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Impact of natural disaster on public sector corruption

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Abstract This paper uses inter-country panel data from 1990 through 2010 to examine how the occurrence of natural disasters affects corruption within the public sector. For a closer analysis, disaster is classified into various categories, including general floods, other floods, tropical storms, other storms, earthquakes, volcanic eruptions, and landslides. Furthermore, this paper explores whether natural disasters have different impacts on corruption levels in developed and developing countries. The study reveals a number of novel findings. (1) Natural disasters that cause substantial damage increase public sector corruption in both developing and developed countries. (2) Natural disasters have a greater impact on public sector corruption in developed countries than in developing countries. (3) In developed countries, natural disaster frequency has a significant impact on the level of corruption. Hence, foreseeable disasters increase corruption in general. In developed countries, an incentive may exist to live within disaster-prone areas because of the potential for disaster compensation payments.

Keywords Corruption · Institution · Disasters · Risk

JEL classification D73 · D81 · Q54

1 Introduction

The devastating damage caused by natural disasters such as Hurricane Katrina that hit the southeast United States in 2005 and the Great East Japan Earthquake in 2011 has led to the investigation of disaster-related issues (Eisensee and Strömberg 2007; Luechinger and Saschkly 2009). Disasters have been observed to have a strong influence on the political

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economy of modern society with regard to the political economy.[1] Studies that address the damage caused by natural disasters have found that low-quality governance, characterized by corruption and income inequalities, increases the resultant death rates (Anbarci et al. 2005; Kahn 2005; Escaleras et al. 2007).[2] The occurrence of natural disasters appears to have an effect on the contracts and incentives offered to public sector employees living in areas prone to such disasters.[3] Public sector corruption is of significant concern when considering the interaction between politics and economics[4] (e.g., Glaeser and Saks 2006; Gokcekus 2008; Apergis et al. 2010; Dreher and Schneider 2010; Escaleras et al. 2010; Johnson et al. 2011; Swaleheen 2011). Natural disasters can generate an incentive to engage in corruption, which is generally defined as the use of public office for private gain (Boettke et al. 2007; Leeson and Sobel 2008). As observed in the United States, individuals can abuse disaster relief windfalls. For example, in the aftermath of Hurricane Katrina some public employees were accused of soliciting bribes from relief-funded contractors and of overbilling the government (Leeson and Sobel 2008). Similarly, the misuse of reconstruction funds was revealed after 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). In the latter case, money earmarked for reconstruction work was improperly spent on projects to improve the earthquake resistance of the central government’s local branch buildings and on measures dealing with anti-whaling groups (Daily Yomiuri 2013). Public choice theory can be used to explain this undesirable situation. In the aftermath of a natural disaster, the national government plays a leading role in reconstruction and accordingly allocates a budget for that purpose. In this case, various groups undertaking public works sought orders from the government. However, either because of information asymmetry or the support of favorable politicians, businesses unconnected to reconstruction received work orders. Moreover, there have been instances where the occurrence of disasters provided politicians with an incentive to misallocate disaster expenditure to increase the probability of their re-election (Garret and Sobel 2003). Such allocative failure prevents disaster relief from reaching those who need it most (Sobel and 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 and Sobel (2008), based on panel data from the United States,[5] provided evidence that disaster relief windfalls increase corruption. Natural disasters vary in type, and the

[1] Specifically, in recent years researchers have investigated the impact of natural disasters on economic growth (Skidmore and Toya 2002; Strobl 2011), death toll (Anbarci et al. 2005; Kahn 2005; Toya and Skidmore 2007), and trust (Toya and Skidmore 2013).

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

[3] Some studies explore the relation between disasters and moral hazard issues (Simmons et al. 2002; Shiue 2004).

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

[5] Numerous studies have attempted to ascertain the determinants of corruption (Treisman 2000; Paldam 2001; Serra 2006; Pellegrini and Gerlagh 2008).

existing literature claims that different disaster characteristics may influence economic outcomes (Skidmore and Toya 2002; Kahn 2005; Kellenberg and Mobarak 2008; Toya and Skidmore 2013). Disaster frequency and damage differ by disaster type. For example, one disaster type may occur frequently with low damage levels sustained at each episode. Another type may occur rarely but can result in extensive damage. Furthermore, the effect of natural disasters differs between developing and developed countries (Toya and Skidmore 2007; Cuaresma et al. 2008).

This paper seeks to explore how and to what extent the effects that disasters have on corruption differ per disaster type and by the existing conditions (economic, development level) of the stricken country, an area not previously studied. For that purpose, this paper uses panel data from 84 countries over a 21-year period (1990–2010). The novel findings of this paper are as follows. (1) As is observed generally, natural disasters increase public sector corruption. (2) Natural disaster frequency rather than its economic damage has a significant impact on the level of corruption in Organization for Economic Co-operation and Development (OECD) countries but not in other countries.

Section 2 of this paper proposes theoretical considerations and the testable hypotheses of the study. In Sect. 3, an overview of disasters is provided and the data and methods used are explained. Section 4 discusses the results of the estimations, and Sect. 5 offers concluding remarks.

2 Theoretical considerations and hypotheses

Theoretical works indicate that countries rich in natural resources have large numbers of entrepreneurs engaged in rent-seeking (Baland and Francois 2000; Torvik 2002). Robinson et al. (2006) provided a model showing that when a politician uses natural resources to promote self-interest a misallocation of resources can result. Moreover, countries with large economic rents stemming from natural resources tend to have high levels of corruption (Ades and Di Tella 1999; Pedro 2010). A similar observation has been made for international aid. Foreign aid is associated with rent-seeking activities and therefore with high corruption levels (Svensson 2000): additional government revenues increase corruption (Brollo et al. 2013). Similarly, a disaster can generate an economic windfall that increases corruption. Natural disasters inevitably increase a government's expenditures for relief and reconstruction. Public choice reasoning suggests that such expenditures will attract lobbying by individuals and groups who benefit from them and that politically self interested government officials will be responsive to the influence of well-organized special interest groups. The rents generated by governmental responses to natural disasters are shaped by the same forces that determine the allocation of spending in more ordinary times. The expenditure is efficiently allocated and effectively used if individuals and government officers do not serve their own self-interests at the expense of the remainder of society. However, the occurrence of natural disasters is thought to generate rents.

This paper follows Svensson (2000) and describes the situation as follows. An economy consists of n social groups. When a disaster occurs, the increase in government reconstruction spending in year t is $y(m_t, s_t)$, where m_t represents the number of natural disasters in year t, with $\partial y/\partial m_t > 0$, and s_t represents the total damage from natural disasters in year t, with $\partial y/\partial s_t > 0$. Expenditure can be appropriated by each individual social group. The appropriation of common resources is costly and so rent-seeking outlays by group i are expressed as c_{it}. The appropriation equation can be 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 a bribe. The 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, the total damage of the natural disaster increases the appropriation, $\partial z_{it}/\partial s_t > 0$. The number of natural disasters also increases the appropriation, $\partial z_{it}/\partial m_t > 0$.

Niskanen (1971) reasoned that government officials seek to maximize the size of their budget rather than deliver social benefit. There is the possibility that natural disasters give officials an opportunity to increase their budget by using aid as a pretext. In the midst of a disaster, a government is unable to observe the actual situation in affected areas and the disaster victims have access to more information about their situation than their government. Hence, there is information asymmetry regarding the damage caused by the disaster between victims and officials. Accordingly, victims can encourage the government to offer generous compensation for any damage caused by the disaster.

Disaster-related benefits can be regarded as rents, and as a consequence of disasters victims (through interventions by officials) may enjoy 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 and Di Tella 1999, p. 983). Victims may be willing to pay bribes to obtain such rents if the cost of the bribe is sufficiently less than the rents. Thus, *Hypothesis 1* is proposed.

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

Leeson and Sobel (2008) argued that the greater the amount of infused government relief, the higher the level of corruption. Where the damage from a disaster is extensive, victims will request generous taxpayer compensation. Hence, the cost of damage is assumed to be positively associated with the inflow of aid. Furthermore, if residents have the prospect of becoming victims of a disaster, then they are likely to receive some disaster-related compensation from the government. The more frequently disasters occur, the larger the expected disaster-related benefit will be. Individuals select a residential area by comparing expected benefits and 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 2006, p. 44). Thus, individuals reside in disaster-prone areas if the perceived benefit of residing there outweighs the cost. This leads to *Hypothesis 2.*

Hypothesis 2 The level of public sector corruption increases when the disaster damage is significant. The level of corruption also increases when disasters are frequent.

3 Data and method

3.1 Overview of natural disaster types

This paper uses country-level panel data similar to previous related research (Anbarci et al. 2006; Toya and Skidmore 2013; Yamamura 2013). The number of natural disasters in each chosen country was sourced from EM-DAT (the International Disaster Database managed by the World Health Organization's Collaborating Centre for Research on the Epidemiology of Disasters). This paper uses a proxy for public sector corruption based on data provided by the International Country Risk Guide (ICRG) prepared by the Political Risk Service Group Inc.: its value ranges from 0 to 6, with larger values indicating higher corruption levels.[6] Figure 1 illustrates the change in degree of corruption and the occurrence of natural disasters. It shows that both perceived corruption and the number of disasters increased 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.

The characteristics of disasters differ and thus, the disaggregation of disasters into various disaster types provides useful information, enabling a closer analysis. Previous research (Skidmore and Toya 2002; Kahn 2005), classifies disaster into numerous categories, including floods, storms, earthquakes, volcanic eruptions, landslides, and others.[7] The number of floods and storms significantly exceed other disaster types. EM-DAT further divides floods into three sub-categories: general floods, flash floods, and storm surges, with general floods being the most common. Storms are further divided into three sub-categories: tropical storms, winter storms, and local windstorms, with tropical storms being the most common.[8] Hence, in this paper, floods are categorized as general floods and other floods (flash floods and storm surges). Storms are categorized as tropical storms and other storms (winter storms and local windstorms). Figure 2 shows the frequency of each disaster (number of disasters per 10,000 km^2) indicating the probability of occurrence, and clearly showing that general floods and tropical storms are the most frequent events. General floods occur approximately 1.4 times per 10,000 km^2 annually and other floods occur approximately 0.5 times per 10,000 km^2. Floods and storms can be categorized as climatic disasters, while earthquakes, volcanic eruptions, and landslides can be categorized as geological disasters (Skidmore and Toya 2002).

In comparison with geological 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 evacuating the afflicted region" (Skidmore and Toya 2002, p. 671). Hence, climatic disasters are less likely to be a threat to property but not to life than geological disasters. The average monetary values of the damage caused by disasters, measured in millions of U.S. dollars, are illustrated in Fig. 3.[9] The damage caused by an earthquake is estimated to cost approximately US$2,400 million, significantly larger than the costs arising from other disasters. Tropical storm damage costs are relatively high at approximately US$200 million, roughly three times that of general floods and other storms. The cost of damage caused by other floods, volcanic eruptions, and landslides is less than US$20 million.

[6] ICRG data scores corruption with a range of 0–6, with 6 indicating no corruption. In this paper, to simplify matters, the score is inverted. Thus, countries with an ICRG score of 6 are given a value of 0 in this paper (i.e., no corruption) and countries with an ICRG score of 0 are given a value of 6 (i.e., very corrupt).

[7] The empirical results of this paper do not change when other classifications are employed.

[8] Definitions of classifications can be found on the EM-DAT website http://www.emdat.be/glossary/9 (accessed on December 7, 2013).

[9] EM-DAT offers alternative ways of measuring the cost of a disaster, including fatalities or injuries. Their relative values for each disaster are almost identical to those illustrated in Fig. 4. Hence, the argument of this paper does not change if other values are used to measure the cost of a disaster.

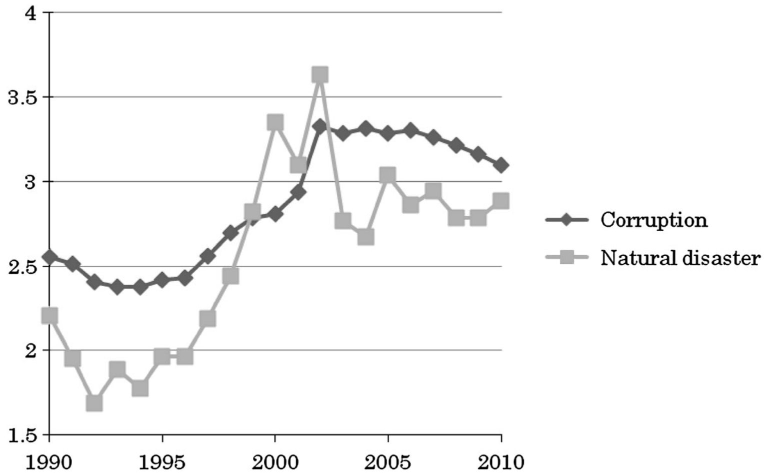

Fig. 1 Degree of corruption and occurrence of natural disasters 1990–2010. *Note* The values are calculated from observation on 84 countries. Table A1 exhibiting the list of countries is available at the author's website (https://www.seinan-gu.ac.jp/~yamaei/)

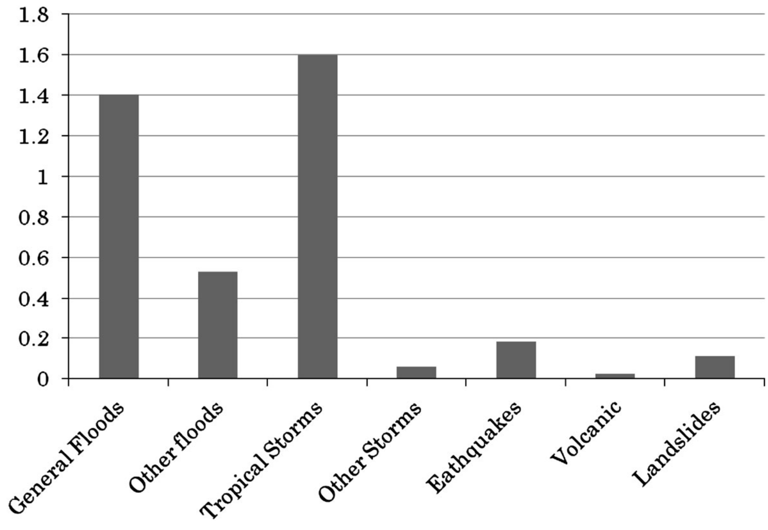

Fig. 2 Annual disaster frequency per 10,000 km^2 of landmass. *Note* The values are calculated from observation on 84 countries. Table A1 exhibiting the list of countries is available at the author's website (https://www.seinan-gu.ac.jp/~yamaei/)

Table 1 summarizes disaster features. The predicted cost is considered to be very high for earthquakes; however, their rate of occurrence is very low. With the exception of earthquakes, the costs arising from other disasters are either low or very low. Hence, victims of earthquakes can request greater amounts of compensation than those of other disasters. Among those disasters with low damage costs, e.g., general floods, other floods and tropical storms, occur rather frequently. Residents in flood- and storm-prone areas can thus anticipate future compensation opportunities. Accordingly, it can be assumed that

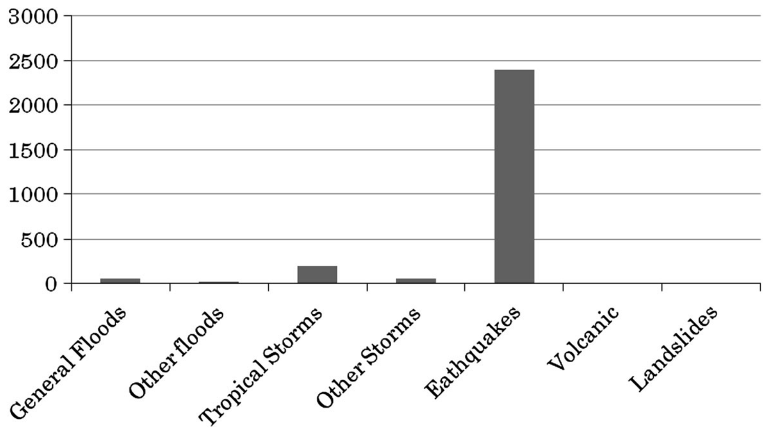

Fig. 3 Average damage cost per disaster (million US$/number of disasters)

relief from natural disasters such as earthquakes, general floods, other floods, and tropical storms could trigger a moral hazard problem. This expectation can also be derived from previous research. For instance, US government-backed insurance caused a moral hazard problem (Vigdor 2009; Jaffe and 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 2010, p. 140). As a consequence of the NFIP, property owners continue to live in areas of frequent flooding. From another perspective, insurers were offered reinsurance against catastrophic losses by their government (Zanjani 2008). Accordingly, insurers can feel free to write policies for floods at overly reasonable rates, safe in the knowledge that their downside risk is limited by the presence of government-subsidized reinsurance. The role of the market in yielding information about the expected cost of various disasters through prices is undone (Vigdor 2009). The frequent occurrence of natural disasters inevitably strengthens the profitable partnership between government and insurers, leading to a structural interlocking between the two.

3.2 Data

Data regarding the number of natural disasters were sourced from EM-DAT.[10] Disasters in the EM-DAT database fulfill at least one of the following criteria: (1) ten or more reported fatalities, (2) no more than 100 people affected, (3) declaration of a state of emergency, and (4) a call for international assistance. Criterion (4) merits further examination. As shown in Fig. 1 and discussed earlier, the number of natural disasters increased from 1990 to 2002. Kurosaki (2013, p. 2) argues that "we should pay attention to the possibility that the reported increase is partly because of an increased tendency to report, not necessarily an increase in the occurrence of disasters". There are suggestions 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 and

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

Toya 2002). Inevitably, measurement errors could cause some degree of bias in estimations regarding developing countries. Measurement error is less likely to exist in developed countries. Hence, estimation errors are minor when the sample is limited to developed countries.

Dividing the sample into developed and developing countries facilitates the avoidance of measurement errors when estimations are conducted. Garret and Sobel (2003) found that both disaster declaration and the level of disaster expenditure are politically motivated rather than driven by disaster severity or frequency. This stems from the system used by the U.S. Federal Emergency Management Agency (FEMA), an organization concerned with the disaster declaration process and the subsequent allocation of disaster relief money. The U.S. president has an incentive to manipulate disaster declarations with the aim of being re-elected. Thus, in the United States, "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 and Leeson 2006, p. 60). Canada, a developed country in the North American continent, has a land area of approximately 9.9 million km^2, similar in size to that of the United States (approximately 9.6 million km^2). Despite their similarities, the data used in this paper show that the average annual number of total disasters is 24.5 in the United States and just 3.0 in Canada.[11] Such a significant difference might be too great to be explained by political factors such as the FEMA system. Countries with over ten reported disasters (such as the United States) in total are regarded as outliers in this study. Therefore, they were removed from the sample to reduce measurement errors and improve robustness.[12] Clearly, countries with greater land area tend to have a larger number of disasters. Thus, estimation bias can result. To control for this, the number of disasters were divided by land area and then used as an independent variable. Data on land area were collected from the World Bank (2010).[13] Institutional condition is also thought to influence degree of corruption (Djankov et al. 2008; La Porta et al. 1999).

The proxy for the public sector corruption variable was based on the ICRG index. The values (indicating the level of corruption) range from 0 (no corruption) to 6 (corrupt). The ICRG data reveal that corruption in business dealings is commonplace. The index is appropriate for capturing financial corruption in the form of demands for special payments and bribes. Integrating both the disaster and corruption data produces panel data that include information on 84 countries over a 21-year period (1990–2010). In addition to the key variables above, control variables such as gross domestic product (GDP) per capita and

[11] When we compare the landmass of Canada and the United States., attention should be paid to population size. (1) The population of Canada is approximately 34 million, while the US population (about 314 million) is almost ten times that. (2) Vast areas of Canada are unpopulated or have very low population densities, thus many natural disasters would go unreported as they did not affect the human population.

[12] Countries included in the sample can be seen at the author's website: (https://www.seinan-gu.ac.jp/~yamaei/).

[13] In the regression estimation, various control variables are included. Latitude, the highest point of elevation, lowest point of elevation, percentage of land area where elevation is below 5 meters, agricultural sector ratio and industrial sector ratio (percentages of GDP) are available from World Bank (2010).

The percent of the population belonging to the Catholic Church is used by Easterly and Levine (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). Legal origin dummies and measure of democracy are available at http://www.economics.harvard.edu/faculty/shleifer/dataset (accessed on June 1, 2011)

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

population are included, and were collected from the University of Pennsylvania's Center for International Comparisons, Penn World Table 7.1.[14]

In this paper, members of the OECD are considered as developed countries, while non-OECD members are classed as developing countries. A comparison of the basic statistics for the variables between OECD and non-OECD countries is presented in Table 2. The degree of corruption is 3.39 for non-OECD countries and 1.19 in OECD countries, consistent with the view that developing countries are generally more corrupt than developed countries. The average number of total disasters is 4.43 in non-OECD countries and 1.12 in OECD countries. This is congruent with Fig. 1, suggesting a positive correlation between the number of natural disasters and the degree of corruption. Furthermore, the larger average number of disasters in non-OECD countries than in OECD countries possibly reflects that the number of disasters is exaggerated by developing countries for the purpose of receiving international aid.

"Flooding in one region can be the result of storm activity upstream" (Toya and Skidmore 2013, p. 12). Storms are often accompanied by floods. Based on the dataset used in this paper, the correlation coefficient between floods and tropical storms is 0.47. 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. In contrast, 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:

$$\begin{aligned} Corruption_{it} = a_0 &+ a_1 Number\ of\ disasters_{it} + a_2 Number\ of\ disasters_{it-1} \\ &+ a_3 Number\ of\ disasters_{it-2} + a_4 GDP_{it} + a_5 Population_{it} + a_6 Time\ trend_t \\ &+ u_i + \varepsilon_{it}, \end{aligned}$$

where the dependent variable is $Corruption_{it}$ in country *i* for year *t*, α represents the regression parameters, the unobservable features of *country i are denoted by* u_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). Previous

[14] The data were available at the website of Penn World Table. https://pwt.sas.upenn.edu/php_site/pwt71/pwt71_form.php (accessed on August 25, 2013).

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 (no corruption)–6 (corrupt)	2.85 (1.41)	3.39 (1.05)	1.19 (1.01)
Natural disasters	Number of natural disasters/land size (million m^2)	3.77 (25.8)	4.43 (28.8)	1.12 (2.67)
General floods	Number of general floods/land size (million m^2)	1.40 (17.6)	1.71 (19.7)	0.17 (0.57)
Other floods	Number of other floods/land size (million m^2)	0.52 (11.4)	0.65 (12.8)	0.04 (0.25)
Tropical storms	Number of tropical storms/land size (million m^2)	1.59 (17.6)	1.98 (19.6)	0.03 (0.18)
Other storms	Number of other storm/land size (million m^2)	0.05 (0.35)	0.02 (0.19)	0.19 (0.66)
Earthquakes	Number of earthquakes/land size (million m^2)	0.18 (4.91)	0.21 (5.49)	0.06 (0.27)
Volcanic eruptions	Number of volcanic eruptions/land size (million m^2)	0.02 (0.46)	0.02 (0.51)	0.01 (0.06)
Landslides	Number of landslides/land size (million m^2)	0.11 (2.51)	0.13 (2.84)	0.02 (0.28)
GDP per capita	In US$	12,014 (13,430)	6,920 (8,580)	32,075 (9,807)
Population	In thousands	47,484 (158,837)	50,263 (174,933)	47,484 (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 ten)

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) research has shown 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 (Treisman 2000; Paldam 2001; Djankov et al. 2003; Serra 2006; Gokcekus 2008; Pellegrini and Gerlagh 2008). These factors are considered as time invariant fixed effects of a country, and are denoted as u_i. Hence, a fixed effects model was primarily used here; however, a random effects model was alternatively used when Hausman test results suggested that the random effect model was more appropriate. Geographic features such as latitude, elevation, and proximity to the sea can be considered as time-invariant characteristics for each country. Hence, when the fixed effects model was used, these effects were captured by the fixed effects. However, when the random effects model was used, these effects were estimated. Other socio-economic factors such as agricultural sector ratio and industrial sector ratio (percentage of GDP), legal origin, and ratio of those belonging to the Catholic Church were included as independent estimation variables.[15]

Furthermore, Fig. 1 suggests the possibility that an unknown third factor is related to both corruption and natural disasters. If the relation between disasters and corruption is caused wholly by a third factor, then the relation is spurious, and the hypothesis cannot be supported. Hence, following the method of Kahn (2005), a time trend was included to exclude the effects of any third factor.

The effect of a natural disaster in year t on corruption in year t changes according to the date of the occurrence of the disaster. If a disaster occurs at the end of year t, the corruption level in year t already has been estimated, and thus the disaster has no effect on corruption. However, the disaster will influence the level of corruption in year $t+1$. As found for the US case, there is a time lag between the influx of disaster relief and the increase in corruption (Leeson and Sobel 2008). Therefore, to capture the time lag effect of disasters, *natural disasters* in year t and *natural disasters* in year $t-1$ were incorporated as independent variables. Furthermore, it is plausible that impact of natural disaster persists for several years. Therefore, the function also included *natural disasters* in year $t-2$.[16] If *Hypothesis 1* is supported, the *number of disasters* t, the *number of disasters* $t-1$, and the *number of disasters* $t-2$ would have positive coefficients. In examining *Hypothesis 2,* the effects of specific types of disasters should be identified. Hence, disaggregated numbers of disasters were incorporated rather than the number of total disasters. With regard to control variables, *GDP* and *Population* were included to capture basic economic conditions.

4 Results

The estimation results are reported in Tables 3 and 4, with Table 3 providing the overall results. There were a number of disasters in multiple years such as in year t, year $t-1$, and year $t-2$. Therefore, whether a variable was significant or not was not determined by looking individually at each coefficient. There was the possibility that they were individually insignificant, but were jointly significant when the level of disasters in year t,

[15] Tables show the results of control variables are available at the author's website (https://www.seinan-gu.ac.jp/~yamaei/).

[16] The association between natural disasters in year $t-3$ and corruption in year t disappears; natural disasters in year $t-3$ therefore are not included.

Table 3 Overall effect of aggregated disasters on corruption

	(1) Full-sample Fixed effects	(2) Full-sample Random effects	(3) Non-OECD Fixed effects	(4) Non-OECD Random effects	(5) OECD Fixed effects	(6) OECD Random effects
Natural disasters in year t	0.001 (0.92)		0.001 (0.89)		0.009** (2.29)	
Natural disasters in year $t-1$	0.004** (2.40)		0.004** (2.34)		0.008*** (3.46)	
Natural disasters in year $t-2$	0.004*** (2.77)		0.004** (2.57)		0.007** (2.13)	
General floods in year t		−0.010 (−1.39)		−0.016*** (−5.89)		0.182*** (4.21)
General floods in year $t-1$		0.005 (1.08)		0.001 (0.77)		0.114*** (3.73)
General floods in year $t-2$		0.001 (0.31)		−0.003** (−2.03)		0.159*** (4.98)
Other floods in year t		−0.013 (−0.16)		−0.041 (−0.41)		0.343*** (3.08)
Other floods in year $t-1$		0.068 (0.52)		0.023 (0.16)		0.482*** (7.08)
Other floods in year $t-2$		0.067 (0.059)		0.035 (0.31)		0.483*** (7.83)
Tropical storms in year t		0.011*** (3.03)		0.015*** (11.5)		0.008 (0.02)
Tropical storms in year $t-1$		0.010*** (6.03)		0.011*** (7.02)		0.078 (0.40)
Tropical storms in year $t-2$		0.008*** (12.5)		0.008*** (12.1)		−0.009 (−0.07)
Other storms in year t		−0.012 (−0.30)		−0.052* (−1.87)		0.082 (1.05)
Other storms in year $t-1$		−0.036 (−1.35)		−0.074 (−1.01)		0.112* (1.66)
Other storms in year $t-2$		0.005 (0.12)		0.036 (0.40)		0.070*** (2.88)
Earthquakes in year t		0.038** (2.13)		0.067*** (2.76)		−0.058 (−0.29)
Earthquakes in year $t-1$		0.102** (2.51)		0.159*** (4.04)		−0.011 (−0.08)
Earthquakes in year $t-2$		0.088*** (2.88)		0.115*** (3.44)		0.277** (1.99)
Volcanic eruptions in year t		−0.054* (−1.78)		−0.083** (−2.38)		0.395 (0.66)
Volcanic eruptions in year $t-1$		−0.238*** (−5.85)		−0.307*** (−10.9)		0.106 (015)
Volcanic eruptions in year $t-2$		−0.192*** (−3.84)		−0.238*** (−5.49)		0.080 (0.16)
Landslides in year t		−0.022 (−1.52)		−0.216 (−1.23)		−1.054 (−0.71)
Landslides in year $t-1$		0.105*** (3.69)		0.064 (0.53)		0.949 (0.68)
Landslides in year $t-2$		0.326*** (4.77)		0.275 (1.47)		1.430 (0.68)

Table 3 continued

	(1) Full-sample Fixed effects	(2) Full-sample Random effects	(3) Non-OECD Fixed effects	(4) Non-OECD Random effects	(5) OECD Fixed effects	(6) OECD Random effects
GDP per capita	−0.792** (−2.06)	−0.308* (−1.96)	−1.031** (−2.42)	−0.236* (−1.81)	0.336 (0.18)	−4.41*** (−6.37)
Population	−1.225 (−1.08)	−0.003 (−0.06)	−1.966 (−1.52)	0.024 (0.37)	−7.680 (−1.17)	−1.36*** (−4.38)
Trend	0.106*** (4.16)	0.080*** (8.22)	0.131*** (3.59)	0.080*** (8.22)	0.03 (0.96)	0.075** (1.97)
Hausman test	*P* value = 0.06	*P*-value = 0.52	*P*-value = 0.01	*P*-value = 0.86	*P*-value = 0.01	*P*-value = 0.68
Within R^2	0.19	0.22	0.21	0.25	0.31	0.33
Observations	777	777	590	590	187	187

Note Values in parentheses are t-statistics in columns (1) and (2), and z-statistics in columns (3) and (4). These statistics are calculated using robust standard errors clustered at the legal origin of the country. *, **, and *** denote significance at the 10, 5, and 1 % levels, respectively. Constants and various control variables such as latitude, the highest point of elevation, lowest point of elevation, percentage of land area where elevation is below 5 meters (%), dummy of country facing sea, legal origin dummies, agricultural sector ratio, industrial sector ratio, and ratio of those belonging to the Catholic Church were included; however, the results are not reported

Table 4 Effect of aggregated disasters on corruption: 3-year disaster average

	(1) Full-sample Fixed effects	(2) Full-sample Random effects	(3) Non-OECD Fixed effects	(4) Non-OECD Random effects	(5) OECD Fixed effects	(6) OECD Fixed effects
Natural disasters	0.008* (1.94)		0.007* (1.94)		0.024*** (2.89)	
General floods		−0.002 (−0.19)		−0.013** (−2.17)		0.279*** (5.93)
Other floods		0.144 (0.45)		0.042 (0.13)		0.837*** (2.87)
Tropical storms		0.012*** (11.6)		0.012*** (9.99)		0.248 (0.35)
Other storms		−0.048 (−0.59)		−0.073 (−0.44)		0.145* (1.95)
Earthquakes		0.221*** (2.77)		0.321*** (3.67)		0.208 (0.49)
Volcanic eruptions		−0.520 (−5.19)		−0.631 (−7.47)		1.152 (0.67)
Landslides		0.176 (0.76)		0.105 (0.22)		2.454 (0.78)
GDP per capita	−0.792** (−2.06)	−0.300** (−2.02)	−0.103** (−2.42)	−0.217* (−1.83)	0.322 (0.18)	−0.428 (−0.25)
Population	−1.24 (−1.09)	0.004 (0.07)	−1.99 (−1.56)	0.035 (0.57)	−7.68 (−1.18)	−7.22 (−1.32)
Trend	0.107*** (4.16)	0.080*** (10.0)	0.131*** (3.62)	0.080*** (5.96)	0.028 (0.97)	0.042 (1.19)
Hausman test	*P*-value = 0.02	*P*-value = 0.23	*P*-value = 0.00	*P*-value = 0.23	*P*-value = 0.00	*P*-value = 0.01
Within R^2	0.19	0.20	0.21	0.22	0.31	0.34
Observations	777	777	590	590	187	187

Note Values in parentheses are t-statistics in columns (1) and (2), while those are z-statistics in columns (3) and (4). These statistics are calculated using robust standard errors clustered at the legal origin of the country. *, **, and *** denote significance at the 10, 5, and 1 % levels, respectively. Constants and various control variables such as latitude, the highest point of elevation, lowest point of elevation, percentage of land area where elevation is below 5 m (%), dummy of country facing sea, legal origin dummies, rate of agricultural sector, rate of industrial sector, and catholic rate were included. But the results are not reported year $t-1$, and year $t-2$ were correlated. For the robustness check, rather than examining the level of disasters in year t, year $t-1$, and year $t-2$, the alternative specification included a 3-year moving disaster average. The alternative specification results are shown in Table 4.

For both Tables 3 and 4, the full sample results are presented in columns (1) and (2). Non-OECD country results are presented in columns (3) and (4), and OECD country results are displayed in columns (5) and (6). The key variables of columns (1), (3) and (5) are the number of total natural disasters in year t, year $t-1$, and year $t-2$ for both tables. The key variables of columns (2), (4), and (6) 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, year $t-1$, and year $t-2$.

4.1 Regression results

Table 3 indicates that the total natural disaster coefficients in years t, $t-1$, and $t-2$ are positive in columns (1), (3) and (5). Furthermore, most are statistically significant. Hence, this result is congruent with *Hypothesis 1*. In relation to the absolute value of the coefficients: the value for year $t-1$ is equivalent to that in year $t-2$ suggesting that the magnitude of their effect is stable.

In columns (2) and (4), the coefficient signs (positive or negative) vary by disaster type. The statistically significant tropical storms and earthquakes have the predicted positive sign in column (4). However, general floods, other storms, and volcanic eruptions have unexpected negative signs. Section 3 explains that a possible estimation bias may cause measurement errors for the number of disasters. Consequently, the results for general floods, other storms, and volcanic eruptions might not be accurate.

In column (6), general floods, other floods, other storms, and earthquakes have the predicted positive sign and are statistically significant. Some coefficients are negative, but are not statistically significant. The frequency of disasters differs between non-OECD and OECD countries as illustrated in Fig. 4a, b; however, their average damage levels per disaster do not differ although this is not shown here.[17] Earthquake-related damage is significantly greater than for other types of disasters in both non-OECD and OECD countries, as demonstrated in Fig. 3. Figure 4b suggests that general floods, other storms and earthquakes occur more frequently than other types of disasters in OECD countries. Taking column (6) of Table 3 and Fig. 4b in conjunction signifies that *Hypothesis 2* is supported in OECD countries.

Regarding the control variables, in most columns, the GDP per capita coefficients are negative and statistically significant. This implies that developed countries are less corrupt. The time trend coefficients are positive in all columns. Furthermore, they are statistically significant at the 1 % level in columns (1)–(4) and significant at 5 % in column (6). This is consistent with the observations in Fig. 1.

Table 4 reports robustness checks. The 3-year moving total disaster average has a positive sign and is statistically significant in columns (1), (3), and (5). The tropical disaster and earthquake coefficients have the predicted positive signs and are statistically significant in columns (2) and (4). General floods are negative and statistically significant in column (4). However, general floods, other floods, and other storms have the predicted positive sign and are statistically significant in column (6). The results presented in Table 4

[17] Figures illustrating average damage levels for the non-OECD and OECD care available on the author's website (https://www.seinan-gu.ac.jp/~yamaei/).

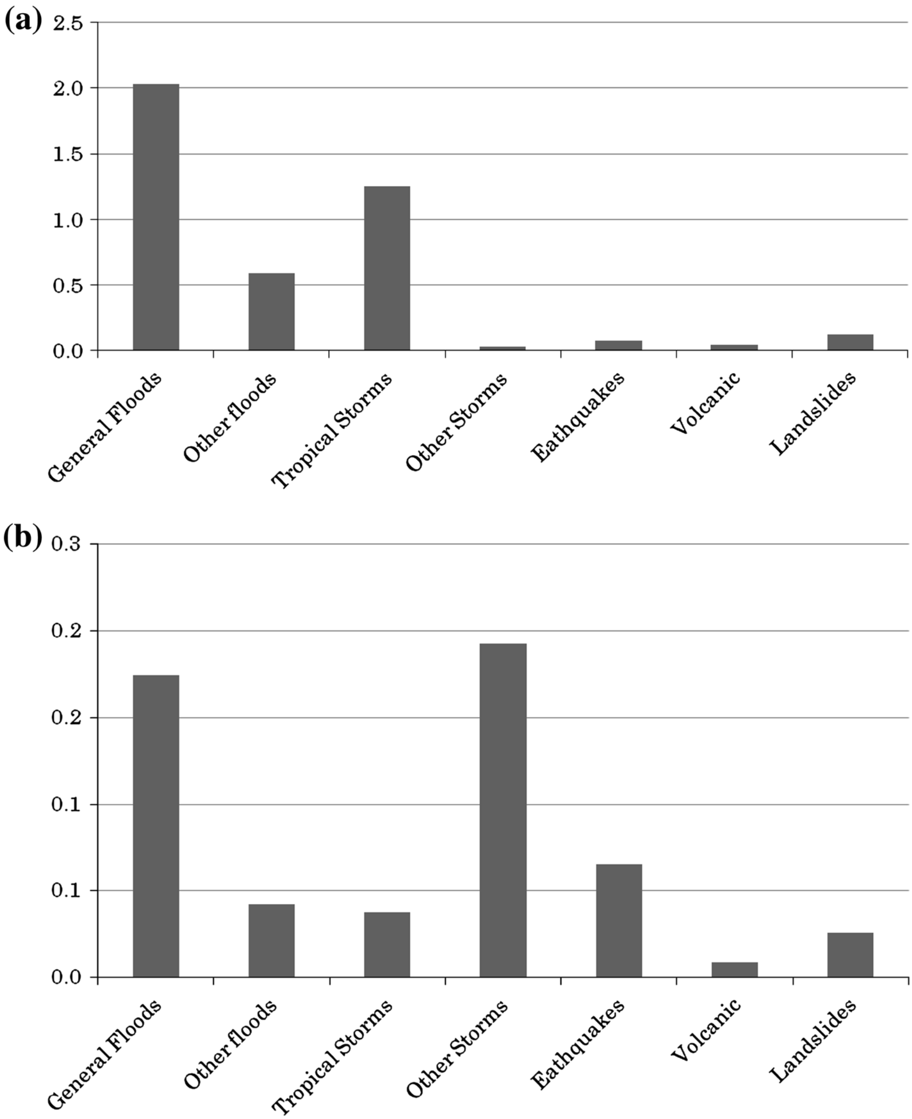

Fig. 4 **a** Frequency of disasters per 10,000 km^2 of landmass during the period 1990–2010: non-OECD countries. **b** Frequency of disasters per 10,000 km^2 of landmass during the period 1990–2010: OECD countries

are in line with those in Table 3. Hence, *Hypothesis 1* is generally supported. *Hypothesis 2* is supported for developed countries but not for the developing countries.

4.2 Total effects of disasters and discussion

Table 3 indicates the effect of each disaster per km^2 on a country's corruption level, over three years, *t*, $t-1$, and $t-2$. If the impact of a disaster on corruption 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, and the total combined effect is 0.27. In this paper, the coefficient values are aggregated only when the individual year effect is statistically significant in columns (2), (4) and (6) of Table 3. For example, in Table 3 other storms are not statistically significant in years *t, t*−*1*, and t−*2*. Hence, there is no effect even if they are combined. In contrast, Table 3 shows that general floods is statistically significant in year *t*−*1* although not in years *t* and t−*2*. In this case, the combined total effect is equivalent to its effect in year *t*−*1*. The top section of Table 5 exhibits the combined total effects of disasters on corruption. Looking at full sample and non-OECD sample results, Table 5 shows that tropical storms and earthquakes increase the level of corruption. However, general floods, other storms and volcanic eruptions decrease corruption. Therefore, the effect varies per disaster type; this result may be due in part to a measurement error. Earthquakes have a significant effect of 0.341 that reflects the considerable damage caused by earthquakes as indicated in Fig. 3. In the OECD sample, the effect of each disaster is positive. Interestingly, with the exception of earthquakes, the effect of each disaster is distinctly larger than those in the non-OECD sample. One reason for such a large effect is that measurement errors are unlikely to exist in the OECD sample and attenuation bias can generally be avoided. Additionally, the combined results of columns (1), (2), and (3) suggest that earthquakes consistently increase corruption levels.

The results of the upper part of Table 5 illustrate the effect of each disaster when it occurs within land areas of the same size. However, the frequency of disasters differs per disaster type, even holding land area constant. The damage an earthquake causes is very severe and hence its effect on corruption seems to be large. However, earthquake frequency is very low. Furthermore, a disaster's frequency depends on the landmass of the specific country. Therefore, the lower section of Table 5 shows the predicted effect of a disaster on corruption when its frequency is considered under real life situations. For this purpose, the effect of the disaster shown in the upper section is multiplied by its frequency per million km^2 and mean land area for each sample. When the results of the lower section of Table 5 are interpreted, Fig. 4a, b are considered together to investigate the relation between frequency and predicted effects of disaster on corruption.

As the lower section of Table 5 shows, in non-OECD countries tropical storms have the greatest impact. Tropical storms increase corruption by 0.348 points for a country with an average land size using the non-OECD countries sample. Earthquakes increase corruption by 0.210 points. As shown in Fig. 3, the damage caused by tropical storms and earthquakes are large. However, general floods, other floods, and tropical storms are more frequent than other types of disasters. Therefore, a country's corruption level tends to reflect the average damage of each disaster, rather than its frequency.

In contrast, in the OECD sample general floods have a distinctly larger effect than other disaster types. General floods increase corruption by 1.128 points for a country with an average land size when the OECD country sample is used, followed by other floods (0.781), other storms (0.498) and earthquakes (0.257). Compared with results from the non-OECD sample, the effect of a disaster on corruption in OECD countries is considerably larger. Furthermore, based on the OECD sample, Fig. 4b reveals that general floods, other storms, and earthquakes occur more frequently than other types of disasters. Therefore, in OECD countries, a disaster with a high frequency has a sizable effect on corruption even if the damage per disaster is low. This is interpreted here as suggesting that people who live in disaster-prone areas do so to benefit from disasters. Overall, *Hypothesis 2* is more strongly supported for developed countries than for developing countries.

Corruption is observed to be negatively associated with economic growth (Mauro 1995; Tanzi and Davoodi 1997; Johnson et al. 2011). However, such an observation is not

Table 5 Effect of disaster on corruption

	(1) Full sample	(2) Non-OECD sample	(3) OECD sample
Effect of a disaster on corruption per million km^2			
General floods		−0.019	0.455
Other floods			1.308
Tropical storms	0.029	0.033	
Other storms		−0.052	0.182
Earthquakes	0.228	0.341	0.277
Volcanic eruptions	−0.484	−0.628	
Land slides	0.433		
Predicted effect of disaster on corruption effect for average size of country in each group.			
General floods		−0.325	1.128
Other floods			0.781
Tropical storms	0.274	0.348	
Other storms		−0.011	0.498
Earthquakes	0.159	0.210	0.257
Volcanic eruptions	−0.145	−0.198	
Land slides	0.402		

Note Coefficients of variables in t, $t-1$, and $t-2$ are aggregated when they are statistically significant. The effect presented in the upper section is calculated based on columns (2), (4) and (6) of Table 3. Values in the lower section are calculated by multiplying the value of the upper part, frequency of disasters per land size (per million km^2) with the average land size in each sample. That is, the effect of disaster (per million km^2) * frequency (per million km^2) * average land size (per million km^2). 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

congruent with the finding that natural disasters cause the public sector to become more corrupt in OECD countries than in non-OECD countries. The effect of frequent disasters (such as floods) on corruption is greater in OECD countries than in non-OECD countries. This may be explained by flooding occurring more frequently in agricultural areas because agricultural land requires irrigation. It is thus difficult for farmers to move to areas where floods are unlikely to occur because such areas are generally not suited to agriculture. The fraction of population working in the agricultural sector is higher in developing countries than in developed nations. Accordingly, there is little opportunity for the population to move from risky areas in developing countries. Hence, people in these countries reside in flood-prone areas because it tends to reflect the nature of their work, rather than a strategic behavior to pursue disaster compensation.

People can benefit from the economic windfalls that may result from a disaster event. If the benefit is greater than the cost, then 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 safety to vulnerable coastal areas" (Shughart 2006, p. 44).[18] Considering the

[18] In the U.S., the National Flood Insurance Program causes a 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, p. 140).

discussion thus far, it can be argued that people in developed countries have an incentive to live in disaster-prone areas because the expected benefits from a disaster are greater than the damage caused. Consequently, a disaster-prone area increases the level of corruption in developed countries.

5 Conclusion

There is the possibility that rational individuals may 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, there is little information on whether different disaster types result in different outcomes. Furthermore, the effects of disasters differ between developed and developing countries. To examine this statistically, this paper used panel data from 84 countries over a 21-year period from 1990 through 2010.

The major findings of this study are as follows. (1) Natural disasters lead the public sector to become corrupt. (2) Disasters that are more frequent and cause considerable damage increase corruption in both developing and developed countries. This indicates that people living in disaster-prone areas (e.g., 'Tornado Alley' in the American heartland and along the US Gulf Coast and Atlantic seaboard, where hurricanes are predictable) anticipate disaster compensation. Analogous to the logic of literature on foreign aid inflow, it is disaster relief money that causes corruption, and more money causes more corruption (Leeson and Sobel 2008). (3) The effect of disasters on corruption is greater in developed countries than in developing countries. (4) In developed countries, disaster frequency plays a significant role in increasing corruption. In contrast, in developing countries, the damage inflicted per disaster plays a significant role in increasing corruption levels.

The findings of this paper are consistent with the claim that "disaster relief is a bad public good also because it fosters corruption and encourages people to put themselves in harm's way" (Shughart 2011, p. 535). However, the degree of corruption caused by a disaster depends on the level of damage, disaster frequency, and damage per disaster. Some people in developed countries may reside in disaster-prone areas to obtain compensation after a disaster. Disaster warning systems are generally thought to be effective in reducing the level of damage caused by disasters in developed countries (Escaleras and Register 2008). The more information people receive about an imminent disaster, the greater the number of people who can escape harm. This may provide an incentive to reside in disaster-prone areas to seek compensation. Unanticipated behavior such as this can be seen as a government failure (Shiue 2004).

This paper used country-level panel data and therefore measurement errors are thought to have caused some estimation bias. Hence, a robustness check was undertaken. Micro-level data offering greater accuracy should be used for a closer examination of the effects of disasters on corruption. Furthermore, the strategic behavior of people regarding their choice of residential area should be scrutinized using experimental methods. These issues require further investigation in future studies.

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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.

Baland, J. M., & Francois, P. (2000). Rent-seeking and resource booms. *Journal of Development Economics, 61*(2), 527–542.

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.

Brollo, F., Nannicini, T., Perotti, R., & Tabellini, G. (2013). The political resource curse. *American Economic Review, 103*(5), 1759–1796.

Chamlee-wright, E. (2010). *The cultural and political economy of recovery: Social learning in a post-disaster environment*. New York: Routledge.

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.

Easterly, W., & Levine, R. (1997). Africa's growth tragedy: Policies and ethnic divisions. *Quarterly Journal of Economics, 112*(4), 1203–1250.

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.

Escaleras, M., & Register, C. A. (2008). Mitigating natural disasters through collective action: The effectiveness of Tsunami early warnings. *Southern Economic Journal, 74*(4), 1017–1034.

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.

Jaffe, D., & Russell, T. (2008). Financing catastrophe insurance: A new proposal. In J. M. Quigley & L. A. Rosenthal (Eds.), *Risking house and home: Disasters, cities, public policy*. San Francisco: Berkley Public Policy Press.

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.

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 and Organization, 15*(1), 222–279.
Leeson, P. T., & Sobel, R. (2008). Weathering corruption. *Journal of Law and 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.
Paldam, M. (2001). Corruption and religion adding to the economic model. *Kyklos, 54*(2–3), 383–413.
Pedro, V. (2010). Does oil corrupt? Evidence from a natural experiment in West Africa. *Journal of Development Economics, 92*(1), 28–38.
Pellegrini, L., & Gerlagh, R. (2008). Causes of corruption: A survey of cross-country analyses and extended results. *Economic Governance, 9*, 245–263.
Robinson, J. A., Torvik, R., & Verdier, T. (2006). Political foundation of the resource curse. *Journal of Development Economics, 79*(1), 447–468.
Serra, D. (2006). Empirical determinants of corruption: A sensitivity analysis. *Public Choice, 126*, 225–256.
Shiue, C. H. (2004). Local granaries and central government disaster relief: Moral hazard and intergovernmental finance in eighteenth- and nineteenth-century China. *Journal of Economic History, 64*(1), 100–124.
Shleifer, A., & Vishny, R. (1993). Corruption. *Quarterly Journal of Economics, 108*, 599–617.
Shughart, W. F, I. I. (2006). Katrinanomics: The politics and economics of disaster relief. *Public Choice, 127*, 31–53.
Shughart, W. F, I. I. (2011). Disaster relief as a bad public good. *Independent Review, 15*(4), 519–539.
Simmons, K. M., Kruse, J. B., & Smith, D. A. (2002). Valuing mitigation: Real estate market response to hurricane loss reduction measures. *Southern Economic Journal, 68*(3), 660–671.
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.
Torvik, R. (2002). Natural resources, rent seeking and welfare. *Journal of Development Economics, 67*(2), 455–470.
Toya, H., & Skidmore, M. (2007). Economic development and the impacts of natural disasters. *Economics Letters, 94*(1), 20–25.
Toya, H., & Skidmore, M. (2013). Do natural disasters enhance societal trust? *CESifo Working papers* 3905.
Treisman, D. (2000). The causes of corruption: A cross-national study. *Journal of Public Economics, 76*(3), 399–457.
Vigdor, J. L. (2009). Book review of "Rising house and home: disasters, cities, public policy". *Journal of Economic Literature, 47*(4), 1156–1157.
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.
Zanjani, G. (2008). Public versus private underwriting of catastrophic risk: Lessons from the California earthquake authority. In J. M. Quigley & L. A. Rosenthal (Eds.), *Risking house and home: Disasters, cities, public policy*. San Francisco: Berkley Public Policy Press.