 0.36998 | 1.49 | 0.1388 |
| Disaster Type[Flood] | -0.884371 | 0.286089 | -3.09 | 0.0025* |
| Killed | 3.1887e-5 | 1.061e-5 | 3.01 | 0.0033* |
| Est. Damage (US$ Million) | 3.4733e-5 | 1.162e-5 | 2.99 | 0.0035* |
| Gini | -0.049563 | 0.028303 | -1.75 | 0.0827 |
| CPI | -0.410788 | 0.19927 | -2.06 | 0.0416* |

TABLE 12— PARAMETER ESTIMATES OF BASE MODEL W/ CPI, GINI AND INTERACTION VARIABLE

| Term | Estimate | Std Error | t Ratio | Prob>\|t\| |
|---|---|---|---|---|
| Intercept | 16.86254 | 1.174379 | 14.36 | <.0001* |
| Disaster Type[Earthquake (seismic | -2.671555 | 1.033753 | -2.58 | 0.0111* |
| Disaster Type[Flood] | 2.5975463 | 1.747185 | 1.49 | 0.1400 |
| Killed | 0.0011409 | 0.000334 | 3.42 | 0.0009* |
| Est. Damage (US$ Million) | 3.2312e-5 | 1.119e-5 | 2.89 | 0.0047* |

Tables 11 and 12 above do not provide any new insights, but rather show us consistency of the relationships that have been identified in other trials of the model; mainly, that Gini and CPI both have a negative relationship with the independent Y variable.

### *E. Final Discussion*

The results section has provided a wealth of interesting sights as it pertains to the original questions. Most notably the Corruption Perception Index seems to have a robust relationship with the donations. As aforementioned, it seems puzzling that a more corrupt government enjoys greater amounts of donations pouring into the economy after a natural disaster. A closer look at the dataset provides a potential explanations: these donations trickle into two channels; external agencies and bilateral governments. It is possible that the higher percentage of donations for every unit change in CPI is due to an increase in flow to external agencies because the international community does not trust the government to take care of the needs of all of the affect. Rather, it may potentially privilege the socially elite.

The Gini coefficient, while has a weaker relationship and its relationship should be re-examined,[19] seems to provide a more intuitive answer. Inequality, like corruption, affects the distribution of resources. A negative parameter estimate for the Gini indicate that a more unequal country may get more donations. The potential explanation may be to help those at the bottom of the pyramid in the recovery process. While the study is not casual in any way, and a very different study would have to be conducted to examine if corruption and inequality actually drive differing donation amounts, this study does find a significant relationship.

Finally, an unintentional but nevertheless interesting finding is in the dispersion effect created by the disaster*killed interaction variable on inequality and corruption. While there is no conclusive findings as to their relationship, curiosity is peaked as to the potential connection. Is it that even with the same disaster type, different numbers of people become casualties based on a country's inequality and corruption profile? One can imagine a situation where there is death at impact of the disaster but also death in the aftermaths of the disaster that is intertwined with the access to resources. While other future research considerations will be discussed in greater depth in the next section, the finding begs a deeper exploration of the relationship.

## III. Limitations and Future Research

The study provides preliminary findings on the relationship between inequality, corruption and donation of aid. Regardless, there are clear limitations of the study. First, by the pure fact

[19] See next section for potential next steps for re-examination of Gini coefficient data

that this is a statistical analysis of phenomenon, there is a lot of noise. With the R-square factor of .35, the model is not comprehensive in identifying the factors that drive aid donations during natural disasters. While it is to be expected of real-world data, it is regardless a limitation worth noting.

Second, a closer look at the data identified not only is a disaster type more likely to occur to some countries, but those countries geologically vulnerable to natural disasters will occur repeatedly. Since there is only one Gini coefficient, those country's Gini coefficients are weighted more heavily than other that may have fewer disasters in the data set.

Finally, outliers, mediated for the independent variable through logarithm exist for the dependent variables as well. The Nepalese and Japanese earthquakes had significantly higher deaths than the typical earthquake, skewing the data. The highly irregular data points make estimation difficult.

Moving forward, an examination of bilateral versus external donations of a country based on their corruption profiles will be worthwhile study in more closely identifying the relationship between corruption and international disaster aid.

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