Impact of natural disaster on public sector corruption

Yamamura, Eiji

5 September 2013

Impact of natural disaster on public sector corruption

September 12, 2013

Eiji Yamamura
Seinan Gakuin University

Abstract. This paper uses inter-country panel data obtained during the period 1990 to 2010 to examine how the occurrence of natural disasters has affected corruption within the public sector. There are a number of major findings from this study. (1) Natural disasters lead to corruption within the public sector. (2) Furthermore, disaggregating disasters into various categories for closer examination reveals that floods, which are foreseeable and affect victims that are limited to a particular group, increase corruption; however, other types of disasters do not have such a consequence. (3) The effect of floods is much greater in developed countries than in developing countries. These findings are observed even after considering the time trend, the various characteristics of the countries affected, and statistical outliers. In developed countries, people have an incentive to live within areas prone to flooding because the benefit expected from the occurrence of a flood is greater than its perceived cost.

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. Public sector corruption is one of the major issues of concern when considering the interaction between politics and economics[3] (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, some money earmarked for reconstruction work was spent improperly on projects to improve the earthquake resistance in buildings of the central government's

---

[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] 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).

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. On the other hand, it has been observed that the occurrence of disasters gives politicians an incentive to misallocate disaster expenditure in order 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[4], provided evidence that disaster relief windfalls increased corruption. They argued that the "disadvantageous location in the Gulf Coast where hurricanes and other bad weather are commonplace may be a large part for the reason why they have historically been more corrupt than states in the Great Plains" (Leeson & Sobel 2008, 678). 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; Skidmore & Toya 2013). According to Skidmore and Toya, disasters should be divided into either climatic or geologic disasters because their characteristics are different. The argument of Leeson and Sobel (2008) is based on the assumption that disasters occur frequently within limited areas. This assumption is suitable for climatic disasters but not for geologic disasters, such as earthquakes and volcanic eruptions. However, in the paper of Leeson and Sobel (2008), proxies used for the degree of disaster are the number of natural disasters or disaster relief payments. Hence, it is not clear whether their assumption holds true because their data do not exclude the effects of geologic disasters. Therefore, to investigate the claims of Leeson and Sobel (2008) more closely, this paper investigates the effects of various types of disasters. Furthermore, it has been observed that the effect of natural disasters differs between developing and developed countries (Toya & Skidmore 2007; Cuaresma et al. 2008). Therefore, this paper compares the effects of each type of

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

disaster.

To a certain extent, the probability of the occurrence of disasters is considered exogenous, because it does not depend on the condition of human society. Hence, a test on the impact of disasters on corruption is thought to be the natural experiment. This paper attempts to investigate how natural disasters influence corruption within the public sector, by using panel data from 84 countries for a 21-year period obtained between 1990 and 2010. It is found that natural disasters lead the public sector to become corrupt. In addition, such a tendency is remarkable for floods, which are foreseeable and affect victims limited to a particular group. The effect of the disaster is greater in developed countries than in developing countries.

The remainder of the paper is organized as follows: section 2 proposes an overview of disasters and the hypotheses to be tested. The data and methods used are explained in section 3. Section 4 discusses the results of the estimations and the final section offers concluding remarks.

2. Hypotheses

2.1. Overview of types of natural disaster

This paper uses country-level panel data generally used in previous works (e.g., Anbarci et al. 2006; Skidmore & Toya 2013; 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, which is provided by the International Country Risk Guide (ICRG). This value ranges from 0 to 6—larger values indicate less corruption; i.e., this is regarded as incorruption. Figure 1 demonstrates the change in degree of incorruption and the occurrence of natural disasters. It shows that the occurrence of disasters tended to increase from 1992 to 2002 and then became constant, whereas incorruption decreased during this period. This trend suggests that the number of disasters has a negative association with the degree of incorruption prior to 2002. From the inter-country viewpoint, Figure 2 presents the average number of disasters on the horizontal axis and incorruption on the vertical axis for each county. The slope of the fitted line reveals a slightly negative 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. Following existing works (Skidmore & Toya 2002; Kahn 2005), disasters are classified into floods, storms, earthquakes, volcanic eruptions, landslides, and others[5]. Figure 3 shows that floods account for approximately 40% of natural disasters, 30% are storms, 7% are earthquakes, 2% are volcanic eruptions, and 5% are landslides. Thus, floods and storms account for around 70% of natural disasters, which can be categorized as climatic disasters (Skidmore & Toya 2002). 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 deaths per disaster are illustrated in Figure 4. Deaths caused by earthquakes are about 1300, which is a significantly larger number than that caused by other disasters. Deaths caused by volcanic eruptions and landslides are about 15 and 50, respectively, and those caused by floods and storms are 50 and 150, respectively. Hence, storms pose a relatively significant risk to life, whereas in comparison, volcanic eruptions, landslides, and floods are not that risky.

Floods occur because of significant rises in water level. Therefore, people who reside on irrigated land and in areas near rivers, waterways, lakes, or reservoirs are at greatest risk from floods. Residents around the perimeter of active volcanoes face the greatest risk from volcanic eruptions. Landslides occur on hillsides and in mountainous districts. Hence, the risk from floods, volcanic eruptions, and landslides is limited to specific areas. On the other hand, storms and earthquakes can have an effect across much wider areas. Storms may have regular routes, but damage caused by storms could possibly be observed in areas of irrigated land, mountainous areas, and around volcanoes. If an earthquake occurs within an area with an active fault line, the damage could possibly extend to other areas.

Table 1 summarizes the characteristics of disasters. The expected death rate is considered very small for floods, volcanic eruptions, and landslides. Hence, even if these events occur frequently in a specific area, there is little incentive for the residents to move to safer areas. Among low-cost disasters, such as floods, volcanic eruptions, and landslides, the probability of occurrence is low for volcanic eruptions and landslides, whereas floods can occur frequently. This causes residents in flood-prone areas to anticipate that they have opportunities to receive compensation.

[5] Empirical results of this paper do not change when other classifications are employed.

Thus, relief from natural disasters such as floods could possibly trigger a moral hazard problem.

2.2. Hypotheses

Countries with higher rents stemming from natural resources tend to have higher levels of corruption (Ades and Di Tella 1999). In a similar manner, the occurrence of natural disasters generates rents, which then increases corruption. According to the claims 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.
Occurrence of natural disaster deteriorates public sector corruption.

Life is thought to be more valuable than are physical assets. Hence, in addition to damage to physical assets, the probability of death is regarded as an expected cost of natural disasters. Furthermore, if the residents 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 expected 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:
Corruption increases when disasters frequently occur; however, its cost is low.

3. Data and method

3.1. Data

Data regarding the number of natural disasters were sourced from EM-DAT (Emergency Events Database).[6] 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). The windfalls generated by foreign aid possibly lead recipient countries to adopt opportunistic behavior such as rent-seeking activities, which impede institutional quality (Ades, & Di Tella 1999; Svensson 2000; Djankov et al. 2008). It has been suggested that in developing countries, the reporting of the impact of natural 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

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

developed country that is part of the North American continent, and has a land area of about 9900000 km^2, which is similar to that of the United States (about 9600000 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 in order to reduce measurement errors and improve the robustness.

With respect to the proxy for public sector corruption, the index of the ICRG is used, which is assembled by the Political Risk Service Group. The values range from 0 (corrupt) to 6 (incorrupt), and can be regarded as indicating the degree of incorruption. The data of the ICRG reveal that corruption experienced directly in business is commonplace. The index is appropriate for capturing 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, population, government size, and land area are collected from the World Bank (2010).

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. "Flooding in one region can be the result of storm activity upstream" (Skidmore & Toya 2013, 12). Storms are often accompanied by floods. Based on the data set of this paper, the correlation coefficient between floods and storms is 0.47. It is interesting to observe that the number of storms is 1.62 in OECD countries and 0.55 in non-OECD countries, whereas the number of floods is 0.91 in OECD countries and 1.08 in non-OECD countries. This shows that storms are less likely to cause floods in developed countries than in developing countries. One possible interpretation is that the inappropriate irrigation systems may make the system vulnerable to storms, increasing the probability of floods. In OECD countries, the maintenance of appropriate irrigation systems is thought to reduce floods.

Consistent with intuition, the value of incorruption in OECD countries is 4.70, which is larger than 2.60, the value for non-OECD countries. That is, OECD countries are less corrupt than non-OECD countries. Similarly, concerning GDP per capita, schooling years, and degree of democracy, these values are larger for OECD than for non-OECD countries. This can be interpreted as a reflection of the degree of economic development. With respect to religion, the ratio of Protestants is larger in OECD countries than in non-OECD countries, which reinforces the argument that Protestant countries are less corrupt (Gokcekus 2008).

3.2. Basic methods

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

$$Incorruption_{it} = \alpha_0 + \alpha_1\ Number\ of\ disasters_{it} + \alpha_2\ Number\ of\ disasters_{it-1} + \alpha_3 GDP_{it} + \alpha_4 Population_{it} + \alpha_5 land\ area_{it} + \alpha_6 Time\ trend_t + X'B + u_i + \varepsilon_{it}, \quad (1)$$

where the dependent variable is *Incorruption* $_{it}$ 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). To capture this, the function includes X, which represents the vector of additional control variables including institutional, social, and cultural factors. Furthermore, as shown in Figure 1, time trends are thought to influence the results, and hence, time tends are also captured following the method of Kahn (2005).

As for *Incorruption,* its lower and upper bounds are 0 and 6, respectively. Therefore, values are left-censored at 0 and right-censored at 6. In the data used, 19 observations are left-censored and 94 observations are right-censored. Therefore, in this study, the Tobit model is used for estimations. Furthermore, even after controlling various country-specific factors by X, unobservable country-specific characteristics u_i exist. Hence, with the aim of controlling for u_i, the random effect Tobit model is used.[7] Furthermore, Figure 1 suggests the possibility that the third factors are related to both incorruption and natural disasters. If the relation between disasters and incorruption 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 incorruption in year t changes according to the date of occurrence of the disaster. If a disaster occurs at the end of year t, the incorruption in year t has been estimated already, and thus, the disaster has no

[7] Leeson & Sobel (2008) used the simple fixed effects model when the effect of disaster relief on corruption is examined. Results reported in the present paper do not change when the simple fixed effects model is used. The results using the fixed effects model are available upon request.

effect on the level of the incorruption. However, the disaster will influence the level of incorruption 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. If *Hypothesis 1* is supported, the *number of disasters* $_t$ and the *number of disasters* $_{t-1}$ will take a negative sign. The slightly negative correlation observed in Figure 2 is congruent with *Hypothesis 1.* The relation, however, seems to be influenced by outliers such as the United States, China, India, Philippines, and Indonesia. 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 *POP* are included to capture basic economic conditions. The larger the land size is, the higher the probability of the occurrence of natural disasters, if all other things are equal. For the purposes of controlling for it, land size is included as an independent variable. Existing works have made it evident that institutional and socio-economic 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). In this paper, in order to capture this, French and English legal origin dummies are used and the ratio of the population that is Protestant in taken as in 1980. These data were sourced from an earlier work (La Porta et al. 1999).[8] Previous studies found that the public sector is more inclined to be corrupt in those countries of French legal origin that are now regarded as civil law countries (Treisman 2000; Serra 2006). It has been suggested that the public sector is less likely to be corrupt in countries in which Protestants are dominant (Gokcekus 2008).

4. Results

The estimations results based on the full sample are reported in Tables 3 and 4. The results based on the sample of non-OECD countries are presented in Tables 5 and 6, and those based on the sample of OECD countries are displayed in Tables 7 and 8. The

[8] It is available at http://www.economics.harvard.edu/faculty/shleifer/dataset (Accessed on May 1, 2011).

key variables of Tables 3, 5, and 7 are the number of total natural disasters in year t and in year t-1. The key variables of Tables 4, 6, and 8 are the disaggregated level variables, such as the number of floods, storms, volcanic eruptions, earthquakes, landslides, other disasters in year t and in year t-1. In each table, the results in columns (1), (3), and (5) do not include year trends, whereas those in columns (2), (4), and (6) do. Outliers are included in the sample for the results shown in columns (1) and (2), whereas they are excluded from the sample for the results shown in columns (3), (4), (5), and (6). Furthermore, the sample used in columns (5) and (6) excludes outliers, but various control variables are included, resulting in a reduction of the sample size because the data of control variables are not available for some observations.

4.1. Results of full sample.

Table 3 indicates that the number of total natural disaster in years t and t-1 have the predicated negative sign in all estimations. Furthermore, they are statistically significant, with the exception of column (4). Hence, this result is congruent with *Hypothesis 1.* As for the absolute value of their coefficients, the value in year t is almost equivalent to that in year t-1, which suggests that the magnitude of their effect does not change; i.e., they are stable. Furthermore, it can be seen from columns (1)–(4) that the value decreased from around 0.04 to 0.01 when the time trend is controlled. In addition, after adding various control variables, columns (5) and (6) suggest that the value decreased from around 0.05 to 0.02. This is interpreted as implying that the occurrence of a disaster reduces incorruption by 0.01 or 0.02 points on a zero-to-six scale. To take an extreme case such as the United States, on average, 25 natural disasters occur each year. If this is true, then incorruption decreases by 0.25 points on a zero-to-six scale over the year. The time trend shows the significant negative sign and the absolute value of the coefficient is 0.06 in columns (2), (4), and (6). This implies that incorruption decreases worldwide by 0.06 points on a zero-to-six scale each year. These results can be interpreted in a number of ways. For instance, a decline of civic virtue possibly leads to an exaggerated report of the number of disasters with the intention of increasing bribery and, thus, corruption. It follows from the results of the number of disasters in Table 3 that natural disasters have a negative effect on incorruption; however, its effect is reduced by about 75% when the time trend is included. This means that natural disasters continue to influence incorruption even after removing the time trend capturing the third factors related to both incorruption and natural disasters. Therefore, the relationship between natural disasters and incorruption is not considered as the spurious correlation.

As for the control variables, the coefficient of GDP per capita shows a negative sign in columns (1), (3), and (5). However, after controlling for the time trend, it becomes positive in columns (2) and (4). All of them are indicated as statistically significant with the exception of column (6). This implies that developed countries are less corrupt after controlling for the time trend, which is consistent with intuition. The coefficients of school years and democracy show a positive sign and statistical significance at the 1% level in columns (5) and (6). These robust results are also consistent with the perception that countries with high levels of education and democracy are less corrupt. Both the legal origin dummies and the ethnic fractionalization show a significant negative sign in column (5). However, their statistical significance disappears after including the time trend, although their signs remain negative. Hence, their effect on incorruption is not robust. The coefficient of the ratio of Protestants has a significant positive sign in columns (5) and (6). This supports the argument that predominantly Protestant countries are less corrupt (Gokcekus 2008).

Table 4 presents the results of disaggregating the natural disasters. It can be seen that the coefficients of the number of floods and of storms have a negative positive sign in most cases. However, it is surprising to observe that with the exception of column (2), the number of floods is statistically significant, whereas that of storms is not significant in any column. This holds true not only for those in year t, but also for year t-1. As presented in columns (4) and (6), after deleting the outliers, the absolute value of the coefficient of the number of floods is around 0.05. Therefore, the occurrence of floods reduces incorruption by 0.05 points on a zero-to-six scale, whereas the occurrence of storms does not reduce it at all. Their effect on incorruption definitely differs, even though they share the same climatic characteristics. The difference between floods and storms is that the victims of floods are limited to people residing on irrigated land and in areas near rivers, waterways, lakes, or reservoirs. On the other hand, the victims of storms tend to reside in wider areas because the effects of storms extend over a greater range. In comparison with the victims of storms, the victims of floods are limited geographically to a specific group. Therefore, the size of this group is small and its collective action thought to be coordinated more easily (Olson 1965). Naturally, an interest group of flood victims is likely to be formed to pursue strategically any benefits. Furthermore, the lower probability of death resulting from floods, compared with that of storms, possibly leads people to reside in flood-prone areas strategically to obtain compensation when a flood occurs. Inevitably, the moral hazard problem becomes more serious when floods occur than when storms occur.

Apart from climatic disasters, the number of volcanic eruptions produces a positive sign in all columns. Furthermore, the number of volcanic eruptions in year t-1 is statistically significant in columns (2), (4), and (6). However, the number of volcanic eruptions in year t is not statistically significant with the exception of column (4). Therefore, the effects of volcanic eruption are not robust and, therefore, unreliable. As for coefficients of the number of earthquakes and landslides, their signs change according to the specifications, and on the timing of the disasters, i.e., in year t or year t-1. Furthermore, they are not statistically significant in most cases. Overall, geologic disasters do not influence corruption. With respect to the number of other disasters, this includes various types of disaster, and hence, the results can be interpreted as being similar to the effect of total disasters, which are reported in Table 3. The information presented in Table 4 supports *Hypothesis 2.*

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

In Table 5, the coefficient of the number total natural disasters in year t and in year t-1 exhibits a negative sign in all columns. It is interesting to observe that it is statistically significant at the 1% level in columns (1), (3), and (5), whereas it is not statistically significant in columns (2), (4), and (6). This suggests that controlling for the time trend nullifies its effect on incorruption. Measurement error is known to attenuate the effect of the variable. As alluded to earlier, the reported number of disasters in developing countries is possibly exaggerated, which results in measurement error. The disappearance of the significance effect of the number of disasters might be, in part, due to the error. Turning to Table 6, with the exception of column (2), the number of floods yields a significant negative sign, not only in year t year but also in year t-1 year. The absolute value of the coefficient is 0.04 for year t and 0.03 for year t-1, as shown in column (4). After including various control variables, it becomes 0.05 in year t year as well as in year t-1. Thus, the degree of its effect is almost equivalent to that of Table 4.

Considering Table 7, the coefficient of the number of total natural disasters in year t year, as well as in year t-1, shows a negative sign in all columns. Different from the results based on the non-OECD sample shown in Table 5, it is statistically significant in most cases with the exception of column (2) in year t-1. Furthermore, its absolute value is around 0.05 in all estimations. This implies that the inclusion of the time trend does not influence the effect of the number of disasters. Therefore, the negative relation between disasters and incorruption is not considered as spurious. 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.

In Table 8, the number of floods yields a significant negative sign, not only in year t but also in year t-1, in all estimations. In most cases, its significance is at the 1% level. Columns (4) and (6) show that the absolute value of the coefficient of floods is reduced by the inclusion of the time trend. However, its value is 0.09 in year t and 0.10 in year t-1, implying that the occurrence of a flood reduces incorruption by 0.09 points on a zero-to-six scale. The degree of its effect is approximately twice that based on the sample of non-OECD countries. On the other hand, the number of storms is not statistically significant in any column, even though it shows a negative sign in columns (1)–(6). Floods and storms occur with similarly frequency, and so, to a certain extent, they can be predicted. Therefore, people can prepare measures to cope with these events. However, there is an obvious difference between them concerning their effect on incorruption. The results for earthquakes, volcanic eruptions, and landslides do not suggest statistical significance in most cases, and therefore, they do not influence corruption. Concerning the number of other disasters, its coefficient shows a significant sign in all estimations. The number of other disasters in year t-1 is not statistically significant in any column, even though in year t it is statistically significant. Therefore, the effect of other disasters is not robust. The combined results of the developed countries indicate that only the occurrence of floods increases corruption.

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 floods on corruption is greater in non-OECD countries than in 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.

If it is accepted that because of a disaster some individuals are dead, then clearly they cannot benefit from any windfalls that may be derived from the event. Costs such as the expected probability of death caused by floods are lower in developed countries, partly because their buildings are less vulnerable to floods. Thus, the expected benefit resulting from the occurrence of a disaster is greater than its cost. In developed countries, 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). Considering what has been discussed thus far leads to the claim that in developed countries, people have an incentive to live in flood-prone areas because the expected benefits of the occurrence of a flood are larger than the costs.

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 expected 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 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) Floods have a significant effect on corruption; however, other types of disaster do not exhibit such effects. This indicates that disasters that are foreseeable but that do not threaten life trigger strategic behavior in the victims. In addition, damage is limited to specific areas, which triggers the formation of interest groups. That is, people living in an area in which floods occur frequently anticipate disaster compensation, which leads to a moral hazard problem. (3) The effect of disasters is greater in developed countries than in developing countries. These findings are observed even after controlling for the time trend, the characteristics of various countries, and outliers. This is consistent with the claim of Leeson and Sobel (2008) that climatic disasters increase corruption. The moral hazard problem caused by a disaster is severe if the cost of the disaster is sufficiently small, such that individuals strategically opt to reside in the disaster-prone area.

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.

References

Ades, A., & Di Tella, R. (1999). Rents, competition, and corruption. *American Economic Review*, *89*, 982-993.

Albala-Bertrand, J. (1993). *Political economy of large natural disasters.* Oxford: Claredon Press.

Anbarci, N., Escaleras, M., & Register, C. (2005). Earthquake fatalities: the interaction of nature and political economy. *Journal of Public Economics*, *89*, 1907–1933.

Anbarci, N., Escaleras, M., & Register, C. (2006). Traffic fatalities and public sector corruption. *Kyklos*, *59*(3), 327–344.

Apergis, N., Dincer, O., & Payne, J. (2010). The relationship between corruption and income inequality in U.S. states: evidence from a panel co-integration and error correction model. *Public Choice*, *145*(1), 125–135.

Boettke, P., Chamlee, E., Gordon, P., Ikeda, S., Leeson, P. T., & Sobel, R. (2007). The political, economic, and social aspects of Katrina. *Southern Economic Journal*, *74*(2), 363–376.

Cuaresma, J. C., Hlouskova, J., & Obersteiner, M. (2008). Natural disasters as creative destruction? Evidence from developing countries. *Economic Inquiry*, *46*(2), 214–226.

Daily Yomiuri (2013). Government launches into reconstruction fund misuse, *Daily Yomiuri,* May 12, 2013.

Djankov, S., La Porta, R., Lopez-de-Silanes, F., & Shleifer, A. (2003). Courts. *Quarterly Journal of Economics*, *118*, 453–517.

Djankov, S., Montalvo, J., & Reynal-Querol, M. (2008). The curse of aid. *Journal of Economic Growth*, *13*, 169–194.

Dreher, A., & Schneider, F. (2010). Corruption and the shadow economy: an empirical analysis. *Public Choice*, *144*(1), 215–238.

Eisensee, T., & Strömberg, D. (2007). News droughts, news floods, and U.S. disaster relief. *Quarterly Journal of Economics*, *122*(2), 693–728.

Escaleras, M., Anbarci, N., & Register, C. (2007). Public sector corruption and major earthquakes: a potentially deadly interaction. *Public Choice*, *132*(1), 209–230.

Escaleras, M., Lin, S., & Register, C. (2010). Freedom of information acts and public sector corruption. *Public Choice*, *145*(3), 435–460.

Garret, T., & Sobel, R. (2003). The political economy of FEMA disaster payment. *Economic Inquiry*, *41*, 496–509.

Glaeser, E. L., & Saks, R. E. (2006). Corruption in America. *Journal of Public Economics*, *90*(6–7), 1407–1430.

Gokcekus, O. (2008). Is it protestant tradition or current protestant population that affects corruption? *Economics Letters*, *99*, 59–62.

Jain, A. (2001). Corruption: A review. *Journal of Economic Surveys*, *15*, 71–121.

Japan Times (2012). Misuse of reconstruction funds (Editorials), *Japan Times,* October 20, 2012.

Johnson, N., La Fountain, C., & Yamarik, S. (2011). Corruption is bad for growth (even in the United States). *Public Choice*, *147*, 377–393.

Kahn, M. (2005). The death toll from natural disasters: the role of income, geography and institutions. *Review of Economics and Statistics*, *87*(2), 271–284.

Keefer, P., Neumayer, E., & Plumper, T. (2011). Earthquake propensity and the politics of mortality prevention. *World Development* 39(9), 1530–1541.

Kellenberg, D., & Mobarak, A. M. (2008). Does rising income increase or decrease damage risk from natural disasters? *Journal of Urban Economics*, *63*, 788–802.

Kurosaki, T. (2013). *Vulnerability of household consumption to floods and droughts in developing countries: evidence from Pakistan*. Center for Economic Institutions Working Paper Series (Hitotsubashi University), no. 2012-10.

La Porta, R., Lopez de Silanes, F., Shleifer, A., & Vishni, R. (1999). Quality of government. *Journal of Law, Economics & Organization* 15(1), 222–279.

Leeson, P. T., & Sobel, R. (2008). Weathering corruption. *Journal of Law & Economics* 51, 667–681.

Leff, N. H. (1964). Economic development through bureaucratic corruption. *American Behavioral Scientist*, *82*(2), 337–341.

Luechinger, S., & Saschkly, P. A. (2009). Valuing flood disasters using the life satisfaction approach. *Journal of Public Economics*, *93*, 620–633.

Lui, F. T. (1985). An equilibrium queuing model of bribery. *Journal of Political Economy*, *93*(4), 760–781.

Mauro, P. (1995). Corruption and growth. *Quarterly Journal of Economics*, *110*, 681–712.

Niskanen, W. A. (1971). *Bureaucracy and Representative Government.* Chicago: Aldine-Atherton.

Olson, M. (1965). *The logic of collective action*. Cambridge, MA: Harvard University Press.

Paldam, M. (2001). Corruption and religion adding to the economic model. *Kyklos*, *54*(2-3), 383–413.

Pellegrini, L., & Gerlagh, R. (2008). Causes of corruption: a survey of cross-country analyses and extended results. *Economic Governance*, *9*, 245–263.

Serra, D. (2006). Empirical determinants of corruption: a sensitivity analysis. *Public Choice*, *126*, 225–256.

Shleifer, A., & Vishny, R. (1993). Corruption. *Quarterly Journal of Economics*, *108*, 599–617.

Shughart II, W. F. (2006). Katrinanomics: the politics and economics of disaster relief. *Public Choice*, *127*, 31-53.

Skidmore, M., & Toya, H. (2002). Do natural disasters promote long-run growth? *Economic Inquiry*, *40*(4), 664–687.

Sobel, R., & Leeson, P. (2006). Government's response to Hurricane Katrina: a public choice analysis. *Public Choice*, *127*, 55–73.

Strobl, E. (2011). The economic growth impact of hurricanes: evidence from U.S. coastal countries. *Review of Economics and Statistics, 93*(2), 575–589.

Svensson, J. (2000). Foreign aid and rent seeking. *Journal of International Economics, 51*, 437–461.

Swaleheen, M. (2011). Economic growth with endogenous corruption: an empirical study. *Public Choice*, *146*(1), 23–41.

Tanzi, B., & Davoodi, H. (1997). *Corruption, public investment, and growth*. IMF working paper WP/97/139.

Toya, H., & Skidmore, M. (2007). Economic development and the impacts of natural disasters. *Economics Letters*, *94*(1), 20–25.

Treisman, D. (2000). The causes of corruption: a cross-national study. *Journal of Public Economics*, *76*(3), 399–457.

World Bank. (2010). *World development indicators 2010* on CD-ROM. The World Bank.

Yamamura, E. (2013). Public sector corruption and the probability of technological disasters. *Economics of Governance*, *14*(3), 233–255.

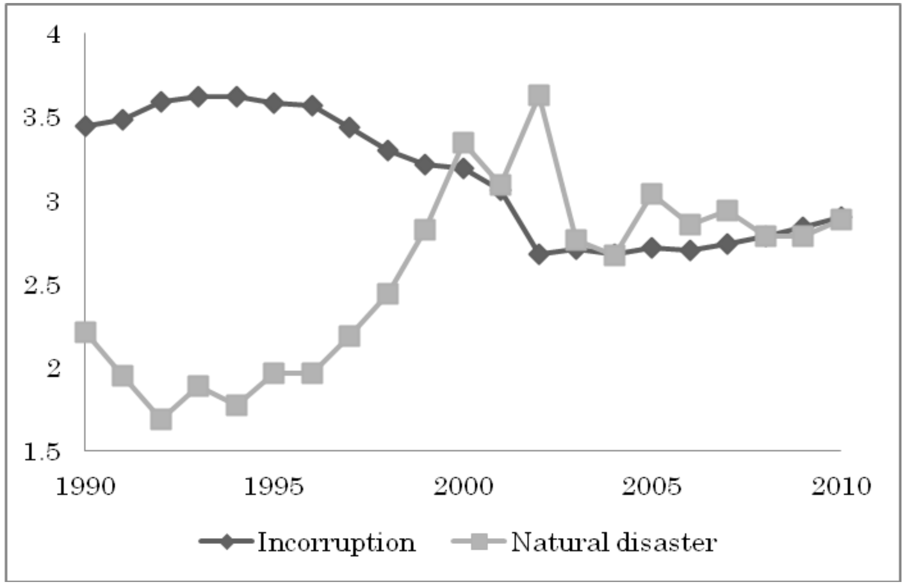

Figure 1. Change in degree of incorruption and occurrence of natural disasters.

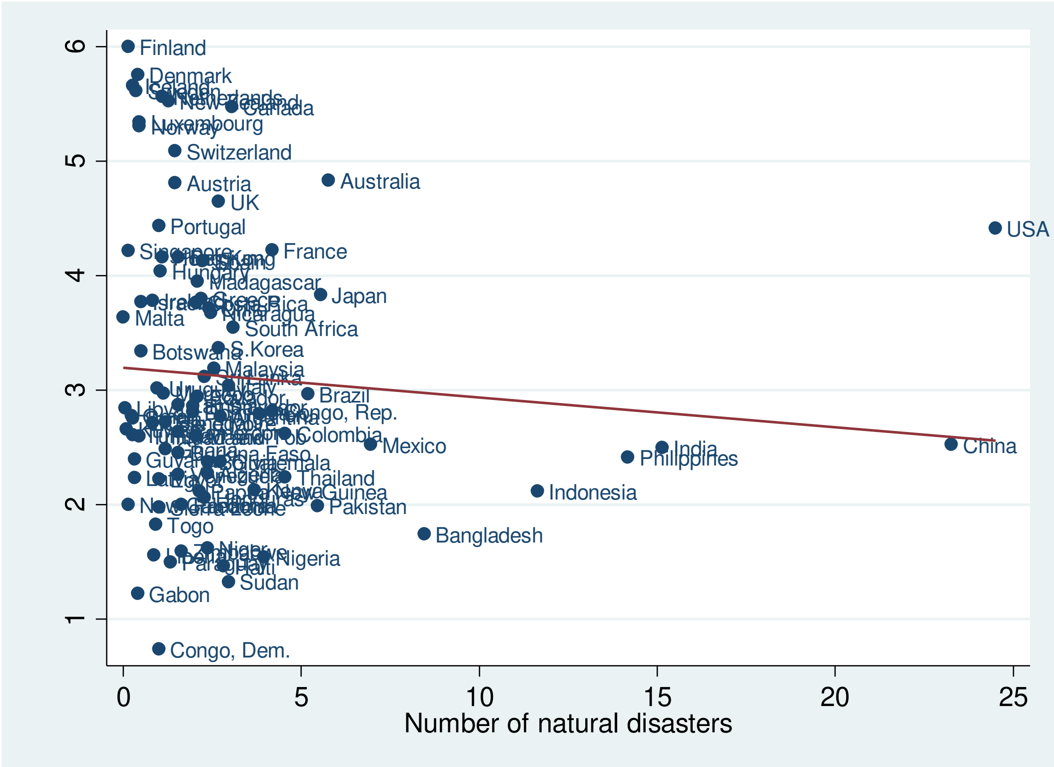

Figure 2. Relation between occurrence of natural disasters and incorruption.

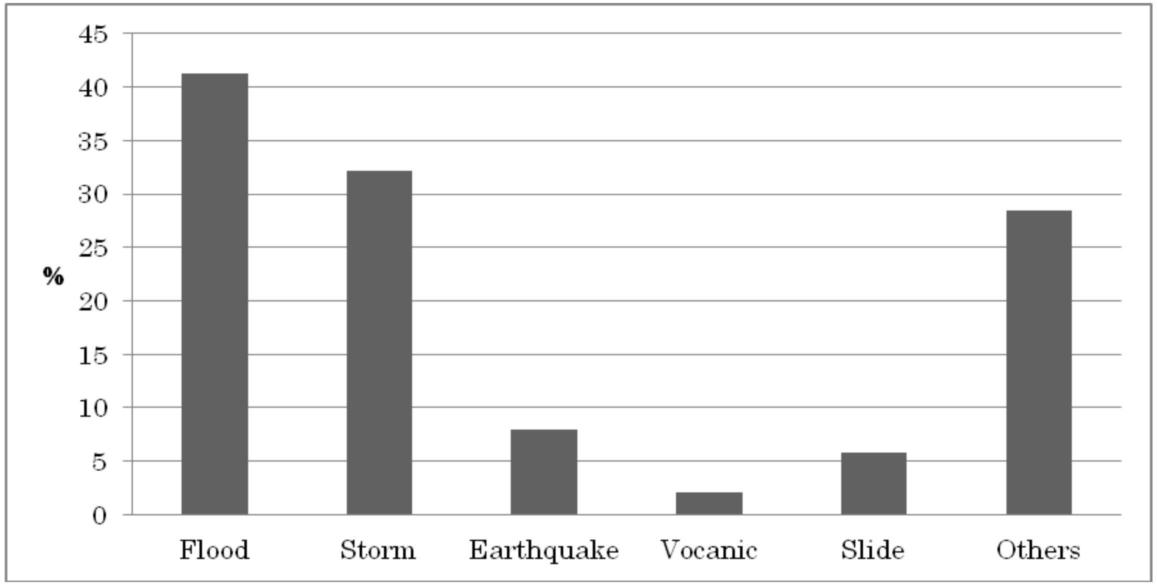

Figure 3. Composition of number of natural disasters.

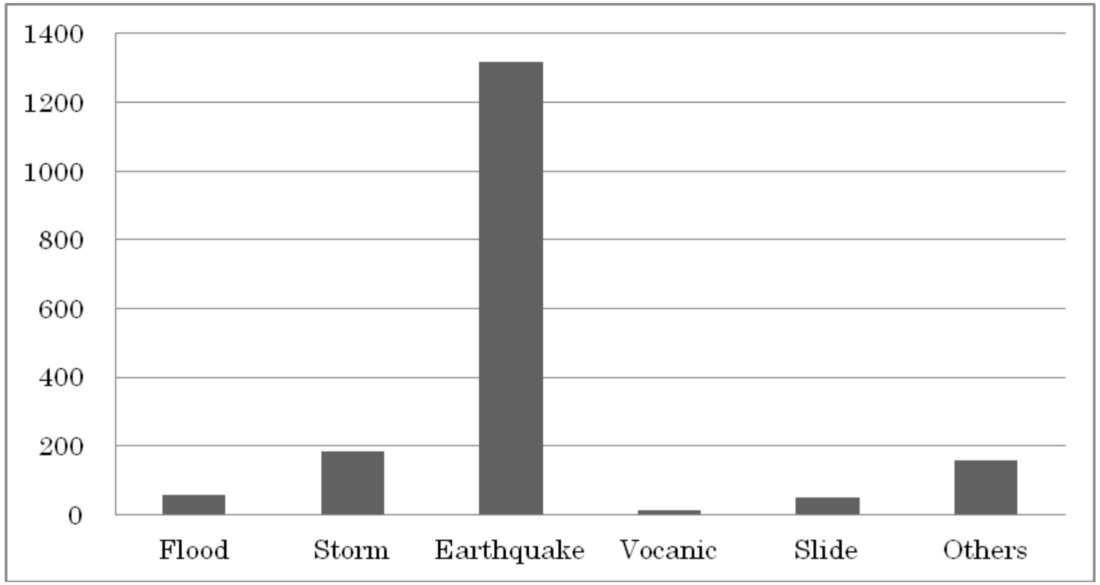

Figure 4. Average death toll per disaster (number of deaths / number of disasters)

Table 1. Characteristics of disasters.

	Flood	Storm	Earthquake	Volcanic	Landslide
Expected cost	Very small	Small	Very large	Very Small	Very Small
Risk	Property	Property	Life and property	Property	Property
Type	Climatic (Frequent)	Climatic (Frequent)	Geologic (Rare)	Geologic (Rare)	Geologic (Rare)
Exposed area and people	Restricted	Extensive	Extensive	Restricted	Restricted

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)
Incorruption	1 (Corrupt)–6 (Incorrupt)	3.15	2.60	4.70
		(1.39)	(1.04)	(1.02)
Number of total natural disasters		3.01	2.85	3.45
		(4.35)	(3.64)	(5.91)
Number of floods		1.03	1.08	0.91
		(1.69)	(1.69)	(1.68)
Number of storms		0.83	0.55	1.62
		(2.24)	(1.35)	(3.65)
Number of earthquakes		0.19	0.19	0.17
		(0.60)	(0.62)	(0.53)
Number of volcanic eruptions		0.06	0.08	0.02
		(0.32)	(0.35)	(0.17)
Number of landslides		0.13	0.16	0.04
		(0.47)	(0.53)	(0.23)
Number of other disasters		0.74	0.76	0.67
		(1.29)	(1.29)	(1.30)
GDP per capita	10 thousand US$	0.81	0.30	2.29
		(1.04)	(0.46)	(0.82)
Population	Million	4.59	4.77	4.08
		(12.4)	(13.9)	(6.47)
Land area	Million m^2	9.83	7.63	16.0
		(19.9)	(13.7)	(31.2)
Schooling years	Log of 1 + average years of school attainment in 1980	1.60	1.40	2.19
		(0.53)	(0.44)	(0.27)

Democracy	1 (Undemocratic)–10 (Democratic)	5.26 (3.17)	3.86 (2.32)	9.24 (1.40)
French legal origin dummy		0.50	0.56	0.35
English legal origin dummy		0.37	0.51	0.32
Ethnic fractionalization	The larger the value, the more ethnically heterogeneous the society is.	0.44 0.27)	0.51 (0.25)	0.24 (0.21)
Ratio of Protestants	%	14.1 (20.6)	9.40 (12.4)	27.5 (30.9)
Observations		1348	997	351

Notes: Values in parentheses are standard deviations. Sample that did not exclude countries considered as outliers whose average number of total disasters is over 10.

Sources: Incorruption data is gathered 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).

Schooling years are used in Easterly and Ross (1997). The data are available from http://econ.worldbank.org/WBSITE/EXTERNAL/EXTDEC/EXTRESEARCH/0,,contentMDK:20700002~pagePK:64214825~piPK:64214943~theSitePK:469382,00.html (accessed June 2, 2011). Data on ethnic fractionalization is available at http://www.econ.upf.edu/~reynal/data_web.htm (accessed on June 1, 2011). French legal and English legal origin dummies and measure of democracy are available at http://www.economics.harvard.edu/faculty/shleifer/dataset (accessed on June 1, 2011). All other data used in this paper are gathered from the World Bank (2010).

Table 3. Effect of aggregated disasters on incorruption (Random Effect Panel Tobit Estimations): Full sample

	(1)	(2)	(3)	(4)	(5)	(6)
Number of total natural disasters in year *t*.	-0.04***	-0.01*	-0.04***	-0.01	-0.05***	-0.02**
	(-4.68)	(-1.80)	(-4.31)	(-1.56)	(-4.52)	(-2.18)
Number of total disasters in year *t*-1.	-0.04***	-0.01*	-0.05***	-0.01	-0.06***	-0.02**
	(-5.20)	(-1.81)	(-4.67)	(-1.52)	(-5.09)	(-2.15)
GDP per capita	-1.02***	0.34***	-1.02***	0.31***	-1.13***	0.14
	(-8.49)	(3.33)	(-8.54)	(2.86)	(-8.48)	(-1.28)
Population	-0.02**	0.003	-0.23***	-0.004	-0.09***	0.002
	(-2.01)	(0.05)	(-5.76)	(-0.14)	(-2.62)	(0.09)
Land area	0.03**	0.01	0.02*	0.01	0.02***	0.01*
	(2.30)	(1.09)	(1.77)	(0.93)	(3.04)	(1.79)
Trend		-0.06***		-0.06***		-0.06***
		(-18.3)		(-17.2)		(-13.7)
Schooling years					0.91**	0.94***
					(2.08)	(3.43)
Democracy					0.33***	0.16***
					(4.52)	(3.41)
French legal origin dummy					-1.63***	-0.22
					(-2.68)	(-0.58)
English legal origin dummy					-1.86***	-0.48
					(-3.10)	(-1.28)
Ethnic fractionalization					-1.19*	-0.49
					(-1.96)	(-1.29)
Ratio of Protestants					0.01*	0.01***
					(1.17)	(3.23)
Constant	4.17***	3.59***	4.66***	3.65***	3.13***	1.87***

	(14.4)	(24.8)	(15.0)	(22.7)	(3.25)	(3.12)
Outliers	Included	Included	Excluded	Excluded	Excluded	Excluded
Observations	1647	1647	1552	1552	1272	1272
Left-censored observations	19	19	19	19	19	19
Right-censored observations	94	94	94	94	72	72
Log likelihood function	–1942	–1802	–1804	–1685	–1467	–1384

Note: Values in parentheses are z-statistics. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 4. Effect of disaggregated disasters on incorruption (Random Effect Panel Tobit Estimations): Full sample

	(1)	(2)	(3)	(4)	(5)	(6)
Number of floods in year *t*.	-0.06***	-0.01	-0.10***	-0.04**	-0.12***	-0.06***
	(-4.10)	(-1.02)	(-5.18)	(-2.39)	(-5.40)	(-2.78)
Number of storms in year *t*.	-0.01	-0.001	-0.01	0.01	-0.01	-0.001
	(-0.87)	(-0.12)	(-0.26)	(0.71)	(-0.48)	(-0.04)
Number of earthquakes in year *t*.	0.02	0.001	0.09*	0.06	0.07	0.04
	(0.76)	(0.05)	(1.93)	(1.42)	(1.53)	(0.98)
Number of volcanic eruptions in year *t*.	0.06	0.07	0.13	0.15*	0.11	0.12
	(0.97)	(1.12)	(1.57)	(1.87)	(1.36)	(1.49)
Number of landslides	-0.05	-0.02	-0.01	-0.01	-0.04	-0.04
	(-1.13)	(-0.51)	(-0.27)	(-0.31)	(-0.74)	(-0.66)
Number of other disasters in year *t*.	-0.06***	-0.04**	-0.06***	-0.03*	-0.06***	-0.04*
	(-3.57)	(-2.43)	(-2.99)	(-1.95)	(-2.82)	(-1.86)
Number of floods in year *t*-1.	-0.07***	-0.02	-0.10***	-0.05**	-0.12***	-0.06***
	(-4.40)	(-1.34)	(-5.25)	(-2.54)	(-5.70)	(-3.00)
Number of storms in year *t*-1.	-0.01	0.001	-0.01	0.02	-0.01	0.002
	(-0.90)	(0.09)	(-0.22)	(0.91)	(-0.68)	(0.08)
Number of earthquakes in year *t*-1.	-0.01	-0.02	0.06	0.03	0.05	0.03
	(-0.16)	(-0.65)	(1.25)	(0.81)	(1.11)	(0.66)
Number of volcanic eruptions in year *t*-1.	0.11	0.13**	0.14	0.18**	0.13	0.16*
	(1.53)	(2.00)	(1.60)	(2.16)	(1.45)	(1.82)
Number of landslides in year *t*-1.	-0.05	-0.03	0.04	0.04	0.01	0.02
	(-1.27)	(-0.77)	(0.74)	(0.71)	(0.25)	(0.33)
Number of other disasters in year *t*-1.	–0.06***	–0.03**	–0.07***	–0.03**	–0.07***	–0.04*
	(–3.75)	(–2.08)	(–3.53)	(–1.97)	(–3.29)	(–1.86)
Trend		-0.06***		-0.06***		-0.05***
		(-17.7)		(-16.2)		(-12.4)

Control variables included	Column (1) of Table 2	Column (2) of Table 2	Column (3) of Table 2	Column (4) of Table 2	Column (5) of Table 2	Column (6) of Table 2
Outliers	Included	Included	Excluded	Excluded	Excluded	Excluded
Observations	1647	1647	1552	1552	1272	1272
Left-censored observations	19	19	19	19	19	19
Right-censored observations	94	94	94	94	72	72
Log likelihood function	–1930	–1795	–1779	–1670	–1443	–1373

Note: Values in parentheses are z-statistics. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 5. Effect of aggregated disasters on incorruption (Random Effect Panel Tobit Estimations): Sample of non-OECD countries

	(1)	(2)	(3)	(4)	(5)	(6)
Number of total natural disasters in year *t*.	-0.04***	-0.01	-0.04***	-0.01	-0.05***	-0.02
	(-4.13)	(-1.34)	(-3.54)	(-1.08)	(-3.46)	(-1.39)
Number of total disasters in year *t*-1.	-0.05***	-0.02**	-0.05***	-0.01	-0.06***	-0.02
	(-5.30)	(-1.98)	(-4.08)	(-1.21)	(-4.20)	(-1.63)
GDP per capita	-0.22	0.45***	-0.34**	0.44***	-0.42**	0.32**
	(-1.32)	(3.40)	(-1.98)	(3.32)	(-2.14)	(2.06)
Population	0.01	0.01	-0.12***	-0.004	-0.07**	0.01
	(1.05)	(1.16)	(-3.53)	(-0.17)	(-2.12)	(0.24)
Land area	0.002	-0.003	0.01	-0.002	0.02**	-0.001
	(0.31)	(-0.51)	(1.64)	(-0.30)	(2.04)	(-0.09)
Trend		-0.05***		-0.05***		-0.05***
		(-14.4)		(-13.8)		(-11.3)
Schooling years					0.67**	0.48*
					(2.07)	(1.85)
Democracy					0.10**	0.10**
					(1.77)	(2.32)
French legal origin dummy					-0.98	-0.56
					(-1.63)	(-1.17)
English legal origin dummy					-0.69	-0.70
					(-1.12)	(-1.41)
Ethnic fractionalization					-0.48	0.02
					(-1.06)	(0.07)
Ratio of Protestants					-0.01	0.001
					(-1.35)	(0.26)
Constant	2.88***	3.10***	3.12***	3.12***	2.91***	2.63***

	(21.6)	(28.2)	(19.3)	(26.3)	(3.52)	(3.99)
Outliers	Included	Included	Excluded	Excluded	Excluded	Excluded
Observations	1249	1249	1173	1173	940	940
Left-censored observations	19	19	19	19	19	19
Right-censored observations	0	0	0	0	0	0
Log likelihood function	–1489	–1393	–1381	–1294	–1126	–1067

Note: Values in parentheses are z-statistics. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 6. Effect of disaggregated disasters on incorruption (Random Effect Panel Tobit Estimations): Sample of non-OECD countries

	(1)	(2)	(3)	(4)	(5)	(6)
Number of floods in year *t*.	-0.06***	-0.01	-0.10***	-0.04*	-0.12***	-0.05*
	(-3.25)	(-0.63)	(-4.45)	(-1.72)	(-4.41)	(-1.93)
Number of storms in year *t*.	-0.01	0.01	0.001	0.02	-0.01	0.003
	(-0.63)	(0.33)	(0.03)	(0.76)	(-0.33)	(0.10)
Number of earthquakes in year *t*.	0.01	-0.01	0.09	0.06	0.07	0.04
	(0.14)	(-0.43)	(1.57)	(1.21)	(1.19)	(0.80)
Number of volcanic eruptions in year *t*.	0.05	0.07	0.11	0.13	0.11	0.13
	(0.74)	(1.00)	(1.17)	(1.57)	(1.20)	(1.42)
Number of landslides	-0.04	-0.02	-0.01	-0.01	-0.30	-0.03
	(-0.90)	(-0.50)	(-0.08)	(-0.23)	(-0.46)	(-0.45)
Number of other disasters in year *t*.	-0.06***	-0.03*	-0.04**	-0.03	-0.04*	-0.02
	(-2.96)	(-1.86)	(-2.18)	(-1.44)	(-1.81)	(-1.18)
Number of floods in year *t*-1.	-0.07***	-0.01	-0.10***	-0.03*	-0.12***	-0.05**
	(-3.88)	(-0.84)	(-4.40)	(-1.66)	(-4.52)	(-1.99)
Number of storms in year *t*-1.	-0.02	-0.01	-0.003	0.02	-0.03	-0.003
	(-0.99)	(-0.38)	(-0.10)	(0.74)	(-0.77)	(-0.10)
Number of earthquakes in year *t*-1.	-0.03	-0.05	0.04	0.01	0.03	0.01
	(-0.76)	(-1.32)	(0.72)	(0.36)	(0.54)	(0.18)
Number of volcanic eruptions in year *t*-1..	0.11	0.13*	0.15	0.19**	0.16	0.19*
	(1.44)	(1.85)	(1.53)	(2.08)	(1.57)	(1.94)
Number of landslides in year *t*-1.	-0.04	-0.02	0.06	0.05	0.04	0.04
	(-0.87)	(-0.58)	(0.91)	(0.81)	(0.56)	(0.59)
Number of other disasters in year *t*-1.	–0.06***	–0.03*	–0.06***	–0.03*	–0.06**	–0.03
	(–3.38)	(–1.92)	(–2.96)	(–1.79)	(–2.49)	(–1.53)
Trend		-0.05***		-0.05***		-0.05***

		(-14.3)		(-13.1)		(-10.4)
Control variables included	Column (1) of Table 2	Column (2) of Table 2	Column (3) of Table 2	Column (4) of Table 2	Column (5) of Table 2	Column (6) of Table 2
Outliers	Included	Included	Excluded	Excluded	Excluded	Excluded
Observations	1249	1249	1173	1173	940	940
Left-censored observations	19	19	19	19	19	19
Right-censored observations	0	0	0	0	0	0
Log likelihood function	–1482	–1387	–1363	–1284	–1110	–1059

Note: Values in parentheses are z-statistics. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 7. Effect of aggregated disasters on incorruption (Random Effect Panel Tobit Estimations): Sample of OECD countries

	(1)	(2)	(3)	(4)	(5)	(6)
Number of total natural disasters in year *t*.	-0.04***	-0.04***	-0.06***	-0.05**	-0.05***	-0.05**
	(-3.03)	(-3.17)	(-2.80)	(-2.56)	(-2.61)	(-2.48)
Number of total disasters in year *t*-1.	-0.03**	-0.02	-0.05***	-0.04*	-0.05**	-0.04*
	(-2.15)	(-1.54)	(-2.73)	(-1.89)	(-2.59)	(-1.92)
GDP per capita	-1.49***	-0.001	-1.46***	-0.002	-1.59***	-0.54***
	(-12.2)	(-0.01)	(-11.8)	(0.01)	(-11.8)	(2.89)
Population	0.003	-0.01	-0.30**	-0.13**	0.10*	0.03
	(0.06)	(-0.32)	(-2.24)	(-2.14)	(1.91)	(0.89)
Land area	0.01	0.01	0.004	0.01	0.004	0.01
	(0.67)	(1.22)	(0.24)	(1.11)	(0.62)	(1.04)
Trend		-0.09***		-0.09***		-0.07***
		(-9.56)		(-9.31)		(-6.77)
Schooling years					0.08	0.54
					(0.09)	(0.73)
Democracy					0.27*	0.01
					(1.66)	(0.13)
French legal origin dummy					-1.38***	-0.42
					(-2.79)	(-1.04)
English legal origin dummy					-1.40***	-0.38
					(-2.97)	(-0.99)
Ethnic fractionalization					1.43	0.76
					(1.65)	(1.11)
Ratio of Protestants					0.03***	0.02***
					(4.35)	(4.90)
Constant	8.82***	6.08***	9.53***	6.46***	5.49***	4.90***
	(15.8)	(15.1)	(14.8)	(15.3)	(2.97)	(3.42)

Outliers	Included	Included	Excluded	Excluded	Excluded	Excluded
Observations	398	398	379	379	332	332
Left-censored observations	0	0	0	0	0	0
Right-censored observations	94	94	94	94	72	72
Log likelihood function	–373	–338	–354	–322	–300	–279

Note: Values in parentheses are z-statistics. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 8. Effect of disaggregated disasters on incorruption (Random Effect Panel Tobit Estimations): Sample of OECD countries

	(1)	(2)	(3)	(4)	(5)	(6)
Number of floods in year *t*.	-0.09***	-0.07***	-0.12***	-0.09***	-0.12***	-0.09***
	(-3.64)	(-2.84)	(-3.52)	(-2.70)	(-3.44)	(-2.75)
Number of storms in year *t*.	-0.02	-0.03*	-0.02	-0.04	-0.01	-0.03
	(-1.18)	(-1.95)	(-0.93)	(-1.41)	(-0.58)	(-1.08)
Number of earthquakes in year *t*.	0.09	0.06	0.15*	0.12	0.13	0.10
	(1.22)	(0.94)	(1.84)	(1.57)	(1.49)	(1.29)
Number of volcanic eruptions in year *t*.	0.25	0.05	0.24	0.09	0.27	0.11
	(1.25)	(0.31)	(1.18)	(0.46)	(1.26)	(0.56)
Number of landslides.	-0.07	-0.10	-0.06	-0.07	-0.06	-0.08
	(-0.53)	(-0.75)	(-0.43)	(-0.55)	(-0.43)	(-0.55)
Number of other disasters in year *t*.	-0.07**	-0.05*	-0.13***	-0.09**	-0.13***	-0.09**
	(-2.15)	(-1.71)	(-2.78)	(-2.02)	(-2.63)	(-2.00)
Number of floods in year *t*-1.	-0.09***	-0.05**	-0.14***	-0.10***	-0.14***	-0.10***
	(-3.34)	(-2.17)	(-4.00)	(-2.88)	(-3.90)	(-2.95)
Number of storms in year *t*-1.	-0.02	-0.02	-0.01	-0.02	-0.01	-0.02
	(-1.15)	(-1.35)	(-0.63)	(-0.88)	(-0.32)	(-0.64)
Number of earthquakes in year *t*-1.	0.08	0.07	0.15*	.0.12	0.15*	0.12
	(1.19)	(1.08)	(1.94)	(1.64)	(1.77)	(1.54)
Number of volcanic eruptions in year *t*-1.	0.11	0.05	-0.03	-0.06	-0.01	-0.06
	(0.59)	(0.32)	(-0.15)	(-0.34)	(-0.06)	(-0.33)
Number of landslides in year *t*-1.	-0.05	-0.06	-0.02	-0.05	-0.01	-0.05
	(-0.37)	(-0.50)	(-0.20)	(-0.38)	(-0.11)	(-0.38)
Number of other disasters in year *t*-1.	–0.07**	–0.02	–0.12**	–0.06	–0.12**	–0.07
	(–1.98)	(–0.82)	(–2.58)	(–1.39)	(–2.49)	(–1.50)
Trend		-0.08***		-0.08***		-0.06***

		(-8.91)		(-8.01)		(-5.60)
Control variables included	Column (1) of Table 2	Column (2) of Table 2	Column (3) of Table 2	Column (4) of Table 2	Column (5) of Table 2	Column (6) of Table 2
Outliers	Included	Included	Excluded	Excluded	Excluded	Excluded
Observations	398	398	379	379	332	332
Left-censored observations	0	0	0	0	0	0
Right-censored observations	94	94	94	94	72	72
Log likelihood function	–364	–333	–341	–315	–287	–273

Note: Values in parentheses are z-statistics. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Appendix: List of countries used in the analysis

Number	Country	Number	Country
1	Argentina	51	The 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	Syrian
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		