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Abstract. This paper uses inter-country panel data obtained during the period 1990–2010 to examine how the occurrence of natural disasters has affected corruption within the public sector. There are a number of new findings from this study. (1) Disaster with the large amount of damage increase corruption not only for developing countries but also for developed countries. (2) The effect of disasters is greater in developed countries than in developing countries. (3) In the developed countries, frequency of occurrence of disaster plays important role on increasing corruption. This suggests that foreseeable disasters increase corruption. In developed countries, people have an incentive to live within disaster-prone areas to seek compensation.

Keywords: Corruption, Institution, Disasters, Risk

JEL classification: D73; D81; Q54

1. Introduction

The devastating damage caused by natural disasters such as Hurricane Katrina in 2005 and the Great East Japan Earthquake in 2011 has led researchers to address disaster-related issues (Eisensee & Strömberg 2007; Luechinger & Saschkly 2009). Disasters have been observed to have critical influence on modern society with regard to the political economy[1]. It has been shown that in addressing the damage caused by natural disasters, low-quality governance, characterized by corruption and income inequality, increases the death rate (Anbarci et al. 2005; Kahn 2005; Escaleras et al. 2007)[2]. The occurrence of natural disasters appears to affect the cost and incentive structures faced by bureaucrats as well as individuals, which include the victims of the disasters[3]. Public sector corruption is one of the major issues of concern when considering the interaction between politics and economics[4] (e.g., Glaeser & Saks 2006; Gokcekus 2008; Apergis et al. 2010; Dreher & Schneider 2010; Escaleras et al. 2010; Johnson et al. 2011; Swaleheen 2011). Natural disasters possibly generate an incentive to practice corruption, which is generally defined as the use of public office for private gain (Boettke et al. 2007; Leeson & Sobel 2008).

As observed in the United States, individuals abuse disaster relief windfalls. For instance, public employees were accused of soliciting bribes from relief-funded contractors and of overbilling the government (Leeson & Sobel 2008). Similarly, the misuse of reconstruction funds was revealed in the case of the Great East Japan Earthquake, when it was reported that "a special account budget to fund the reconstruction of communities devastated by the 3/11 earthquake, tsunami, and nuclear disasters has been used to pay for unrelated projects" (Japan Times 2012). For instance,

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[1] In particular, after entering the 21st century, a growing number of researchers are attempting to investigate the impact of natural disasters on economic growth (Skidmore & Toya 2002; Strobl 2011), death toll (e.g., Anbarci et al. 2005; Kahn 2005; Toya & Skidmore 2007), and trust (Skidmore & Toya 2013).

[2] Public sector corruption is also observed to increase the frequency of technological disasters (Yamamura 2013).

[3] Existing researches explore the realtion between disaster and moral hazard problem (Simmons et al., 2002; Shiue, 2004).

[4] In part, because of the limitations of data on corruption, there are few empirical analyses of corruption before the 1990s, although a number of classical anecdotal and theoretical research works existed (Leff 1964; Lui 1985; Shleifer & Vishny 1993; Jain 2001). The seminal work of Mauro (1995) was the first to explore empirically the effects of corruption. Subsequently, the number of empirical works on corruption have mushroomed (e.g., Anbarci et al. 2006; Glaeser and Saks 2006; Apergis et al. 2010; Dreher & Schneider 2010; Escaleras et al. 2010; Johnson et al. 2011; Swaleheen 2011).

some money earmarked for reconstruction work was spent improperly on projects to improve the earthquake resistance in buildings of the central government's local branch offices and on measures to deal with anti-whaling groups (Daily Yomiuri, 2013). Such an undesirable situation can be explained within the framework of public choice theory as follows. Government is anticipated to play a leading role in reconstruction and so allocates a budget for that purpose. In this case, various groups related to public works attempt to receive orders from the government. However, because of information asymmetry or the support of favor-based politicians, groups are able to seek benefits even though their works are not associated with reconstruction. Conversely, it has been observed that the occurrence of disasters gives politicians an incentive to misallocate disaster expenditure to increase the probability of their re-election (Garrett & Sobel 2003). Consequently, this allocative failure prevents disaster relief from reaching those who need it most (Sobel & Leeson 2006).

Empirical analysis of the impact of disasters on corruption is considered instructive for designing appropriate incentive schemes to deal with disasters. The seminal work of Leeson & Sobel (2008), based on the Panel data of the United States[5], provided evidence that disaster relief windfalls increased corruption. There are various types of disaster and the existing literature claims that the different characteristics of disasters possibly influence the outcome (e.g., Skidmore & Toya 2002; Kahn 2005; Kellenberg & Mobarak 2008;Toya & Skidmore 2012). Frequency and damage per disaster are considered to be very different according to types of disaster. One type of disaster frequently occurs and its damage per disaster is small. Another type of disaster rarely occurs and its damage per disaster is large. However, total damage of the former type is possibly equivalent to that of the latter type. Furthermore, it has been observed that the effect of natural disasters differs between developing and developed countries (Toya & Skidmore 2007; Cuaresma et al. 2008).

The purpose of this paper is to explore how and the extent to which effect of disaster on corruption differ among characteristics of disaster and conditions of stricken country because there is no work to examine it. For this purpose, this paper used panel data from 84 countries for a 21-year period obtained between 1990 and 2010. The new findings of this paper are as follows; (1) Disaster with the large amount of damage increase corruption not only for developing countries but also for developed countries. (2) The effect of disasters is greater in the developed countries than in the developing

[5] Many works attempted to ascertain the determinants of corruption (Treisman 2000; Paldam 2001; Serra 2006; Pellegrini & Gerlagh 2008).

countries. (3) In the developed countries, frequency of occurrence of disaster plays more important role on increasing corruption.

The remainder of the paper is organized as follows: section 2 proposes theoretical consideration and the testable hypotheses. In section 3, an overview of disasters is provided and the data and methods used are explained. Section 4 discusses the results of the estimations and the final section offers concluding remarks.

2. Theoretical considerations and Hypotheses

2.1. Hypotheses

Theoretical works indicate that natural resources increases the number of entrepreneurs engaged in rent seeking (Baland and Francois 2000; Torvik 2002). Robinson et al. (2006) provides the theoretical model showing that the amount of resources that politician can use for the self-interest causes resources misallocation. Countries with higher rents stemming from natural resources tend to have higher levels of corruption (Ades and Di Tella 1999; Pedro 2010). Apart from natural resources, the similar observation is provided. Foreign aid is associated with rent seeking activities and so higher corruption (Svensson 2000). That is, additional government revenues increase corruption (Brollo et al., 2013). Similar to the cases of foreign aid, disaster gmenerates the windfall, which increase corruption. Natural disasters inevitably increase the government expenditure for reconstruction. The expenditure is efficiently allocated and effectively used if individuals and government officers do not behave to increase self interest at the expense of rest of the society. However, the occurrence of natural disasters is thought to generate rents.

In this paper, following the Svensson (2000), the situation is simply described as below: An economy consist of *n* social groups. When disaster occurs, increase of the government expenditure for the reconstruction in t year is $y(m_t, s_t)$. m_t represents the number of natural disasters in *t* year and $\partial y/\partial m_t > 0$. s_t represents the total damage of natural disasters in *t* year and $\partial y/\partial s_t > 0$.. Expenditure can be appropriated by each individual social group. Appropriation of common resources is costly and so rent seeking outlays by group *i* is expressed as c_{it}. The total appropriation equal is expressed as:

$$z_{it} = y(m_t, s_t)\frac{c_{it}}{\sum_{j=1}^{n} c_{it}} - c_{it}$$

Organized social groups can obtain a large share of government expenditure by manipulating the political system to implement favorable transfers. Its cost, c_{it}, is considered as bribe. Total appropriation is larger than 0 if $y(m_t, s_t)\frac{c_{it}}{\sum_{j=1}^{n} c_{it}} > c_{it}$. In this case, corruption increases. Furthermore, total damage of natural disasters increase the appropriation, $\partial z_{it}/\partial s_t > 0$. In addition, number of natural disasters increase the appropriation, $\partial z_{it}/\partial m_t > 0$.

The private According to the claim of Niskanen (1971), government bureaucrats seek to maximize the size of their budget, rather than deliver social benefit. Natural disasters possibly give bureaucrats the opportunity to increase their budget by using aid as a pretext. In the midst of a disaster, a government cannot observe the real situation in those areas affected. Information about the disaster is more abundant for the victims than for the government. Hence, there is information asymmetry regarding the damage caused by the disaster between the victims and the bureaucrats. Accordingly, victims can encourage the government to compensate excessively for damage caused by the disaster.

Disaster-related benefits can be regarded as rents and as a consequence of disasters, victims under the influence of a bureaucrat enjoy the rents, and the value of controlling the rents is high. Hence, "bureaucrats can reap some of this value by surrendering their control rights in exchange for bribes" (Ades & Di Tella 1999, 983). Victims would pay bribes to obtain the rents if the cost of the bribe were sufficiently lower than the rents. Here, *Hypothesis 1* is proposed.

Hypothesis 1.
The level of public sector corruption increases when natural disaster occurs.

Leeson and Sobel (2008) argued that the larger the dollar amount of infused government relief, the more corruption is. The larger damage of disasters allows victims of disasters to request the larger the amount of government compensation. That is, the cost of damage is assumed to be positively associated with inflow of aid. Furthermore, if the residents are more inclined to become victims, then they are likely to receive some disaster-related compensation from the government. The more frequently that disaster occurs, the higher the expected disaster-related benefit. Individuals select a residential area by comparing the expected benefits and the predicted costs. This inference is consistent with the claim that "people who voluntarily put themselves in harm's way," are "taking on the additional risk of living and working in disaster-prone areas," and of "adequately insuring their lives" (Shughart II 2006, p.44). Thus, individuals reside in disaster-prone areas if the perceived benefit of residing there outweighs the cost. This leads to the proposal of *Hypothesis 2:*

Hypothesis 2:
The level of public sector corruption increases when the damage of disaster is large. The level also increases with high frequency of disasters.

3. Data and method

3.1. Overview of types of natural disaster

This paper uses country-level panel data generally used in previous works (e.g., Anbarci et al. 2006; Toya & Skidmore 2012; Yamamura 2013). As will be explained later, the number of natural disasters in each country was sourced from EM-DAT (Emergency Events Database). In addition, this paper uses a proxy for public sector corruption calculated based on data provided by the International Country Risk Guide (ICRG). This value is in the range 0–6, larger values indicate more corruption[6]. Figure 1 demonstrates the change in degree of corruption and the occurrence of natural disasters. It shows that both of degree of corruption and the occurrence of disasters tended to increase from 1992 to 2002 and then became constant. This trend suggests that the number of disasters has a positive association with the degree of corruption prior to 2002. From the inter-country viewpoint, Figure 2 presents the average number of disasters on the horizontal axis and corruption on the vertical axis for each county. The slope of the fitted line reveals a slightly positive association between them, indicating that natural disasters increase corruption. A similar relationship was also observed in the state-level data of the United States (Boettke et al. 2007; Leeson & Sobel 2008).

The characteristics of disasters differ, and thus, the disaggregation of disasters into various types provides useful information, enabling closer analysis. According to existing works (Skidmore & Toya 2002; Kahn 2005), disasters are classified into floods, storms, earthquakes, volcanic eruptions, landslides, and others[7]. Number of floods and

[6] The data of ICRG provided variable which is in the range 0–6, larger values indicate more corruption. In order to make it easier on their reader by simply inverting the score, In this paper, new variable is defined by 6 minus the original variable. Thus, countries with a score of 6 are now 0 and countries with 0 are now 6.
[7] Empirical results of this paper do not change when other classifications are employed.

storms are remarkably larger than other types of disasters. According to classification of EM-DAT, floods can be further divided into three sub-categories, such as general floods, flash floods and storm surges. Storms can be also further divided into three sub-categories, such as tropical storms, winter storms and local windstorm[8]s. Among them, number of general floods and tropical storms are distinctly larger. Hence, in this paper, floods are divided into general floods and other floods (flash floods and storm surges). Storms are divided into tropical storms and other storms (winter storms and local windstorm). Figure 3 shows frequency of each disaster (number of disasters per land), which suggesting its probability of occurrence. It is obvious that general floods and tropical storms are frequently occurred. They occurred about 1.5 times per 10 thousands km^2 every year. Then, other floods occurred about 0.5 time per 10 km^2 every year. Floods and storms can be categorized as climatic disasters while Earthquakes, volcanic eruptions, and landslides can be categorized as geologic disasters (Skidmore & Toya 2002).

In comparison with geologic disasters, "climatic disasters tend to occur more frequently and during a particular time of the year. In addition, forecasting makes it possible for agents to protect themselves by taking cover or evaluating the afflicted region" (Skidmore & Toya 2002, 671). Hence, climatic disasters are thought to be a threat to property but not to life. Average damage measured by million US $ per disaster are illustrated in Figure 4[9]. The damage of an earthquake is approximately estimated as 2400 million US $, which is a significantly larger than that caused by other disasters. Apart from earthquake, the damage of tropical storms is considered as relatively large. The damage of tropical storms is approximately 200 million US $, which is roughly 3 times larger than that of general flood and other storm. The damage of other flood, volcanic eruption, and landslide is smaller than 20 million US $.

Table 1 summarizes the characteristics of disasters. The predicted cost is considered to be very large for earthquakes. Occurrence of earthquake is, however, very low. Apart from earthquake, cost of disasters is low or very low. Hence, victims of earthquake can request the larger amount of compensation than those of other disasters. Among low-cost disasters, occurrence of general floods, other floods, and tropical storms is

[8] Definition of classification can be see at the website of EM-DAT http://www.emdat.be/glossary/9. (Accessed on December 7, 2013).

[9] In EM-DAT, there are alternative values to measure the cost of disaster such as number of deaths, or number of injured. Their relative values in each disaster are almost the same as those illustrated in Figure 4. Hence, the argument of this paper does not change if other values are used to measure the cost of disaster.

frequent, suggesting their probability of occurrence is high. This causes residents in flood-prone areas and storm-prone areas to anticipate that they have opportunities to receive compensation. Considering them together leads to expect that relief from natural disasters such as earthquake, general floods, other floods, and tropical storms, could possibly trigger a moral hazard problem. Such expectation is can be derived from the existing works. For instance, in the United States, the government-backed insurance caused the moral hazard problem (Vigdor 2009; Jaffe & Russell, 2008). "Though private insurers increase the premium on repetitive loss properties, or deny coverage altogether, the NFIP (National Flood Insurance Program) rarely forces property owners to consider the full costs of their decision to live in flood-prone areas" (Chamlee-wright 2011, 140). As a consequence of NFIP, property owners continue to live the area where flood frequently occurs. From another viewpoint, government offered to reinsure the insurers against catastrophic losses (Zanjani, 2008). Accordingly, insurers "can feel free to write policies for floods at overly reasonable rates, safe in the knowledge that their downside risk in yielding information about the expected cost of various disasters" (Vigdor 2009, 1156). Under this condition, there seems to collusive ties between the bureaucrats and insurers. Frequent occurrence of natural disaster inevitably strengthens the profitable partnership between government and insurers, leading to the structural interlocking.

3.2. Data

Data regarding the number of natural disasters were sourced from EM-DAT (Emergency Events Database).[10] In the data, for a disaster to be entered into the database at least one of the following criteria must be fulfilled: (1) ten or more people reported killed., (2) hundred or more people reported affected, (3) declaration of a state of emergency, (4) call for international assistance. Among four criteria, a careful attention should be called for with respect to criteria (4). As shown in Figure 1 and discussed earlier, an increasing trend in the number of disasters over time is observed. Concerning the trend, there is an argument that "we should pay attention to the possibility that the reported increase is partly due to an increased tendency to report, not necessarily an increase in the occurrence of disasters" (Kurosaki 2013, p.2). It has been suggested that in developing countries, the reporting of the impact of natural

[10] Natural disaster data were gathered from the International Disaster Database. http://www.emdat.be (accessed on August 25, 2013).

disasters tends to be exaggerated for the purposes of obtaining international aid from developed countries (Albala-Bertrand 1993; Skidmore & Toya 2002). Inevitably, measurement errors cause some degree of bias in the estimations in developing countries. Measurement error is less likely to exist in developed countries. Hence, estimation error seems trivial when the sample is limited to developed countries.

Dividing the sample into developed and developing countries facilitates the avoidance of measurement error when estimations are conducted. As demonstrated in Figure 2, the number of disasters in the United States is significantly larger than in other countries, even though it is a developed country. Garret and Sobel (2003) made it evident that disaster declaration and the level of disaster expenditure are both politically motivated rather than driven by the severity or frequency of disaster. This is because of the system of the Federal Emergency Management Agency (FEMA), which is concerned with the disaster declaration process and the subsequent allocation of disaster relief money. It is important for the President to manipulate disaster declaration with the aim of being re-elected. Thus, "the vast majority of disasters declared over the last decade have been for weather events that most people would not consider disasters at all" (Sobel & Leeson 2006, 60). Canada is a developed country that is part of the North American continent, and has a land area of about 9.9 million km^2, which is similar to that of the United States (about 9.6 million km^2). Despite the similarities shared by the United States and Canada, based on the data used in this paper, the average number of total disasters is 24.5 for the United States and 3.0 for Canada. Such a remarkable difference might be too large to be explained by political factors such as the system of FEMA. In addition to the United States, countries with a total number of disasters over 10 can be regarded as outliers. Therefore, they are removed from the sample to reduce measurement errors and improve the robustness[11]. Clearly, the more land area the more disasters, resulting in estimation bias. Hence, in order to control for it, the number of disasters is divided by land area and then is used as independent variable. Data of land area are collected from the World Bank (2010).

With respect to the proxy for public sector corruption, as is earlier explained, the variable made based on the index of the ICRG, which is assembled by the Political Risk Service Group. The values range from 0 (incorrupt) to 6 (corrupt), and can be regarded as indicating the degree of corruption. The data of the ICRG reveal that corruption experienced directly in business is commonplace. The index is appropriate for capturing

[11] Countries included in the sample are exhibited in the Table of the Appendix.

financial corruption in the form of demands for special payments and bribes. Integrating the disaster and corruption data leads the panel data to include 84 countries over a 21-year period (1990–2010). In addition to the key variables above, control variables such as GDP per capita and population are collected from the Penn World Table 7.1.

In this paper, members of the Organization for Economic Co-operation and Development (OECD) are considered as developed countries, while non-members of the OECD are classed as developing countries. A comparison of the basic statistics for the variables between the OECD and the non-OECD countries is presented in Table 2. The degree of corruption is 3.39 in non-OECD countries, whereas the degree is 1.19 in OECD countries, which is consistent with the view that the developing countries is generally more corrupted than the developed countries. Average number of total disasters is 4.43 in non-OECD countries, whereas the degree is 1.12 in OECD countries. This is congruent to Figure 1 and 2 suggesting positive correlation between number of natural disasters and the degree of corruption. Further, larger value of average number of disasters in the non-OECD than that in the OECD countries possibly reflects that number of disasters is exaggerated in the developing countries for the purpose of receiving international aids. "Flooding in one region can be the result of storm activity upstream" (Toya & Skidmore 2012, 12). Storms are often accompanied by floods. Based on the data set of this paper, the correlation coefficient between floods and tropical storms is 0.47. It is observed that the average number of tropical storms (other storms) is 1.98 (0.02) in non-OECD countries and 0.03 (0.19) in OECD countries. This seems to reflect that non-OECD countries are likely to be located in tropical areas. On the other hand, the average number of general floods (other floods) is 1.71 (0.65) in non- OECD countries and 0.17 (0.04) in OECD countries. This is in line with the positive correlation between floods and storms.

3.3. Basic methods

To examine *Hypothesis 1*, the estimated function takes the following form:

$$Corruption_{it} = \alpha_0 + \alpha_1\, Number\ of\ disasters_{it} + \alpha_2\, Number\ of\ disasters_{it-1} + \alpha_3\, Number\ of\ disasters_{it-2} + \alpha_4 GDP_{it} + \alpha_5 Population_{it} + \alpha_6 Time\ trend_t + u_i + \varepsilon_{it},$$

where the dependent variable is $Corruption_{it}$ in country i for year t, α represents the regression parameters, u_i represents the unobservable feature of country *i, and* ε_{it} represents the error term. "Public sector corruption is commonly known to be highly correlated with … omitted institutional factors" (Escaleras et al. 2007, p. 219). Existing works have made it evident that institutional and socioeconomic conditions are related closely to the outcomes of natural disasters (Kahn 2005; Toya and Skidmore 2007). For instance, it was found that legal origin, ethnic heterogeneity, and religion determine the level of corruption (e.g., Treisman 2000; Paldam 2001; Djankov et al. 2003; Serra 2006; Gokcekus 2008; Pellegrini & Gerlagh 2008). These factors are considered as time invariant fixed effects of country, which is denoted as u_i.. Hence, the Fixed Effects model is basically used. However, instead of the Fixed Effects model, the Random Effects model is alternatively used when result of the Hausman test suggests that the Random Effect model is preferred.

Furthermore, Figure 1 suggests the possibility that the third factors are related to both corruption and natural disasters. If the relation between disasters and corruption is caused completely by the third factors, the relation is spurious, and thus, the hypothesis cannot be supported. Hence, following the method of Kahn (2005), the time trend is included to exclude the effects of the third factors.

Obviously, the effect of a natural disaster in year t on corruption in year t changes according to the date of occurrence of the disaster. If a disaster occurs at the end of year t, the corruption in year t has been estimated already, and thus, the disaster has no effect on the level of the corruption. However, the disaster will influence the level of corruption in year t+1. As found in the case of the United States, there is a time lag between the influx of disaster relief and the increase in corruption (Leeson & Sobel, 2008). Therefore, to capture the time lag effect of disasters, *natural disasters* in year t and *natural disasters* in year t-1 are incorporated as independent variables. Further, it seems plausible that impact of natural disaster persists for several years. Therefore, in addition, the function also includes *natural disasters* in year t-2[12]. If *Hypothesis 1* is supported, the *number of disasters* $_t$, the *number of disasters* $_{t-1}$ and the *number of disasters* $_{t-2}$ will take a positive sign. The slightly positive correlation observed in Figure 2 is congruent with *Hypothesis 1.* Furthermore, in examining *Hypothesis 2,* the effects of specific types of disaster should be identified. Hence, instead of the number of total disasters, disaggregated numbers of disasters are incorporated. With regard to control variables, *GDP* and *Population* are included to capture basic economic conditions.

[12] Association between natural disasters in year *t-3* and corruption in year t disappears and so natural disaster in year *t-3* is not included.

4. Results

The estimations results based on the full sample are reported in Table 3. The results based on the sample of non-OECD countries are presented in Table 4, and those based on the sample of OECD countries are displayed in Table 5. In each Table, the key variables of columns (1) and (2) are the number of total natural disasters in year *t*, in year *t*-1 and in year *t*-2. The key variables of columns (3) and (4) are the disaggregated level variables, such as the number of general floods, other floods, tropical storms, other storms, volcanic eruptions, earthquakes, landslides, and other disasters in year *t*, in year *t*-1 and in year *t*-2. In each table, the results in columns (1) and (3) are obtained based on sample including outliers. For robustness check, results in columns (2) and (4) are based on sample excluding outliers. There are number of disasters in multiple years such as in year *t*, in year *t*-1 and in year *t*-2. Therefore, whether a variable is significant or not is not done by looking individually at each coefficient. There is possibility that they are individually insignificant, but jointly significant when levels of disasters in year *t*, in year *t*-1 and in year *t*-2 are correlated. Hence, it is necessary to conduct the F-test of joint significance of variables in year *t*, in year *t*-1 and in year *t*-2 simultaneously. So, F-test of each disaster is exhibited.

As for Table 3-5, the results of Hausman-test are checked. The null hypothesis is that estimates of the Fixed effects model are not systematically different from those the Random effects. The hypothesis is rejected in columns (1) and (2) and so the Fixed Effects model is preferred. On the other hand, the hypothesis is not rejected in columns (3) and (4), and so the Random Effects model is preferred. Hence, the Fixed Effects model is used in columns (1) and (2), while the Random Effects model is used in columns (3) and (4).

4.1. Results of full sample.

Table 3 indicates that the number of total natural disaster in years *t*, *t*-1, and *t*-2 have the predicated positive sign in columns (1) and (2). Furthermore, those in years *t*-1 and *t*-2 are statistically significant. Hence, this result is congruent with *Hypothesis 1.* As for the absolute value of their coefficients, the value in year *t-1* is equivalent to that in year *t*-2, which suggests that the magnitude of their effect is stable.

It can be seen from columns (3) and (4) that the coefficients of the number of general floods and of other flood have positive and negative sign. And its statistical significance also depends on whether year is in *t*, *t*-1, or *t*-2. As explained in the section 3, there seems to be measurement error of number of disaster, possibly causing estimation biases. As a consequence, results of general flood and other flood might not be stable. In most cases, coefficients of tropical storm, earthquake, and landslide have a positive sign, while being statistically significant. Further, absolute values of coefficient of earthquake are approximately from 0.11 to 0.14 in *t*-1 and *t*-2. Those values of earthquake are distinctly larger than those of tropical storm and landslide. This might be because of large damage caused by earthquake demonstrated in Figure 4. Apart from earthquake, damage of tropical storm is larger than other types of disasters. Furthermore, tropical storm most frequently occurs among various types of disasters. They might be reason why tropical storm persistently increases corruption level. This information presented in Table 3 supports *Hypothesis 2*. However, significant positive sign of landslide is not due to damage and frequency because landslide results in small damage and is less frequent. For checking the robustness of landslide, it is necessary to see the results based on OECD sample because the OECD data is less likely to suffer measurement error.

As for the control variables, the coefficient of GDP per capita shows a negative sign and statistically significant in columns (1) - (4). This implies that developed countries are less corrupt, which is consistent with intuition. Coefficient of time trend indicates a positive sign and statistically significant at the 1 % level in columns (1) - (4). This is consistent with the observation of Figure 1.

4.2. Estimation results based on the samples of non-OECD countries and OECD countries.

Results presented in Table 4 are almost equivalent to those of Table 5, telling that similar effects of disaster on corruption are commonly observed not only in full-sample but also in developing countries. *Hypotheses 1 and 2* continue to be supported. However, concerning results of general flood and other flood are not stable and those of landslide are not in line with these hypotheses. Hence, now switching attention to results based on the OECD sample.

In Table 5, coefficients of the number of total natural disaster in years *t*, *t*-1, and *t*-2 have the predicated positive sign in columns (1) and (2). Furthermore, those in years *t* and t-1 are statistically significant. Considering results of number of total natural disaster in Tables 3-5 together suggests that *Hypothesis 1* is supported.

Coefficients' sign of general flood and other flood is the predicted positive in columns (1) and (2). Further, statistical significance is observed about general flood in year t, and other flood in years t-1 and t-2. Further, result of F-test about general flood rejects the null hypothesis and so suggests joint significance of number of general floods in year t, in year t-1 and in year t-2. Hence, statistical insignificance of general flood in years t-1 and t-2 is possibly due to correlation among number of general flood among years t, t-1 and t-2. The same result is obtained for result of F-test about other flood. These means that number of general and other floods increase corruption. With respect to storms, number of tropical storm yields the predicted positive sign in years t, t-1 and t-2. Statistical significance is observed in year t-1 of column (3). Tropical storms are climatic disaster and so generally hit the same country every year. In line with it, result of F-test about tropical storm rejects the null hypothesis and so suggests joint significance of number of tropical storms in year t, in year t-1 and in year t-2. Number tropical storms in year t seems to be correlated with those in year t-1 and in year t-2. Therefore, number of tropical storms is considered to increase corruption. On the other hand, number of other storm yields the negative sign in years t-1 and t-2. Further, it is statistically significant in year t-1. Turning to result of F-test, however, the null hypothesis is not rejected and so does not indicate joint significance of number of other storm. Coefficients' sign of earthquake is the predicted positive in all years and columns although only it shows statistical significance only in year t-2. However, result of F-test about earthquake rejects the null hypothesis and so suggests joint significance of number of earthquake in year t, in year t-1 and in year t-2. Number earthquake in year t appears to be correlated with those in year t-1 and in year t-2. Therefore, number of earthquake is considered to increase corruption. General floods, other floods and tropical storm occur more frequently. Further damage of earthquake is remarkably larger. Hence, all in all, *Hypotheses 2* is supported. As a whole, the sign of each disaster is positive, with the exception of other storms. This might be, in part, because that number of disasters is measured more accurately than in non-OECD countries and so the attenuation bias is trivial.

4.3. Total effects of disasters and discussion.

What is observed in Tables 3-5 suggests the effect of each disaster per km^2 on corruption level of a country. However, these suggest the effect separately for year *t, t-1* and t-2. If the impact of a disaster on corruption in year in year *t* is 0.09, the impact in year *t-1* is 0.10, and the impact in year *t-2* is 0.08, the total combined effect is considered as 0.27. In this paper, values of coefficient are aggregated only when individual year effect is statistically significant in column (3) of Table 3-5. For instance, other storm in Table 3 is not statistically significant in year *t, t-1* and t-2. Hence, there is no effect even if they are combined. On the other hand, general flood in Table 3 is statistically significant in year *t-1* although it is not statistically significant in year *t* and t-2. In this case, combined total effect is equivalent to its effect in year *t-1.* The upper part of Table 6 exhibits such total combined effect. Concerning results based on full sample and non-OECD sample, the Table 6 tells that general flood, tropical storm, earthquake, and other disaster increase corruption. However, other flood and volcanic eruption decrease corruption. Therefore, effect of each disaster varies according to type of disaster. This might be partly because of measurement error. Effect of earthquake is 0.289, which is remarkably large, reflecting the large damage of earthquake as indicated in Figure 4. With respect to result of OECD sample, with the exception of other storm, effect of each disaster is not negative. Further, it is interesting to observe that effect of each disaster is distinctly larger than those based on full sample or non-OECD sample. The reason of such large effect is partly that measurement error is unlikely to exist on OECD sample and so attenuation bias can be avoided. In addition, combined results for columns (1), (2) and (3) suggests that general flood, tropical storm and earthquake consistently increase corruption level. The predicted damage of each disaster is calculated by multiplying the value in Figure 3 and that in Figure 4. Figure 5 demonstrated the predicted damage of each disaster. Figure 5 reveals that general flood, tropical storm and earthquake are distinctly higher than other types of disasters. Hence, impact of general flood, tropical storm and earthquake on corruption can be explained by their large damage.

The results of upper part suggest effect of each disaster when it occurred in the same land size. However, frequency of disasters differs according to type of disasters even if land size is constant. Damage of earthquake is very large and so its effect on corruption seems to be large. However, frequency of occurrence of earthquake is very low. Therefore, it is unknown whether the predicted damage of earthquake is larger than those of flood or storm which more frequently occur. Furthermore, in the real situation, its frequency depends on land size of a country. Therefore, in the lower part of Table 6, predicted effect of disaster on corruption is shown when its frequency is considered under the real situation. For this purpose, effect of disaster shown in the upper part is multiplied by its frequency per million km^2 and mean land size in each sample. This value is interpreted by the effect of disaster for the country with mean land size in each sample. When results of the lower part of Table 6 are interpreted, Figures 6 and 7 are also considered together. These figures demonstrate predicted damage per disaster for non-OECD and OECD countries.

As is presented in the lower part of Table 6, effect of earthquake is the largest among various types of disasters when non-OECD is used. Earthquake increases corruption about 0.178 points for a country with average land size of non-OECD countries. Then, tropical storm and general flood increase corruption by 0.095 and 0.034 points, respectively. Figure 6 indicates that damages of general flood, tropical storm and earthquake are remarkably large. To put it more precisely, the damages of general flood and tropical storm are distinctly larger than that of earthquake. Therefore, corruption level does not simply reflect the predicted damage of each disaster. For non-OECD countries, damage of an earthquake is about 8 times larger than general floods, while general floods occur more frequently by about 28 times than earthquake. Accordingly, effect of disaster is large when if damage per disaster is large even though the disaster rarely occurs.

On the other hand, effect of general flood is larger than that of earthquake when OECD sample is used. General flood increases corruption about 0.513 points for a country with average land size of OECD countries, whereas earthquake increases corruption about 0.449 points for the country. These imply that effect of disaster for OECD countries is remarkably larger than that for non-OECD countries. However, Figure 7 tells that the predicated damage of earthquake is overwhelmingly larger than that of other types of disaster for OECD countries. This means that in the case of OECD countries, the predicated damage of disaster does not simply result in increase of corruption. For OECD countries, general floods occur more frequently by about 3 times than earthquake, whereas damage of an earthquake is about 23 times larger than general floods. That is, disaster with high frequency has sizable effect on corruption even if damage per disaster is low. This is interpreted as suggesting that the people are live in disaster-prone area to seek for benefited from disaster.

Corruption is observed to be negatively associated with economic growth (Mauro 1995; Tanzi & Davoodi 1997; Johnson et al. 2011). However, such an observation is not congruent with the finding that natural disasters cause the public sector to become more corrupt in OECD countries than in non-OECD countries. The fact that the effect of frequent disasters such as floods on corruption is greater in OECD countries than in non-OECD countries can be interpreted as follows. Floods tend to occur in the agricultural land because agricultural land requires irrigation. It is difficult for farmers to move to areas where floods are unlikely to occur because such areas are not suited to agriculture. The population working in the agricultural sector is larger in developing countries than in developed nations. Accordingly, the opportunity for the movement of population away from risky areas is low in developing countries. Hence, this is the reason why people in these countries reside in areas at risk of floods; it tends to reflect the nature of their work, rather than their strategic behavior to pursue disaster compensation.

People can benefit from windfalls that may be derived from the disastrous event. If the benefit is larger than the damage, residents in disaster-prone-areas have an incentive to continue to live there. Thus, under such conditions in developed countries, there is the possibility of an inflow of population into disaster-prone areas because "the prospect of receiving federal and state reconstruction assistance after the next hurricane strikes supplies incentives for others to relocate their homes and businesses from inland areas of comparative safely to vulnerable coastal areas" (Shughart II 2006, p.44)[13]. Considering what has been discussed thus far leads to the claim that in developed countries, people have an incentive to live in disaster-prone areas because the expected benefits of the occurrence of a disaster are larger than the damages. As a consequence, disaster-prone area increases corruption.

5. Conclusion

Rational individuals may possibly exploit devastating incidents such as natural disasters. Political rent-seeking activities possibly sacrifice direct benefits to disaster-hit areas in favor of self-interest. Leeson and Sobel (2008) found that disaster-relief windfalls increased corruption. The characteristics of disasters differ, and thus, they are predicted to have different influences on corruption. However, little is known about whether the different disaster types result in different outcomes. Furthermore, the effects of disaster seem to be different between developed and

[13] In the United States, the National Flood Insurance Program causes the moral hazard problem. "The program dramatically distorts the signaling mechanism that would otherwise guide property owners away from the areas prone to flooding from any source" (Chamlee-wright 2010, 140).

developing countries. To examine this statistically, this work used panel data from 84 countries for a 21-year period from 1990 to 2010.

The major findings of this study are the following. (1) Natural disasters lead the public sector to become corrupt. (2) Disaster with the large predicated damage increase corruption not only for developing countries but also for developed countries. This indicates people living in disaster-prone area anticipate disaster compensation. Analogous to the logic of literature on foreign aid inflow, it is the disaster relief money inflow that cases the corruption, and more money causes more corruption (Leeson & Sobel 2008). (3) The effect of disasters is greater in developed countries than in developing countries. (4) In the developed countries, frequency of occurrence of disaster plays more important role on increasing corruption. On the other hand, in the developing countries, damage per disaster plays more critical role on it.

From what has been examined in this paper, I derive the argument that the moral hazard problem occurs because victims require the compensation for disaster, which is larger than its damage. However, degree of corruption caused by disaster depends not only on the amount of damage of disasters, but also on its frequency and damage per disaster. People of the developed countries are likely to reside in disaster-prone area to seek for compensation of disaster. The disaster warning systems is generally thought to be effective to reduce the damage of disasters in the developed countries (Escaleras et al., 2008). The more information about disaster is provided, the more people are able to evacuate from it. This possibly gives incentive of people to reside the disaster-prone area to seek for compensation. Such unanticipated behavior possibly caused the government failure (Shiue, 2004).

This paper uses country-level panel data and so measurement errors are thought to cause an estimation bias, although a robustness check is conducted in the paper. For closer examination about the effects of disasters on corruption, micro-level data with greater accuracy should be used. Furthermore, the strategic behavior of people regarding their choice over their residential area should be scrutinized more closely by using experimental methods. These remaining issues require further investigation in future studies.

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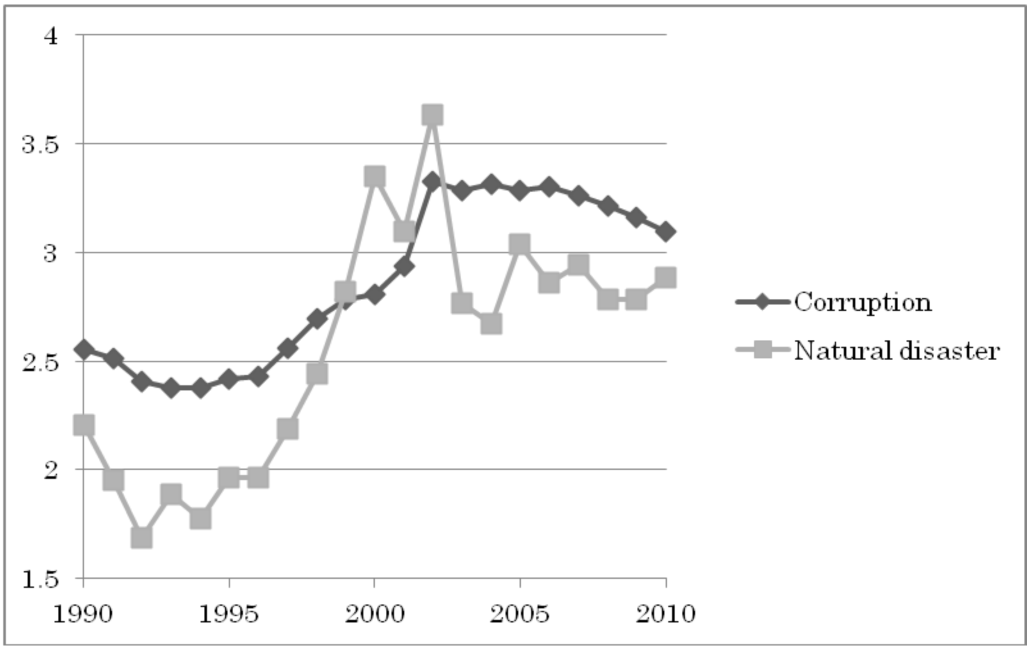

Figure 1. Degree of corruption and occurrence of natural disasters from 1990 to 2010

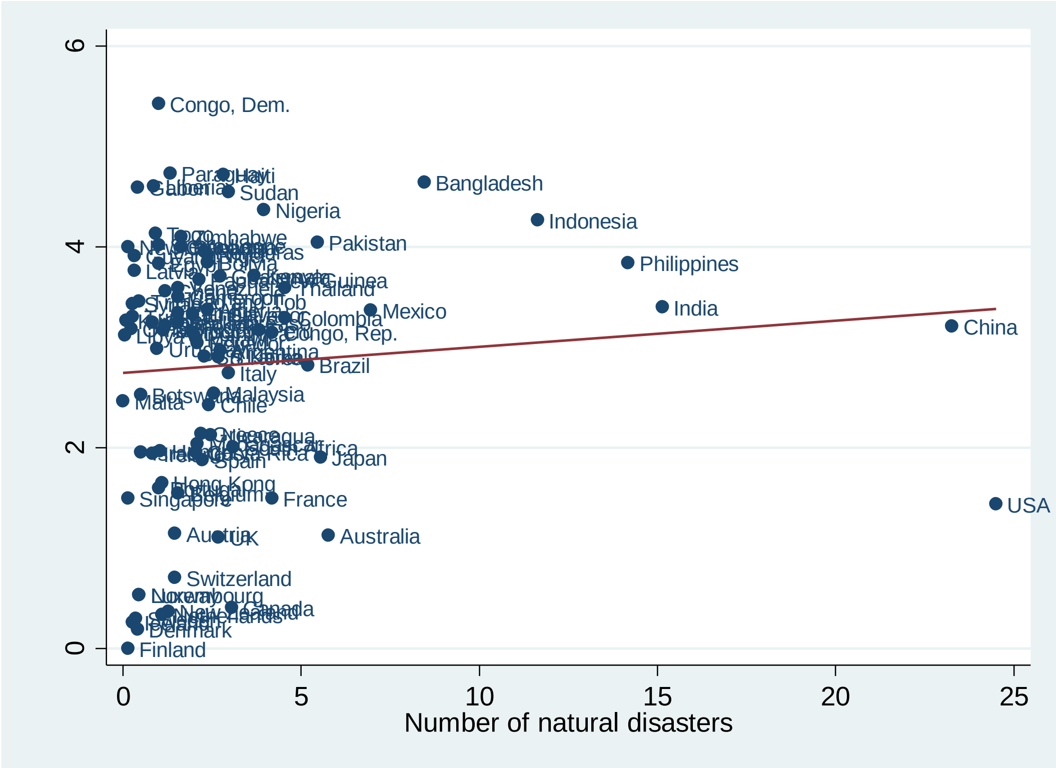

Figure 2. Relation between occurrence of natural disasters and corruption

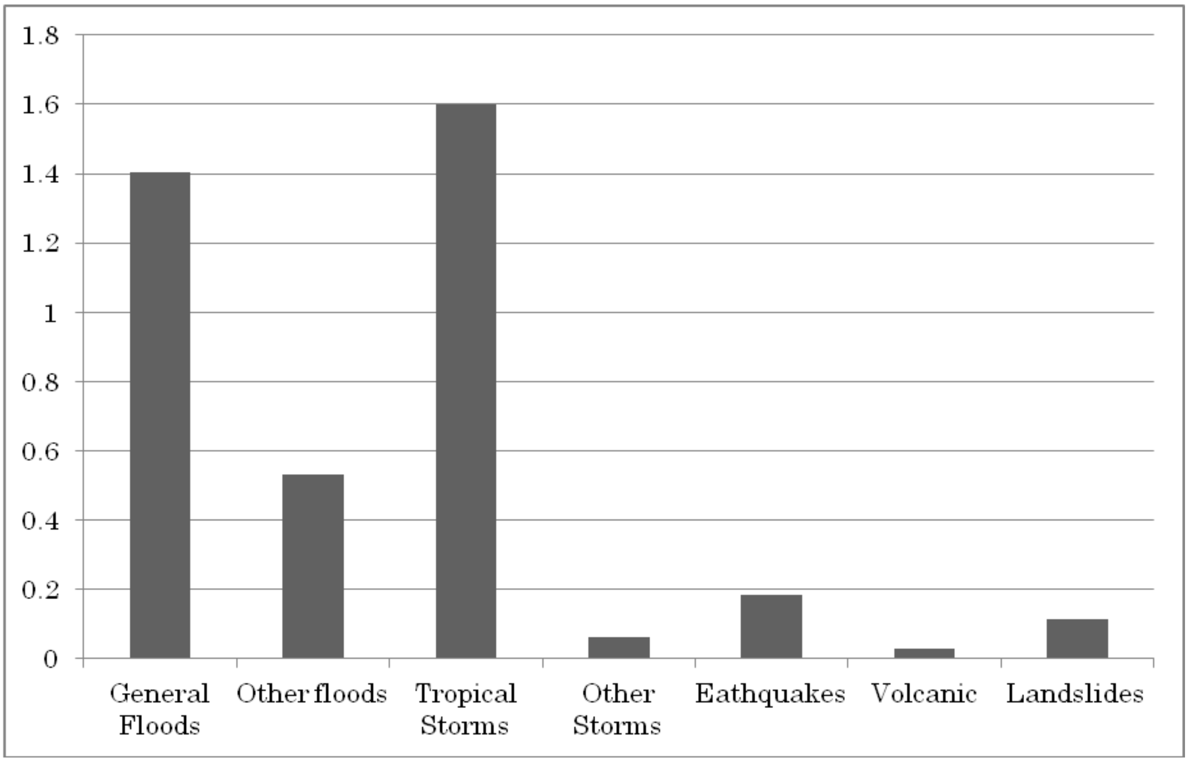

Figure 3. Frequency of disasters per land size (10,000 km^2)

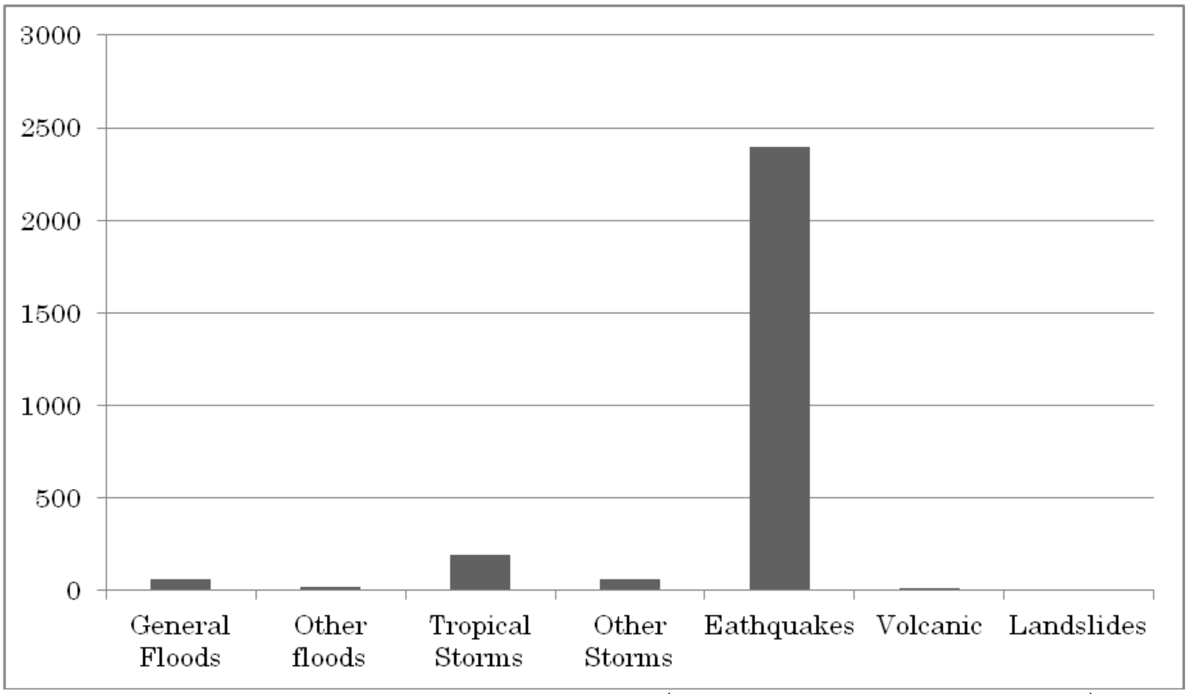

Figure 4. Average damage level per disaster (million US$/number of disasters)

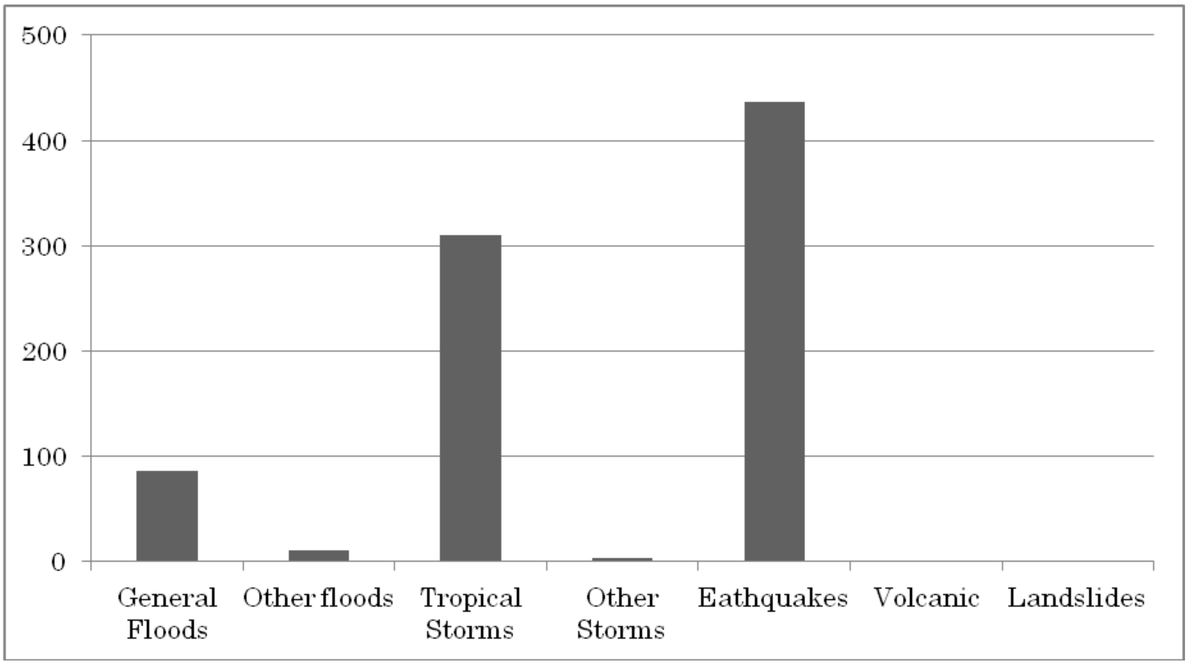

Figure 5. Predicted damage per disaster

Note: Predicted damage per disaster is calculated by multiplying average damage level per disaster with frequency per land size.

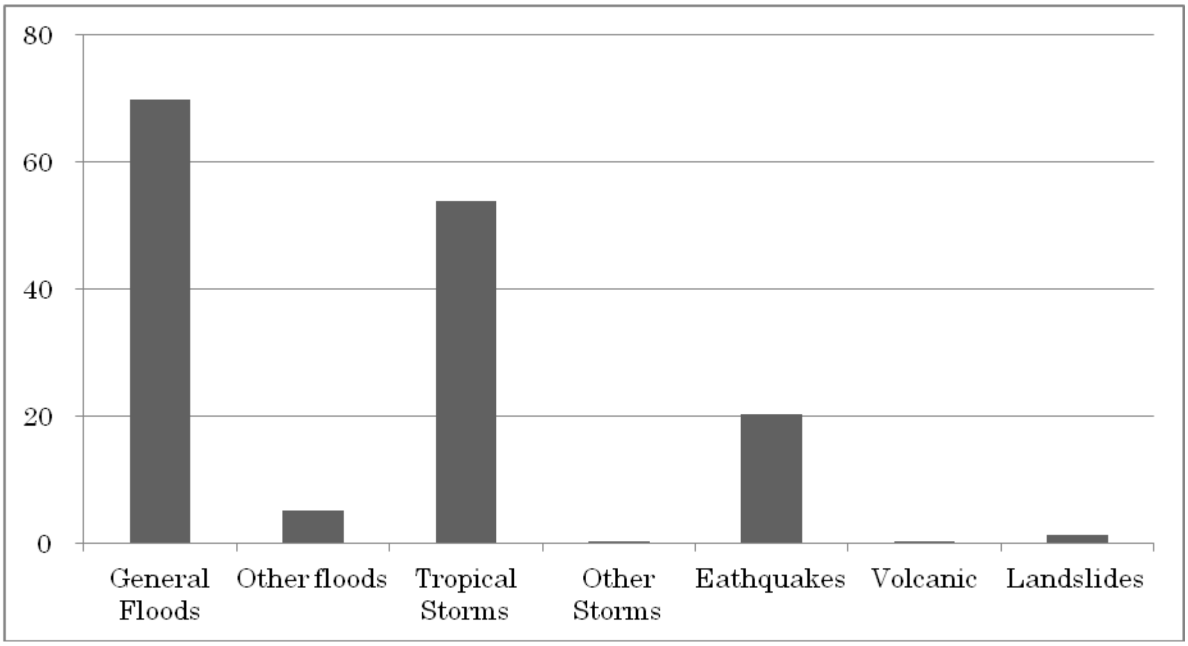

Figure 6. Predicted damage per disaster for non-OECD countries

Note: Predicted damage per disaster calculated by multiplying average damage level per disaster for non-OECD with frequency per land size for non-OECD.

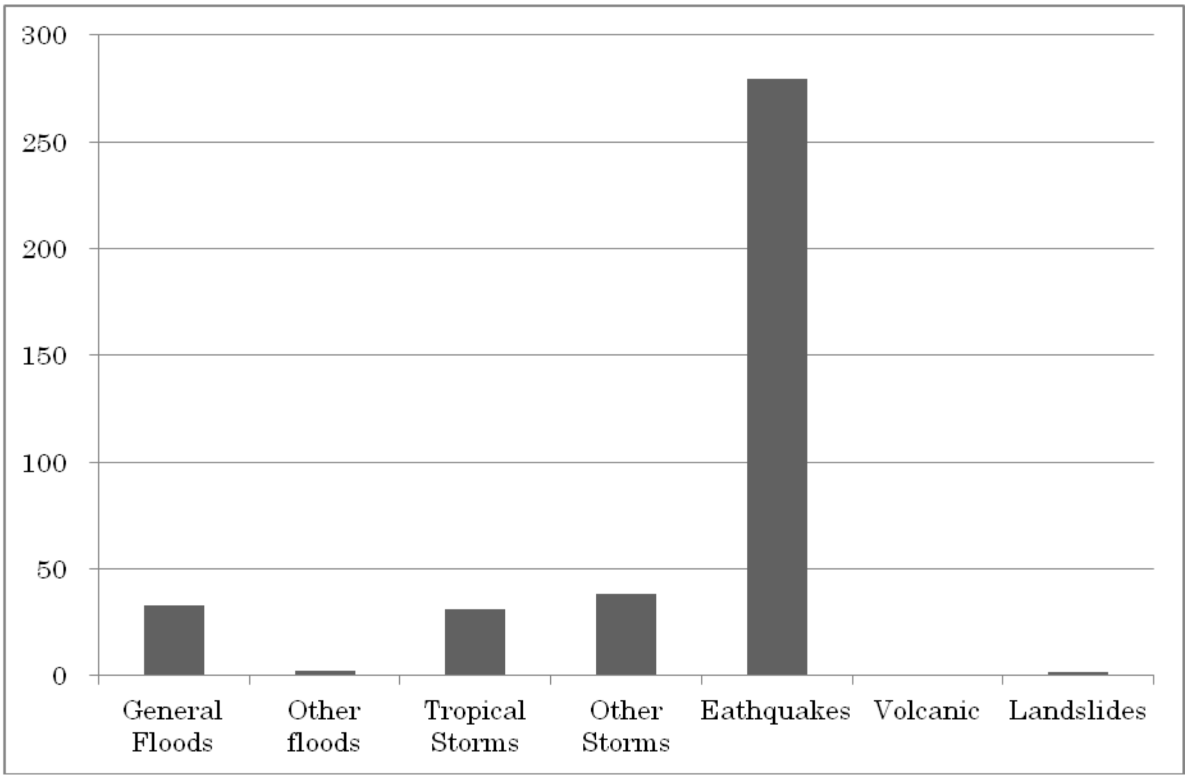

Figure 7. Predicted damage per disaster for OECD countries

Note: Predicted damage per disaster calculated by multiplying average damage level per disaster for OECD with frequency per land size for OECD.

Table 1. Characteristics of disasters

	Predicted damage level	Frequency	Type
General floods	Very low	Frequent	Climatic
Other floods	Very low	Frequent	Climatic
Tropical storms	Low	Frequent	Climatic
Other storms	Very low	Very rare	Climatic
Earthquakes	Very high	Rare	Geologic
Volcanic eruptions	Very low	Very rare	Geologic
Land slides	Very low	Rare	Geologic

Table 2. Comparison of average value of each variable between non-OECD and OECD countries

	Definition and unit	Full sample (1)	Non-OECD (2)	OECD (3)
Corruption	0 (incorrupt)–6 (corrupt)	2.85	3.39	1.19
		(1.41)	(1.05)	(1.01)
Natural disasters	Number of natural disasters /	3.77	4.43	1.12
	land size (million m^2)	(25.8)	(28.8)	(2.67)
General floods	Number of general floods	1.40	1.71	0.17
	/ land size (million m^2)	(17.6)	(19.7)	(0.57)
Other floods	Number of other floods	0.52	0.65	0.04
	/ land size (million m^2)	(11.4)	(12.8)	(0.25)
Tropical storms	Number of tropical storms	1.59	1.98	0.03
	/ land size (million m^2)	(17.6)	(19.6)	(0.18)
Other storms	Number of other storm	0.05	0.02	0.19
	/ land size (million m^2)	(0.35)	(0.19)	(0.66)
Earthquakes	Number of earthquakes	0.18	0.21	0.06
	/ land size (million m^2)	(4.91)	(5.49)	(0.27)
Volcanic eruptions	Number of volcanic eruptions	0.02	0.02	0.01
	/ land size (million m^2)	(0.46)	(0.51)	(0.06)
Landslides	Number of landslides	0.11	0.13	0.02
	/ land size (million m^2)	(2.51)	(2.84)	(0.28)
Other disasters	Number of other disasters	0.73	0.83	0.33
	/ land size (million m^2)	(7.95)	(8.83)	(2.05)
GDP per capita	In US$	12,014	6,920	32,075
		(13,430)	(8,580)	(9,807)
Population	In thousands	47,484	50,263	47,484
		(158,837)	(174,933)	(158,837)
Observations		1,348	997	351

Notes: Values in parentheses are standard deviations. Sample does not exclude countries considered as outliers (countries with an average number of total disasters greater than 10).

Sources: Corruption data were sourced from Corruption Index of International Country Risk Guide (ICRG). Data concerning natural disasters were obtained from http://www.emdat.be (accessed on August 20, 2013).

All other data used in this paper are gathered from the Penn World Table 7.1 (accessed on August 20, 2013).

Table 3. Effect of aggregated disasters on corruption: Full sample

	(1) Fixed effects	(2) Fixed effects	(3) Random effects	(4) Random effects
Natural disasters in year *t*	0.0003	0.0003		
	(0.34)	(0.36)		
Natural disaster in year *t-1*	0.002***	0.002***		
	(3.48)	(3.69)		
Natural disasters in year *t-2*	0.002*	0.002*		
	(1.73)	(1.73)		
General floods in year *t*			−0.0001	−0.0001
			(−0.14)	(−0.17)
General floods in year *t-1*			0.002***	0.002***
			(6.44)	(6.55)
General floods in year *t-2*			0.0002	0.0001
			(0.21)	(0.16)
Other floods in year *t*			−0.002***	−0.002***
			(−6.78)	(−7.00)
Other floods in year *t-1*			0.002***	0.002***
			(4.11)	(4.32)
Other floods in year *t-2*			−0.004***	−0.005***
			(−10.5)	(−10.5)
Tropical storm in year *t*			0.001*	0.005
			(1.97)	(1.57)
Tropical storms in year *t-1*			0.005***	0.005***
			(5.39)	(5.11)
Tropical storms in year *t-2*			0.005***	0.005***
			(11.6)	(11.1)
Other storms in year *t*			−0.015	−0.019
			(-0.42)	(−0.52)
Other storms in year *t-1*			−0.003	−0.044
			(−1.27)	(−1.40)
Other storms in year *t-2*			−0.003	−0.007
			(−0.09)	(−0.16)
Earthquakes in year *t*			0.021	0.027
			(0.38)	(0.46)
Earthquakes in year *t-1*			0.115**	0.121**
			(2.01)	(2.05)
Earthquakes in year *t-2*			0.134*	0.139*
			(1.87)	(1.87)
Volcanic eruptions in year *t*			−0.032	−0.038
			(−0.51)	(−0.58)
Volcanic eruptions in year *t-1*			−0.136**	−0.143**
			(−2.02)	(−2.07)

Volcanic eruptions in year *t-2*			−0.159**	−0.164**
			(−2.08)	(−2.09)
Landslides in year *t*			0.025	0.024**
			(1.63)	(2.11)
Landslides in year *t-1*			0.024**	0.023**
			(2.23)	(2.10)
Landslides in year *t-2*			0.025*	0.024*
			(1.77)	(1.73)
Other disasters in year *t*			0.004***	0.004***
			(8.77)	(8.93)
Other disasters in year *t-1*			0.001	0.001
			(0.82)	(0.88)
Other disasters in year *t-2*			−0.003**	−0.004**
			(−2.01)	(−2.02)
Ln(GDP)	−0.861***	−0.72**	−0.629***	−0.612***
	(−2.64)	(−2.08)	(−8.87)	(-8.21)
Ln(Population)	−1.349	−1.511	0.059	0.049
	(−1.35)	(−1.50)	(1.06)	(0.67)
Trend	0.116***	0.117***	0.088***	0.090***
	(5.79)	(5.72)	(8.46)	(8.37)
F-test (Natural disasters)	14.2	14.8		
	P-value = 0.00	P-value = 0.00		
F-test (General floods)			492.3	493.2
			P-value = 0.00	P-value = 0.00
F-test (Other floods)			128.0	127.9
			P-value = 0.00	P-value = 0.00
F-test (Tropical storms)			260.6	277.0
			P-value = 0.00	P-value = 0.00
F-test (Other storms)			13.3	13.9
			P-value = 0.00	P-value = 0.00
F-test (Earthquakes)			28.3	27.1
			P-value = 0.00	P-value = 0.00
F-test (Volcanic eruptions)			32.7	31.5
			P-value = 0.00	P-value = 0.00
F-test (Landslides)			5.74	5.83
			P-value = 0.12	P-value = 0.12
F-test (Other disasters)			78.4	80.3
			P-value = 0.00	P-value = 0.00
Hausman test	10.5	12.8	17.9	19.4
	P-value = 0.10	P-value = 0.05	P-value = 0.90	P-value = 0.85
Outliers	Included	Excluded	Included	Excluded
Within R-square	0.24	0.25	0.25	0.27

Observations	1,129	1,064	1,129	1,064

Note: Values in parentheses are t-statistics in columns (1) and (2), while those are z-statistics in columns (3) and (4). *, **, and *** denote significance at the 10, 5, and 1% levels, respectively. Constants were included in columns (3) and (4), but the results are not reported.

Table 4. Effect of aggregated disasters on corruption: Non-OECD sample

	(1) Fixed effects	(2) Fixed effects	(3) Random effects	(4) Random effects
Natural disasters in year *t*	0.0001	0.0001		
	(0.07)	(0.11)		
Natural disasters in year *t-1*	0.002***	0.002***		
	(3.71)	(4.02)		
Natural disasters in year *t-2*	0.002*	0.002*		
	(1.76)	(1.76)		
General floods in year *t*			−0.0003	-0.0003
			(-0.32)	(-0.34)
General floods in year *t-1*			0.002***	0.002***
			(7.23)	(7.32)
General floods in year *t-2*			0.0001	−0.0001
			(0.02)	(−0.02)
Other floods in year *t*			−0.003***	−0.003***
			(−7.20)	(−7.32)
Other floods in year *t-1*			0.002***	0.002***
			(4.21)	(4.41)
Other floods in year *t-2*			−0.005***	−0.005***
			(−11.3)	(−11.1)
Tropical storms in year *t*			0.0002	0.0002
			(0.66)	(0.46)
Tropical storms in year *t-1*			0.005***	0.005***
			(5.07)	(4.85)
Tropical storms in year *t-2*			0.005***	0.005***
			(10.6)	(9.59)
Other storms in year *t*			0.002	−0.001
			(0.02)	(−0.05)
Other storms in year *t-1*			−0.029	−0.033
			(−0.34)	(−0.38)
Other storms in year *t-2*			0.069	0.069
			(0.51)	(0.51)
Earthquakes in year *t*			0.033	0.040
			(0.52)	(0.59)
Earthquakes in year *t-1*			0.146**	0.152**
			(2.06)	(2.05)
Earthquakes in year *t-2*			0.145*	0.150*
			(1.78)	(1.78)
Volcanic eruptions in year *t*			−0.042	−0.049
			(−0.58)	(−0.65)
Volcanic eruptions in year *t-1*			−0.165**	−0.173**

			(−2.04)	(−2.04)
Volcanic eruptions in year *t-2*			−0.170**	−0.176**
			(−1.99)	(−2.00)
Landslides in year *t*			0.019	0.023*
			(1.37)	(1.83)
Landslides in year *t-1*			0.020*	0.018*
			(1.83)	(1.65)
Landslides in year *t-2*			0.020	0.017
			(1.59)	(1.50)
Other disasters in year *t*			0.004***	0.004***
			(7.84)	(8.16)
Other disasters in year *t-1*			0.0004	0.0005
			(0.42)	(0.54)
Other disasters in year *t-2*			−0.004**	−0.004**
			(−2.22)	(−2.20)
Ln(GDP)	−1.013***	−0.859**	−0.410***	−0.396***
	(−3.14)	(−2.55)	(−4.92)	(−4.56)
Ln(Population)	−2.105*	−2.320**	0.040	0.024
	(−1.98)	(−2.17)	(0.83)	(0.38)
Trend	0.138***	0.141***	0.085***	0.088***
	(5.81)	(5.83)	(6.97)	(6.93)
F-test (Natural disasters)	12.4	13.8		
	P-value = 0.00	P-value = 0.00		
F-test (General floods)			582.2	586.1
			P-value = 0.00	P-value = 0.00
F-test (Other floods)			145.3	141.7
			P-value = 0.00	P-value = 0.00
F-test (Tropical storms)			211.6	231.4
			P-value = 0.00	P-value = 0.00
F-test (Other storms)			2.63	2.31
			P-value = 0.45	P-value = 0.51
F-test (Earthquakes)			25.2	24.1
			P-value = 0.00	P-value = 0.00
F-test (Volcanic eruptions)			33.2	31.7
			P-value = 0.00	P-value = 0.00
F-test (Landslides)			4.06	4.20
			P-value = 0.25	P-value = 0.24
F-test (Other disasters)			67.7	72.0
			P-value = 0.00	P-value = 0.00
Hausman test	29.3	28.1	32.2	29.7
	P-value = 0.00	P-value = 0.00	P-value = 0.22	P-value = 0.32
Outliers	Included	Excluded	Included	Excluded

	(1)	(2)	(3)	(4)
Within R-square	0.26	0.28	0.26	0.28
Observations	868	816	868	816

Note: Values in parentheses are t-statistics in columns (1) and (2), while those are z-statistics in columns (3) and (4). *, **, and *** denote significance at the 10, 5, and 1% levels, respectively. Constants were included in columns (3) and (4), but the results are not reported.

Table 5. Effect of aggregated disasters on corruption: OECD sample

	(1) Fixed effects	(2) Fixed effects	(3) Random effects	(4) Random effects
Natural disasters in year *t*	0.021*	0.021*		
	(1.79)	(1.76)		
Natural disasters in year *t-1*	0.017*	0.017*		
	(1.70)	(1.66)		
Natural disasters in year *t-2*	0.013	0.013		
	(1.35)	(1.30)		
General floods in year *t*			0.207**	0.207**
			(2.50)	(2.52)
General floods in year *t-1*			0.104	0.103
			(1.51)	(1.50)
General floods in year *t-2*			0.132	0.129
			(1.64)	(1.62)
Other floods in year *t*			0.217	0.214
			(0.97)	(0.97)
Other floods in year *t-1*			0.326**	0.318**
			(2.04)	(2.03)
Other floods in year *t-2*			0.412***	0.406***
			(2.96)	(3.04)
Tropical storms in year *t*			0.150	0.148
			(0.74)	(0.70)
Tropical storms in year *t-1*			0.348*	0.339
			(1.75)	(1.41)
Tropical storms in year *t-2*			0.312	0.294
			(0.68)	(0.59)
Other storms in year *t*			−0.124*	−0.129*
			(−1.78)	(−1.77)
Other storms in year *t-1*			−0.109	−0.114
			(−1.16)	(−1.18)
Other storms in year *t-2*			−0.128	−0.132
			(−1.31)	(−1.28)
Earthquakes in year *t*			0.291	0.289
			(1.58)	(1.56)
Earthquakes in year *t-1*			0.090	0.093
			(0.45)	(0.46)
Earthquakes in year *t-2*			0.485**	0.489**
			(2.00)	(1.98)
Volcanic eruptions in year *t*			0.550	0.590
			(0.81)	(0.82)
Volcanic eruptions in year *t-1*			0.505	0.542
			(0.91)	(0.94)

Volcanic eruptions in year *t-2*			0.227	0.257
			(0.47)	(0.51)
Landslides in year *t*			0.084	0.085
			(1.37)	(1.41)
Landslides in year *t-1*			0.148	0.149
			(1.54)	(1.56)
Landslides in year *t-2*			0.130	0.130
			(1.57)	(1.55)
Other disasters in year *t*			0.024***	0.024***
			(2.61)	(2.63)
Other disasters in year *t-1*			0.020**	0.020**
			(2.43)	(2.42)
Other disasters in year *t-2*			0.020**	0.019**
			(2.05)	(2.04)
Ln(GDP)	2.587	2.479	−0.599	−0.569
	(1.16)	(1.07)	(−1.52)	(−1.19)
Ln(Population)	−5.940	−5.644	0.235**	0.245*
	(−1.23)	(−1.11)	(2.44)	(1.86)
Trend	0.042	0.044	0.087***	0.091***
	(0.99)	(1.19)	(3.55)	(3.44)
F-test (Natural disasters)	1.23	1.22		
	P-value = 0.32	P-value = 0.33		
F-test (General floods)			11.2	12.1
			P-value = 0.01	P-value = 0.00
F-test (Other floods)			13.5	14.5
			P-value = 0.00	P-value = 0.00
F-test (Tropical storms)			22.8	22.1
			P-value = 0.00	P-value = 0.00
F-test (Other storms)			4.33	4.14
			P-value = 0.22	P-value = 0.24
F-test (Earthquakes)			6.90	7.06
			P-value = 0.07	P-value = 0.07
F-test (Volcanic eruptions)			1.46	1.51
			P-value = 0.69	P-value = 0.67
F-test (Landslides)			3.33	3.21
			P-value = 0.34	P-value = 0.35
F-test (Other disasters)			9.09	9.44
			P-value = 0.02	P-value = 0.02
Hausman test	27.3	26.9	17.7	31.7
	P-value = 0.00	P-value = 0.00	P-value = 0.91	P-value = 0.24
Outliers	Included	Excluded	Included	Excluded
Within R-square	0.24	0.26	0.15	0.16

Observations	261	248	261	248

Note: Values in parentheses are t-statistics in columns (1) and (2), while those are z-statistics in columns (3) and (4). *, **, and *** denote significance at the 10, 5, and 1% levels, respectively. Constants were included in columns (3) and (4), but the results are not reported.

Table 6. Effect of disaster on corruption

	(1) Full sample	(2) Non-OECD sample	(3) OECD sample
	Effect of a disaster per million km²		
General floods	0.002	0.002	0.207
Other floods	−0.005	−0.005	0.738
Tropical storms	0.011	0.009	0.347
Other storms			−0.124
Earthquakes	0.251	0.289	0.485
Volcanic eruptions	−0.296	−0.333	
Land slides	0.051	0.020	
Other disasters			0.063
	Predicted effect of disaster for a country in a year		
General floods	0.031	0.034	0.513
Other floods	−0.022	−0.025	0.440
Tropical storms	0.104	0.095	0.185
Other storms			−0.339
Earthquakes	0.175	0.178	0.449
Volcanic eruptions	−0.089	−0.105	
Land slides	0.047	0.020	
Other disasters			0.302

Note: Coefficients of variables in t, t-1, and t-2 are aggregated when they are statistically significant. The effect presented in the upper part is calculated based on column (3) of Tables 3, 4, and 5. Values in the lower part are calculated by multiplying the value of the upper part, frequency of disasters per land size (per million km²) with the average land size in each sample. That is, the effect of disaster (per million km²) * frequency (per million km²) * average land size (per million km²). Average land size is

9.80 million km^2 based on the full sample. Median land size is 8.42 million km^2 based on the non-OECD sample, and 14.21 million km^2 based on the OECD sample.

Appendix: List of countries used in the analysis

Number	Country	Number	Country
1	Argentina	51	Netherlands
2	Australia	52	New Zealand
3	Austria	53	Nicaragua
4	Bangladesh	54	Niger
5	Belgium	55	Nigeria
6	Bolivia	56	Norway
7	Brazil	57	Oman
8	Burkina Faso	58	Pakistan
9	Cameroon	59	Panama
10	Canada	60	Papua New Guinea
11	Chile	61	Paraguay
12	China	62	Peru
13	Colombia	63	Philippines
14	Congo, Dem.	64	Portugal
15	Congo, Rep.	65	Senegal
16	Costa Rica	66	Sierra Leone
17	Cote d'Ivoire	67	Singapore
18	Denmark	68	South Africa
19	Dominican	69	Spain
20	Ecuador	70	Sri Lanka
21	Egypt	71	Sudan
22	El Salvador	72	Sweden
23	Finland	73	Switzerland
24	France	74	Syria
25	Gabon	75	Thailand
26	Ghana	76	Togo
27	Greece	77	Trinidad and Tobago
28	Guatemala	78	Tunisia
29	Guyana	79	United Kingdom
30	Haiti	80	United States
31	Honduras	81	Uruguay
32	Hong Kong	82	Venezuela
33	Hungary	83	Zambia
34	India	84	Zimbabwe
35	Indonesia		
36	Ireland		
37	Israel		
38	Italy		
39	Japan		
40	Kenya		

41	S. Korea		
42	Kuwait		
43	Liberia		
44	Libya		
45	Luxembourg		
46	Madagascar		
47	Malawi		
48	Malaysia		
49	Mexico		
50	Morocco		