Public sector corruption and the probability of technological disasters

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Abstract. A growing number of works have explored the influence of institution on the outcomes of disasters and accidents from the viewpoint of political economy. This paper focuses on the probability of the occurrence of disasters rather than disaster outcomes. Using panel data from 98 countries, this paper examines how public sector corruption is associated with the probability of technological disasters. It was found that public sector corruption raises the probability of technological disasters. This result is robust when endogeneity bias is controlled.

Keywords: Corruption, Institution, Disasters, Risk
JEL classification: D73; D81; Q54

1. Introduction

As shown in various historical records, the occurrence of disasters appears to inevitably influence social and economic conditions. In the field of social science, an increasing number of works have investigated the effect of natural disasters and associated outcomes. Controversy exists regarding the effect of natural disasters on economic growth. Cross-country analysis has been used to show that natural disasters have a positive effect on economic growth, by enhancing human capital accumulation (Skidmore & Toya 2002). In contrast, county-level data from the United States was used to suggest that economic growth rates fall, on average, by 0.45% points, and that nearly 28% of the growth effect is because of the emigration of wealthier citizens (Strobl 2011). In addition, it has been asserted that (Cuaresma et al. 2008) the effect of natural disasters on growth differs between developing and developed countries. Further studies have also investigated the influence of natural disasters on welfare (Sawada 2007; Luechinger & Saschkly 2009). With regard to deaths caused by natural disasters, GDP per capita, economic openness, the development of financial sectors, and human capital formation are all negatively associated with such deaths, especially in less developed countries (Toya & Skidmore 2007).[1]

The level of damage caused by natural disasters has been explained not only by economic factors but also by political and institutional factors.[2] Low-quality governance, characterized by corruption and income inequality, increases the death rate in a natural disaster, whereas democracy and social capital reduces deaths (Anbarci et al. 2005; Kahn 2005; Escaleras et al. 2007; Yamamura 2010).[3] These factors, however, do not affect the probability of a natural disaster occurring because such a probability depends on natural conditions.[4] In other words, economic and institutional factors are important when we analyze how to mitigate, and to what extent, the damage caused by natural

[1] Kellenberg and Mobarak (2008) suggest that the relationship between GDP levels and the damage caused by natural disasters takes the inverted U shape, rather than being monotonically negative.
[2] Media is also considered to be a critical determinant of damage caused by natural disasters (Eisensee & Strömberg 2007).
[3] Disasters have both direct and indirect detrimental effects on economic conditions. One indirect effect is the distortion of allocation through political economy channels. Garret and Sobel (2003) examined the flow of Federal Emergency Management Administration money and found that nearly half of all disaster relief is motivated politically rather than by need.
[4] Kahn (2005) provides evidence that area dummies, absolute value of latitude, and land area are important determinants in the occurrence of natural disasters, whereas GDP per capita is not considered to be a determinant.

disasters. However, these factors are not important when we analyze how to prevent natural disasters from occurring.

According to the Center for Research on the Epidemiology of Disasters, disasters can generally be divided into two categories: natural and technological disasters. In contrast to a natural disaster, human errors are associated with the probability of technological disasters because technological disasters are regarded as manmade disasters. Hence, economic and institutional factors are thought to play a crucial role in determining the probability of technological disasters. Among the various institutional factors, corruption is regarded as a major institutional facet. The corruption of bureaucrats is considered to influence the cost and incentive structures faced by firms and individuals, and economists have long been interested in analyzing how corruption affects the performance of an economy. Due in part to a lack of data on corruption, an empirical analysis of corruption did not exist prior to the 1990s, although there are number of classical anecdotal and theoretical works (Leff 1964; Lui 1985; Shleifer & Vishny 1993).[5] Seminal works from the 1990s (Mauro 1995), which empirically examined the effect of corruption, and the compilation of data on corruption, have lead the way for researchers to empirically investigate the political and economic outcomes of public sector corruption (e.g., Glaeser and Saks 2006; Apergis et al. 2010; Dreher & Schneider 2010; Escaleras et al. 2010; Johnson et.al. 2011; Swaleheen 2011).

With regard to the interactions between politics and economics, investigations (Anbarci et al. 2006) have shown that corruption increases the rate of fatal traffic accidents, suggesting that corruption is thought to have a sizable effect on the occurrence and outcome of accidents by human error. Therefore, it is important to investigate the influence of corruption on manmade disasters when considering a political economy mechanism. However, little is known about the effect of corruption on the probability of technological disasters; thus, it is a topic worth investigating. This paper uses panel data from 98 countries to explore the influence of corruption on technological disasters. The key finding is that a technological disaster is more likely to occur in a country with greater levels of corruption in the public sector.

The remainder of the paper is organized as follows: section 2 proposes the hypothesis 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 observations.

2. Hypothesis

[5] Jain (2001) provided a literature review of the classical works and introduced the current debate among researchers.

Corruption in general is defined as the use of public office for private gains (Bardhan 1997). The main forms of corruption include bribes received by public officials, the embezzlement of resources by public officials that they are entrusted to administer, fraud in the form of manipulating information to further public officials' personal interests, extortion, and favoritism (Andvig & Fjeldstad 2001). Corruption is considered to affect the probability of accidents and manmade disasters via two channels; a brief explanation follows.

First, a key reason for market failure is information asymmetry between market demand and supply. An anticipated and necessary role of government is to attenuate this failure. In various industries, firms and individuals are obliged to obtain a license to commence a business, to ensure a quality service is supplied. Public officials have the right to grant these firms and individuals such licenses. For instance, pilots are required by law to obtain a pilot license. Airplane companies are obliged by public officials to employ pilots with such a license. For the purpose of reducing information asymmetry between airplane companies and customers, it is anticipated that public officials play an industry-regulating role to ensure flight safety. In reality, however, public officials have an incentive to pursue their own self-interest: these public officials may accept bribes from firms and individuals to ignore various regulations.

Assuming that the qualifying standards for obtaining a license are effective in determining the techniques, skills, and quality of pilots, these will deteriorate when pilots illegitimately receive their pilot license. Individuals make a decision regarding how to obtain the license by considering whether the cost of illegitimately purchasing the license is lower than the cost of obtaining license legitimately. The corruption of public officials results in the "price of a license" in the illegitimate market to fall below the cost of passing a legitimate qualifying standard for licensing. Accordingly, individuals will purchase the license illegitimately. Consequently, the safety of airplanes declines and in turn the probability of airplane accidents increases. Evidence regarding the relationship between corruption and traffic accidents (Anbarci 2006) supports this inference. The more corrupt a public official is, the cheaper the cost of purchasing a license, and the lower the quality and skill of drivers (Bertland et al. 2007). Inevitably, accidents are more likely to occur. As with airplane pilots and car drivers, this inference holds true, in general, within any industries where licenses are required.

The second reason for market failure is that corruption weakens existing infrastructure (Vito & Davoodi 1997). The rate of return of projects, as calculated using cost–benefit analysis, is a criterion for project selection. In reality, however, corruption motivates bureaucrats to direct public expenditure via channels that make it easier to collect bribes. Thus, the productivity of the project is not taken into account when the investment project is selected, leading to the distortion of resource allocation. This causes a bias towards large-scale construction projects rather than maintenance expenditure. Thus, corruption reduces the public spending that is required to keep the existing physical infrastructure in a good and safe condition. A previous study (Vito & Davoodi 1997) found, using regression analysis, that corruption reduced the percentage of total paved roads in good condition, and increased the percentage of electricity power system losses over total power output. Based on those results, the authors concluded that corruption reduces expenditure on maintenance and operations, resulting in low-quality infrastructure (Vito & Davoodi 1997). It seems plausible that the deterioration of physical infrastructure increases the likelihood of transport or industrial accidents. Corruption inevitably increases the probability of accidents, resulting in manmade disasters.

These inferences lead me to propose the following hypothesis.

Hypothesis:

A corrupt public sector raises the probability of technological accidents and therefore disasters.

3. Data and method

3.1. Data

Data regarding the number of technological disasters (*TECDIS*) from 1900 to 2010 was sourced from EM-DAT (Emergency Events Database).[6] In this paper, however, a proxy for public sector corruption was available from 1984 as explained later in the paper, and as such I used *TECDIS* data from 1984 to 2010.[7]

Definitions and the basic statistics for the variables used in this paper are presented in Table 1. The mean value of *TECDIS* (number of technological disasters) is 1.70 while its standard deviation is 4.76, which is nearly three times larger than the mean value.

[6] According to the Centre for Research on the Epidemiology of Disasters, technological disasters can be categorized into three categories: industrial, miscellaneous, and transport accidents. http://www.emdat.be/explanatory-notes (accessed on June 15, 2011).

[7] TECDIS was sourced from the International Disaster Database. http://www.emdat.be (accessed on June 1, 2011).

The maximum and minimum values of *TECDIS* are 71 and 0, respectively, indicating a significant gap between them. Table 2 shows more detailed statistics regarding *TECDIS* and the frequency of technological disasters. Interestingly, 56.5% of *TECDIS* had a value of 0 and 18.4% just 1. Considering them jointly suggests that *TECDIS* is over-dispersed, a situation that is often observed in the case of disasters and accidents (e.g., Kahn 2005; Anbarci et al. 2006; Escaleras et al. 2007).

With respect to the proxy for corruption, *CORR_ICRG* and *CORR_WD* are used. My primary measure of public sector corruption (*CORR_ICRG*) is collected from the International Country Risk Guide (ICRG), which includes 146 countries over 27 years (1984–2010). ICRG is assembled by the Political Risk Service Group. *CORR_ICRG* has the advantage of covering a longer period than the alternative measure (*CORR_WD*). *CORR_ICRG* values range from 0 to 6—larger *CORR_ICRG* values indicate less corruption. According to ICRG, the most common form of corruption experienced directly in business is financial corruption in the form of demands for special payments and bribes connected with licenses. *CORR_ICRG* captures financial corruption. With regard to the alternative measure of corruption, the World Bank constructed the World Governance Indicators, which provided the *CORR_WD* data for 213 countries over 14 years (1996–2009).[8] In comparison with *CORR_ICRG*, *CORR_WD* has the advantage of including a larger number of countries, although over a shorter time period.[9] *CORR_WD* captures perceptions regarding the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capturing" corruption by the elite and private interests (Kaufman et al. 2010). According to data provided originally by the World Bank, *CORR_WD* ranges from 0 to 100, where the larger values suggest less corruption. In this paper, with the aim of standardizing the values of the proxy for corruption, I converted *CORR_WD* to take a value range of 0 to 6. This change allows me to compare the effect of *CORR_ICRG* on *TECDIS*, and that of *CORR_ICRG* on *TECDIS*. As exhibited in Table 1, the mean value and the standard deviation for *CORR_ICRG* are 3.19 and 1.46, respectively. In addition, the mean value and the standard deviation for *CORR_WD* are 3.17 and 1.83, respectively. This shows that the values for *CORR_ICRG* are similar to those of

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[8] It is available from http://info.worldbank.org/governance/wgi/index.asp (accessed on June 1, 2011).

[9] As with *CORR_ICRG* and *CORR_WD*, Transparency International also provides the proxy for corruption. This data covers 1995 to 2010, which is a shorter period than *CORR_ICRG*. The number of countries included in the data from Transparency International is smaller than *CORR_WD*. That is, the data from Transparency International is not as helpful. Therefore, this paper does not use that data in estimations.

CORR_WD. As shown in Appendix 1, the countries used in the estimations change depending on whether *CORR_ICRG* or *CORR_WD* is used.

GDP (GDP per capita), *POP* (population), *GOVSIZ* (government size), and *INDRAT* (value-added of industry/GDP) are collected from the World Bank (2010). The available data for these variables covered 1960 to 2008. Thus, the data used in the estimations do not include 2009, and as such I cannot use 2009 data in the regression, although there was 2009 data available regarding *TECDIS, CORR_ICRG*, and *CORR_WD*.

3.2. Basic methods

To examine the hypothesis raised previously, this paper uses the negative binominal model. The estimated function takes the following form:

$$TECDIS_{it} = \alpha_0 + \alpha_1\, CORR\_ICRG \text{ (or } CORR\_WD)_i + \alpha_2 GDP_{it} + \alpha_3 POP_{it} + \alpha_4 GOVSIZ_{it} + \alpha_5 OPEN_{it} + \alpha_6 INDRAT_{it} + \alpha_7 AFRIC_i + \alpha_7 ASIA_i + u_i + \varepsilon_{it}, \qquad (1)$$

where the dependent variable is $TECDIS_{it}$ in country i, for year t. α represents the regression parameters, u_i the unobservable time-invariant feature of country i, and m_t represents the unobservable year effects of year t. The effects of u_i *are* controlled for by including country dummies. ε_{it} represents the error term. When *CORRU_ICRG* is used as the proxy for the degree of corruption the data includes 86 countries, from 1984 to 2008. In contrast, when *CORRU_WD* is used as a proxy for the degree of corruption, the data includes 92 countries, from 1996 to 2008. *TECDIS* is the number of technological disasters, which does not take the negative value. In this study, the Poisson model is used as the basic method of estimation. However, in the Poisson model, it is assumed that mean of a dependent variable is equal to its variance. As discussed in subsection 3.1, *TECDIS* is over-dispersed and its variance is large. The use of the Poisson model here causes a downward bias and inflates z-statistics, and as such, the negative binominal model is preferred (Wooldridge 2002, Ch. 19). The negative binominal model is applied for empirical analysis to examine the effect of disasters in existing works (e.g., Anbarci et al. 2006; Escaleras et al. 2007; Kellenberg & Mobarak 2008), because the damage caused by natural disasters is characterized by over-dispersion. In line with previous literature, the negative binominal model is used in this paper, although this paper focuses on the number of technological disasters rather than the resulting damage.

If the hypothesis is supported, *CORR_ICRG* (or *CORR_WD)* will take the negative sign. Figures 1(a) and (b) demonstrate the relationship between a country's average

TECDIS from 1984 to 2008 and a country's average corruption (*CORR_ICRG*) from 1984 to 2008. Figure 1(a) shows that *TECDIS* is negatively related to corruption, although outliers (China, India, and Nigeria), which experience on average at least 10 times more technological disasters, appear to affect the relationship. As presented in Table 2, the number of technological disasters is less than 10 for 97% of observations. Therefore, outliers with an average *TECDIS* larger than 10 are removed from the sample, and the relationships are illustrated in Figure 1(b). A cursory examination of Figure 1(b) reveals that the negative relationship between *TECDIS* and corruption continues to be observed. The findings demonstrated in Figures 1(a) and (b) are congruent to the hypothesis. A closer examination of the influence of corruption on *TECDIS* is explored using the regression analysis presented in section 4.

With regard to control variables, *GDP* and *POP* are included to capture basic economic conditions. *GDP* is considered to reflect the degree of economic development within a country. In addition to *GDP*, region dummies such as *AFRIC* (Africa dummy) and *ASIA* (Asia dummy) are also considered to capture economic development because African and Asian countries are generally considered to be less developed than Western countries. Higher levels of technology are more likely to be found in developed countries. As a consequence, there are greater preventative measures against technological disasters, resulting in a lower probability of these occurring. Therefore, *GDP* is expected to take the negative sign, whereas *AFRIC* and *ASIA* are predicted to take the positive sign. In contrast, technology is less likely to be used in less developed countries because technology-intensive sectors have not yet been well established. If this holds true, technology is less likely to be used and so the probability of industrial disasters is lower in less developed countries. Therefore, technological disasters are more likely to occur in developed countries. That is, the effect of *GDP* on *TECDIS*, and that of *AFRIC* and *ASIA* will be contrasting. For the purpose of controlling for the differing effects caused by economic structure, *INDRAT* (value-added of industry/GDP) is used. Higher rates of industry lead to higher rates of technological disasters. Thus, *INDRAT* is predicted to take the positive sign.

The presence of government is captured by *GOVSIZ.* Even after controlling for quality of government with *CORR_ICRG* (or *CORR_WD*), government appears to envelop the private sector. Technological disasters in the private sector result in a decrease in the demand for goods, and therefore a decrease in profits. Thus, private firms have an incentive to avoid disasters so as to not reduce profit. As a result, private firms make various invests in accident prevention. In contrast to the private sector, governments do not have such an incentive, leading to a higher probability that a technological disaster will occur in the public sector. In light of the above, it is possible to infer that *GOVSIZ* increases the probability of disasters and so takes the positive sign. *OPEN* is considered to reflect the importance of technology via trade. *OPEN* appears to have the opposite effect as follows: importing technology increases the frequency of using technology, raising the probability of disasters. In contrast, imported technology is accompanied by disaster prevention measures, reducing the possibility of disasters. Therefore, the sign for *OPEN* depends on whether the positive effect outweighs the negative.

3.3. Two-stage method to control for endogeneity bias

"Public sector corruption is commonly known to be highly correlated with … omitted institutional factors" (Escaleras et al. 2007, p. 219). Thus, *CORR_ICRG* (or *CORR_WD*) is regarded as an endogenous variable, causing the estimation results to suffer from bias. The inclusion of country dummies controls for unobserved country-specific time-invariant features, which is represented as u_i in Equation (1). This allows u_i to be arbitrarily related to the observable *CORR_ICRG* (or *CORR_WD*), (Wooldridge 2002, 265–266). That is, the inclusion of country dummies attenuates the endogeneity bias. In addition, for the purpose of controlling for bias and following the methodology of previous studies (Escaleras et al. 2007), I estimated the predicted values of *CORR_ICRG* (or *CORR_WD*) in the first stage estimation and included the predicted values as independent variables in the second stage. The first stage regression, in the form of Equation (2), is estimated with *CORR_ICRG* (or *CORR_WD*) as the dependent variable:

$$CORR\_ICRG \text{ (or } CORR\_WD)_{it} = \beta_0 + \beta_1 LEGA\_FRE_i + \beta_2 CATHO_i + \beta_3 GDP_{it} + \beta_4 POP_{it} + \beta_5 GOVSIZ_{it} + \beta_6 OPEN_{it} + \beta_7 INDRAT_{it} + \varepsilon_{it} \quad (2)$$

The dependent variables *CORR_ICRG* (or *CORR_WD*) take a value between 0 and 6, and so the sample includes each extreme value. Therefore, I used the two-limit Tobit, where the lower and upper bounds are 0 and 6, respectively. Existing literature has clearly stated that institutional factors such as legal origin, ethnic heterogeneity, and religion determine the level of corruption (e.g., Treisman 2000; Paldam 2001; Djanskov et al. 2003; Serra 2006; Gokcekus 2008; Pellegrini & Gerlagh 2008). In this paper, I use *LEGA_FRE* (French legal origin dummy) and *CATHO* (percentage of the population that is Catholic in 1980) as instrumental variables.[10] *LEGA_FRE* and *CATHO* were

[10] Previous works generally used the percentage of Protestants to examine corruption. In this paper, however, this data is not used because it did not create a good fit with the

sourced from an earlier work (La Porta et al. 1999).[11] It was observed in previous studies (Treisman 2000; Serra 2006) that the public sector is more inclined to be corrupt in those French legal origin countries that are now regarded as civil law countries. Pre-reform Christians have been previously defined as including Catholics, and Orthodox and other 'Old' churches (Paldam 2001). It has been suggested that the public sector is more likely to be corrupt in the countries where Pre-reform Christians are dominant (Paldam 2001). If this holds true, then Catholics are negatively associated with *CORR_ICRG* and *CORR_WD*. Thus, the predicted signs of *LEGA_FRE* and *CATHO* are negative. These instrumental variables are time-invariant and are removed when country dummies are included. Therefore, the country dummies were not incorporated in the two-stage estimations.

4. Results

4.1. Basic results

The estimations results when *CORR_ICRG* is used are set out in Tables 3, 4(a), and (b). Results when *CORR_WD* is used are reported in Tables 5, 6(a) and (b). As shown in Figure 1, there are outliers with regard to *TECDIS*. From Table 1, the mean of TECDIS is 1.70 and the maximum value is 71, indicating that that the sample is skewed. Outliers are thought to significantly influence the estimation results. To address this, estimations are conducted using a sub-sample that excludes outliers. A closer look to determine robustness shows that there are two outliers in *TECDIS* larger than 10 and 20. In the sub-sample that excludes *TECDIS* observations larger than 20, the mean and standard deviation are 1.28 and 2.55, respectively. In the sub-sample excluding *TECDIS* observations larger than 10, the mean and standard deviation are 1.06 and 1.85, respectively. The significance of the fall in mean for *TECDIS* can be seen by considering the ratio of *TECDIS*'s standard deviation to its mean value. For instance, the ratio is 2.80 in the full sample shown in Table 1, while the ratio is 1.75 for the sub-sample excluding *TECDIS* observations larger than 10. Tables 4(a) and 6(a) show the results where outliers defined as *TECDIS* larger than 20 are excluded, and Tables 4(b) and 6(b) present the results excluding outliers defined as *TECDIS* larger than 10. In each table, results without country dummies are shown in columns (1)–(3), while results with country dummies are in columns (4)–(6). In all estimations, z-statistics are calculated

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estimated model when used as an independent variable.

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

using robust standard errors to control for heteroscedasticity.

I will now discuss the results shown in Table 3. Consistent with my prediction, the coefficients of *CORR_ICRG* take the negative sign in all estimations and are statistically significant at the 1% level. The absolute values of the coefficients are between 0.11 and 0.17 in columns (1)–(6). With respect to control variables, *GDP* yields a significant positive sign in columns (2) and (3). In contrast, *GDP* produces the negative sign while being statistically significant at the 1% level in columns (4)–(6). The contrasting results for *GDP* are mainly because of the inclusion of country dummies. Furthermore, the results for *GDP* exhibited in Table 4 are similar to those of Table 3. Thus, it follows that *GDP* is correlated with unobserved country-specific time-invariant features such as institutional conditions. This result implies that economic development reduces the possibility of technological disasters after controlling for institutional factors. The results for the other control variables *POP, GOVSIZ, OPEN*, and *INDRAT* (Table 3) differ from those of Table 5, implying that their estimation results are not robust.[12] Concerning regional dummies, *AFRIC* and *ASIA* produce the positive sign and are statistically significant at the 1% level, which is similar to the results of Table 5. This implies that technology is not able to be used appropriately in less developed countries, in part because human capital has not, as yet, been sufficiently accumulated.[13]

I now turn to the results for *CORR_ICRG* in Tables 4(a) and (b), to check for robustness in Table 3. *CORR_ICRG* continues to yield the negative sign and be statistically significant at the 1% level. In addition, its absolute values are between 0.10 and 0.17, which are similar to those exhibited in Table 3. Therefore, the effect of *CORR_ICRG* on *TECDIS* is significantly negative even when outliers are excluded.

In Table 5, concerning results without country dummies, the sign for *CORR_WD* is negative in columns (1) and (3), and positive in column (2). Furthermore, *CORR_WD* is not statistically significant in columns (2) and (3). The inclusion of country dummies significantly changes the results of *CORR_WD*. *CORR_WD* takes the negative sign and is statistically significant at the 1% level in columns (4)–(6). Furthermore, absolute values of *CORR_WD* are 0.21 and 0.22, which shows the results of *CORR_WD* are stable and in line with the expectation. The significant difference of results between samples with and without country dummies show that *CORR_WD* is strongly correlated

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[12] The results for the control variables in Tables 4 (a) and (b) also differ from Tables 6(a) and (b), although these results are not reported. These results are available upon request from the author.

[13] Long-term panel data for the proxy for human capital could not be obtained and as such the proxy was not included as an independent variable.

with unobserved country-specific time-invariant features. Tables 6(a) and (b) show that similar results can be observed in the results of the sub-samples excluding observations with *TECDIS* larger than 10 and 20. However, the statistical significance of Tables 6(a) and (b) declined to the 5% or 10% levels. Furthermore, the absolute values of *CORR_WD* are between 0.11 and 0.14, which are approximately half the value of those in Table 5. The omission of outliers reduces the effect of *CORR_WD.* I interpret these results to indicate that the smaller sample size of Table 5 (compared with Table 4) has caused the results to be unstable and dependent on the specification.

4.2. Estimation results using instrumental variables.

The second stage results when the predicted *CORR_ICRG* is used as a proxy for corruption are shown in Tables 7, 8(a) and (b). The second stage results when the predicted *CORR_WD* is used are shown in Tables 9, 10(a) and (b). The first stage results of Tables 7 and 9 are exhibited in Appendixes 2 and 3, respectively. Tables 8(a) and 10(a) show the results excluding observations from the sample with *TECDIS* larger than 20, and Tables 8(b) and 10(b) present the results excluding observations from the sample with *TECDIS* larger than 10.

In Appendixes 2 and 3, the Wald Chi-square values are sufficiently large, indicating a high statistical significance regarding the determination of corruption.[14] Furthermore, concerning instrumental variables, as exhibited in Appendixes 2 and 3, *CATHO* yields the predicted negative sign and is statistically significant in all columns. *LEGA_FRE* takes the expected negative sign and is statistically significant at the 1% level in columns (1)–(3) of Appendix 2, although the sign for *LEGA_FRE* is not negative in Appendix 3. Therefore, to a certain extent, the Tobit model is appropriately specified, supporting the predicted values of *CORR_ICRG* and *CORR_WD.* Furthermore, in column (1), the log pseudo-likelihood is –3175 in Appendix 2, and –1745 in Appendix 3. With regard to the number of extreme values for the proxy for corruption in Appendix 2 for 2007 observations, there were 40 left-censored observations and 158 right-censored. In contrast, in Appendix 3, among the 1,157 observations, there were 4 left-censored observations and 11 right-censored. Overall, the two-limit Tobit model is a better fit to estimate *CORR_ICRG* than *CORR_WD.* The predicted values of *CORR_ICRG* appear to be more reliable than those of *CORR_WD* when we jointly consider the results from the first stage. Thus, careful attention must be paid to reliability when we interpret estimation results using the predicted value of *CORR_ICRG* and *CORR_WD.*

[14] The first stage results of Tables 8(a) and (b), and 10(a) and (b) are not reported because of space limitations. The results are available upon request from the author.

In Table 7, the significant negative sign of *CORR_ICRG* in all estimations suggests that the results of Table 3 are robust even after controlling for endogeneity bias. I see from Tables 8(a) and (b) that *CORR_ICRG* continues to yield a significant negative sign in all estimations when outliers are removed from the sample, which is similar to the results in Tables 4(a) and (b). Furthermore, its absolute values range from 0.40 to 0.68, meaning that a 1-point increase in *CORR_ICRG* reduces the probability of technological disasters by 0.40–0.68 times. With the mean value of *TECDIS* at 1.70 and the values for *CORR_ICRG* ranging between 0 and 7, the effect of *CORR_ICRG* on TECDIS is significant. In contrast, the absolute values (exhibited in Tables 3, 4 (a) and (b), ranging between 0.10 and 0.17) are four times larger. This implies that endogeneity results in the under-estimation of the size of the effect.

With respect to Table 9, *CORR_WD* continues to produce the negative sign and be statistically significant at the 1% level in all estimations. The same results can be observed in Tables 10(a) and (b), implying that the removal of the outliers' effect does not change the result. Its absolute values range between 1.20 and 2.99, showing that the size of the effect is unstable and varies significantly depending on the specification. The fact that the absolute values, as shown in columns (4)–(6) of Tables 5 and 6, range between 0.11 and 0.22 suggest that the effects of *CORR_WD* become approximately 10 times larger than those where endogeneity bias is not controlled for. Furthermore, considering that the mean value of *TECDIS* is 1.70 and the values for *CORR_ICRG* range between 0 and 7, infers that the absolute values of *CORR_ICRG* are unreasonably large, suggesting that the results are not accurate. A reason for this could be that the sample size of Tables 9 and 10 are smaller than those for Tables 7 and 8. Aside from sample size, as explained in subsection 3.1, *CORR_ICRG* captures the demands for special payments and bribes whereas *CORR_WD* does not capture these directly. Thus, *CORR_ICRG* is more appropriate to examine the hypothesis because the bribes for licenses are considered to be an important aspect of the hypothesis. That is, measurement error may be a reason why the effect of *CORR_WD* is biased. However, the combined results of *CORR_WD* that appeared in Tables 5, 6, 9, and 10 made it evident that *CORR_WD* has a negative effect on *TECDIS*.

The results of Table 3–5 discussed so far strongly support the hypothesis that corruption increases the probability of technological disasters. Considering the results jointly leads me to argue that institutional quality plays a crucial role in determining the probability of manmade technological disasters, and should, therefore, be taken into account when mechanisms regarding manmade disasters are explored.

5. Conclusion

Disasters have a tremendous impact on economic and political conditions, even in modern society. Increasingly, researchers are paying greater attention to the issue of disasters and a growing number of works are attempting to ascertain the determinants of the damage caused by natural disasters. The probability of a natural disaster occurring, however, depends on geographical features rather than economic or political factors. Therefore, it is beyond the scope of social science to prevent natural disasters. In contrast, manmade disasters, such as technological disasters, appear to be affected by institutions formed via long-term interactions between individuals. For instance, previous literature has provided evidence that public sector corruption influences economic condition via various channels. It has also been suggested (Escaleras et al. 2007) that public sector corruption results in increases in fatalities caused by natural disasters. This claim is supported by further evidence that the rate of traffic fatalities is also influenced by corruption (Anbarci et al. 2006). However, there is little information regarding the relationship between public sector corruption and the probability of manmade disasters. Thus, this paper attempts to investigate how corruption influences the probability of technological disasters, and the extent of that influence, using panel data from 98 countries from 1984 to 2008.

The major finding is that public sector corruption increases the probability of technological disasters. The result does not change even when country dummies are included or endogeneity bias is controlled for. Thus, it can be argued that the higher the level of corruption within a public sector, the higher the risk of industrial, transport, or other accidents. These accidents occur less frequently than traffic accidents, however, they cause greater economic and social loss. As a result, individuals change their behavior regarding risk. Therefore, the roles of both risk-coping behavior and the insurance market will change with regard to corruption. Corruption is believed to impede the function of the market. Thus, an indirect detrimental effect of corruption is that it reduces social welfare. This indirect effect of corruption needs to be taken into account, although few researchers do. An analysis of risk-coping behavior and the insurance market is important when the effects of disasters are required to be considered (Sawada and Shimizutani 2007; 2008;).

The probability of technological disasters is explored in this paper. However, the effect of public sector corruption on the damage (and its extent) caused by technological disasters was not included in the scope of this study. Jointly analyzing the probability and damage caused by technological disasters would provide useful evidence for policy making. Furthermore, this paper used aggregated-level data for estimations. Thus, a detailed individual-level analysis was not conducted. Accordingly, how individual behavior relates to manmade disasters with regard to institutional conditions requires future investigation. To this end, field (or laboratory) experiments are desirable. Furthermore, aside from corruption, other institutional factors appear to affect the probability of manmade disasters. Thus, the effects of various institutional factors on the probability of manmade disasters should be examined. These remaining issues require further investigation in future studies.

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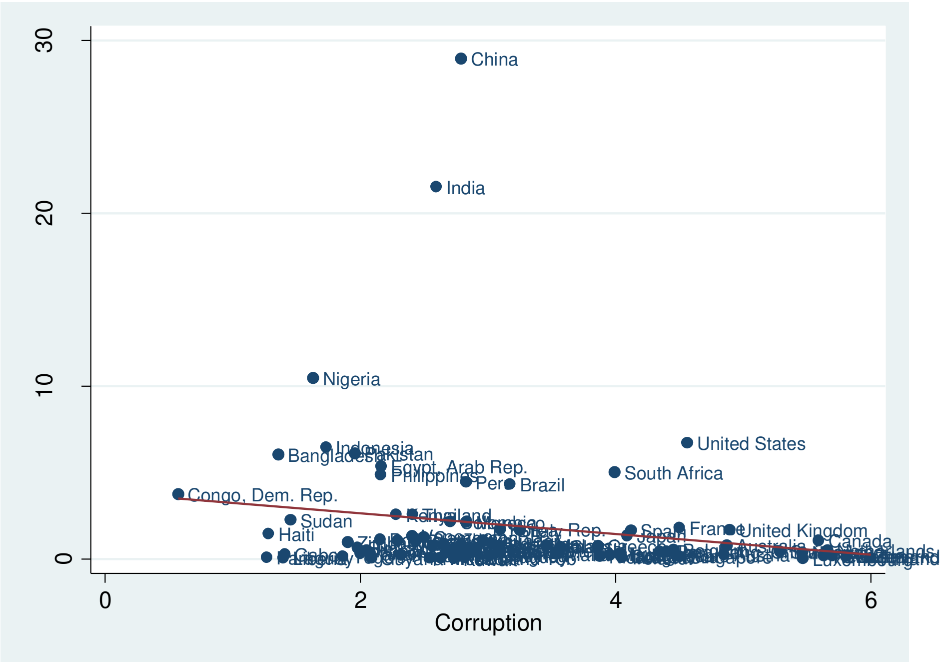
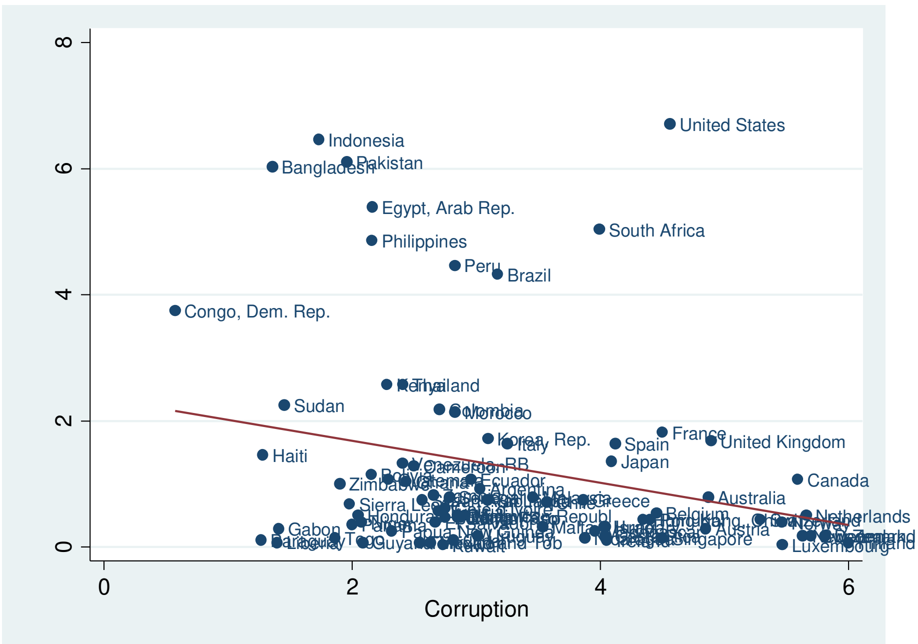


(a) Full sample



(b) Outliers (number of technological disasters is larger than 10) are excluded.

Figure 1. Association between corruption (CORR_ICRG) and number of technological disasters

Table 1. Variable definitions and basic statistics

Variable	Definition	Mean	Standard deviation	Maximum	Minimum
TECDIS	Number of technological disasters	1.70	4.76	71	0
	Independent variables				
CORR_ICRG	Corruption index of international country risk guide (ICRG).	3.19	1.46	6	0
CORR_WD	Corruption index of World Bank.	3.17	1.83	6	0
GDP	GDP per capita (thousand US$)	7.46	10.0	56.3	0.06
POP	Population (million)	44.3	151.1	1300	0.06
GOVSIZ	Government consumption expenditure/ GDP	0.15	0.06	0.76	0.02
OPEN	Trade/GDP	0.77	0.51	4.56	0.11
INDRAT	Value-added of industry /GDP.	0.30	0.10	0.78	0.01
AFRIC	Africa country dummy	---	---	---	---
ASIA	Asia country dummy	---	---	---	---
	Instrumental variables				
LEGA_FRE	French legal origin dummy	---	---	---	---
CATHO	Share of population that is Catholic	0.39	0.37	0.97	0

Note: CORR_WD is the value between 1996 and 2008. All other variables show the values for 1984–2008.

Table 2. Frequency of technological disasters

Number of TECDIS	Frequency	%
0	1,574	56.21
1	517	18.46
2	243	8.68
3	141	5.04
4	77	2.75
5	49	1.75
6	33	1.18
7	27	0.96
8	22	0.79
9	23	0.82
10	15	0.54
11	8	0.29
12	5	0.18
13	5	0.18
14	4	0.14
15	4	0.14
16	6	0.21
17	1	0.04
18	1	0.04
19	7	0.25
20	38	1.36
Total	2,800	100

Table 3. Negative binominal estimation (*TECDIS* is a dependent variable; *CORR_ICRG* is a proxy for corruption): 1984–2008

	(1)	(2)	(3)	(4)	(5)	(6)
CORR_ICRG	–0.17***	–0.11***	–0.13***	–0.13***	–0.12***	–0.13***
	(–5.71)	(–4.01)	(–4.39)	(–4.29)	(–3.77)	(–4.28)
GDP	0.003	0.01***	0.01***	–0.03***	–0.04***	–0.04***
	(0.73)	(3.09)	(3.07)	(–2.86)	(–3.28)	(–2.97)
POP	0.004***	0.002***	0.002***	0.004***	0.003***	0.003***
	(8.70)	(17.3)	(16.6)	(4.79)	(3.64)	(3.63)
GOVSIZ		–1.82***	–1.13		–4.02***	–3.70***
		(–2.62)	(–1.48)		(–3.79)	(–3.33)
OPEN		–1.15***	–1.28***		0.62***	0.51***
		(–11.8)	(–12.7)		(3.26)	(2.48)
INDRAT			0.82**			0.27**
			(2.39)			(1.06)
AFRIC	0.50***	0.49***	0.50***			
	(5.48)	(5.23)	(5.20)			
ASIA	0.58***	0.99***	1.01***			
	(6.67)	(10.5)	(10.3)			
Constant	0.32**	1.06***	0.82***	0.09	0.43	0.27
	(3.03)	(7.91)	(5.13)	(0.32)	(1.11)	(0.06)
Country dummies[3]	No	No	No	Yes	Yes	Yes
Wald Chi-square	332.9***	1463.0***	1499.9***	41266.4***	15226.4***	23682.6***
Observations	2077	1984	1873	2077	1984	1873

1. Numbers in parentheses are z-statistics calculated using robust standard errors.
2. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.
3. “No” means that dummies are not included while “Yes” means that dummies are included.

Table 4. Negative binominal estimation (*TECDIS* is a dependent variable; *CORR_ICRG* is a proxy for corruption): 1984–2008 and excludes outliers

(a) *TECDIS* is smaller than 20

	(1)	(2)	(3)	(4)	(5)	(6)
CORR_ICRG	–0.13*** (–4.07)	–0.14*** (–4.51)	–0.16*** (–4.92)	–0.11*** (–3.42)	–0.10*** (–3.06)	–0.12*** (–3.55)
Country dummies[3]	No	No	No	Yes	Yes	Yes
Wald Chi-square	183.4***	370.3***	369.3***	10485.5***	14816.8***	31766.4***
Observations	2044	1956	1845	2044	1956	1845

1. Numbers in parentheses are z-statistics calculated using robust standard errors.
2. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.
3. "No" means that dummies are not included while "Yes" means that dummies are included.
4. In each column, constant and control variables corresponding to Table 3 are included but not reported because of space limitations.

(b) *TECDIS* is smaller than 10

	(1)	(2)	(3)	(4)	(5)	(6)
CORR_ICRG	–0.17*** (–5.71)	–0.11*** (–4.01)	–0.13*** (–4.39)	–0.13*** (–4.29)	–0.12*** (–3.77)	–0.13*** (–4.28)
Country dummies[3]	No	No	No	Yes	Yes	Yes
Wald Chi-square	332.9***	1463.0***	1499.9***	41266.4***	15226.4***	23682.6***
Observations	2001	1918	1807	2001	1918	1807

1. Numbers in parentheses are z-statistics calculated using robust standard errors.
2. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.
3. "No" means that dummies are not included while "Yes" means that dummies are included.
4. In each column, constant and control variables corresponding to Table 3 are included but not reported because of space limitations.

Table 5. Negative binominal estimation (*TECDIS* is a dependent variable;

CORR_WD is a proxy for corruption): 1996–2008

	(1)	(2)	(3)	(4)	(5)	(6)
CORR_WD	–0.17***	0.006	–0.003	–0.21***	–0.22***	–0.22***
	(–4.14)	(0.15)	(–0.07)	(–3.46)	(–3.42)	(–3.42)
GDP	0.003	–0.008	–0.006	–0.13***	–0.14***	–0.14***
	(0.53)	(–1.27)	(–0.92)	(–4.75)	(–4.71)	(–4.64)
POP	0.004***	0.002***	0.002***	0.001	0.002	0.003
	(6.20)	(13.6)	(11.9)	(0.82)	(0.20)	(0.24)
GOVSIZ		–0.75	–0.03		–1.46	–0.80
		(–0.81)	(–0.03)		(–0.86)	(–0.46)
OPEN		–1.49***	–1.72***		0.42	0.33
		(–11.5)	(–11.3)		(1.48)	(1.04)
INDRAT			1.61***			0.008
			(3.65)			(0.72)
AFRIC	0.62***	0.49***	0.57***			
	(5.26)	(4.27)	(4.85)			
ASIA	0.65***	1.12***	1.15***			
	(5.44)	(8.51)	(8.46)			
Constant	0.29**	1.03***	0.60***	0.66**	0.63	0.40
	(2.30)	(6.18)	(2.98)	(2.41)	(1.27)	(0.76)
Country dummies[3]	No	No	No	Yes	Yes	Yes
Wald Chi-square	242.6***	1015.9***	1099.4***	39385.4***	27014.7***	26053.3***
Observations	1157	1092	1035	1157	1092	1035

1. Numbers in parentheses are z-statistics calculated using robust standard errors.
2. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.
3. “No” means that dummies are not included while “Yes” means that dummies are included.

Table 6. Negative binominal estimation (*TECDIS* is a dependent variable; *CORR_WD* is

a proxy for corruption): 1984–2008 and excludes outliers

(a) *TECDIS* is smaller than 20

	(1)	(2)	(3)	(4)	(5)	(6)
CORR_WD	–0.07* (–1.83)	–0.008 (–0.20)	–0.03 (–0.69)	–0.11* (–1.87)	–0.14** (–2.31)	–0.14** (–2.31)
Country dummies[3]	No	No	No	Yes	Yes	Yes
Wald Chi-square	164.5***	289.7***	294.2***	1328.7	1246.1	1189.2
Observations	1132	1072	1015	1132	1072	1015

1. Numbers in parentheses are z-statistics calculated using robust standard errors.
2. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.
3. "No" means that dummies are not included while "Yes" means that dummies are included.
4. In each column, constant and control variables corresponding to Table 5 are included but not reported because of space limitations. 5. In columns (4)–(6), Wald Chi-square could not be obtained and so the absolute values of log pseudo-likelihood are reported.

(b) *TECDIS* is smaller than 10

	(1)	(2)	(3)	(4)	(5)	(6)
CORR_WD	–0.01 (–0.52)	0.03 (0.87)	0.02 (0.53)	–0.11* (–1.79)	–0.13** (–2.07)	–0.14** (–2.07)
Country dummies[3]	No	No	No	Yes	Yes	Yes
Wald Chi-square	417.0***	493.5***	475.3***	20103.6***	21975.2***	25610.9***
Observations	1108	1053	996	1108	1053	996

1. Numbers in parentheses are z-statistics calculated using robust standard errors.
2. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.
3. "No" means that dummies are not included while "Yes" means that dummies are included.
4. In each column, constant and control variables corresponding to Table 5 are included but not reported because of space limitations.

Table 7. Negative binominal estimation using predicted value of *CORR-ICRG* (*TECDIS* is a dependent variable): 1984–2008

	(1)	(2)	(3)
CORR_ICRG	–0.40***	–0.67***	–0.65***
	(–3.14)	(–4.34)	(–4.50)
GDP	0.02**	0.06***	0.05***
	(2.09)	(4.59)	(4.67)
POP	0.004***	0.002***	0.002***
	(7.26)	(16.0)	(15.5)
GOVSIZ		1.17	1.91*
		(1.13)	(1.76)
OPEN		–1.27***	–1.39***
		(–12.4)	(–13.4)
INDRAT			0.36
			(1.00)
AFRIC	0.42***	0.23**	0.25**
	(3.51)	(1.98)	(2.14)
ASIA	0.47***	0.84***	0.88***
	(4.28)	(8.14)	(8.56)
Constant	0.91***	2.26***	2.06***
	(2.54)	(6.22)	(5.52)
Wald Chi-square	263.4***	1418.1***	1428.7***
Observations	2077	1984	1873

1. Numbers in parentheses are z-statistics calculated using robust standard errors.
2. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 8. Negative binominal estimation using predicted value of *CORR-ICRG* (*TECDIS* is a dependent variable): 1984–2008 and excludes outliers

(a) *TECDIS* is smaller than 20

	(1)	(2)	(3)
CORR_ ICRG.	–0.48***	–0.68***	–0.64***
	(–4.07)	(–4.19)	(–4.41)
Wald Chi-square	251.0***	618.7***	623.3***
Observations	2044	1956	1845

1. Numbers in parentheses are z-statistics calculated using robust standard errors.
2. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.
3. In each column, constant and control variables corresponding to Table 7 are included but not reported because of space limitations.

(b) *TECDIS* is smaller than 10

	(1)	(2)	(3)
CORR_ ICRG.	–0.43***	–0.44***	–0.48***
	(–3.73)	(–2.85)	(–3.41)
Wald Chi-square	308.0***	615.9***	623.4***
Observations	2001	1918	1807

1. Numbers in parentheses are z-statistics calculated using robust standard errors.
2. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.
3. In each column, constant and control variables corresponding to Table 7 are included but not reported because of space limitations.

Table 9. Negative binominal estimation using predicted value of *CORR-WD*

(TECDIS is a dependent variable): 1996–2008

	(1)	(2)	(3)
CORR_WD	–1.20***	–2.99***	–2.54***
	(–4.57)	(–5.57)	(–4.93)
GDP	0.12***	0.27***	0.23***
	(4.04)	(5.36)	(4.71)
POP	0.004***	0.002***	0.001***
	(4.80)	(12.9)	(9.67)
GOVSIZ		20.8***	18.5***
		(5.33)	(4.87)
OPEN		–1.09***	–1.52***
		(–7.89)	(–10.1)
INDRAT			2.41***
			(4.86)
AFRIC	–0.16	–1.72***	1.33***
	(–0.68)	(–4.26)	(3.40)
ASIA	0.39**	0.70***	0.77***
	(2.50)	(4.61)	(4.97)
Constant	2.83***	5.33***	4.18***
	(4.28)	(6.67)	(5.52)
Wald Chi-square	214.6***	1105.1***	1147.5***
Observations	1157	1092	1035

1. Numbers in parentheses are z-statistics calculated using robust standard errors.
2. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 10. Negative binominal estimation using predicted value of *CORR-WD*

(*TECDIS* is a dependent variable): 1996–2008 and excludes outliers

(a) *TECDIS* is smaller than 20

	(1)	(2)	(3)
CORR_ WD.	–1.21***	–2.93***	–2.57***
	(–4.65)	(–5.36)	(–4.83)
Wald Chi-square	269.2***	533.2***	478.6***
Observations	1132	1072	1015

1. Numbers in parentheses are z-statistics calculated using robust standard errors.
2. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.
3. In each column, constant and control variables corresponding to Table 9 are included but not reported because of space limitations.

(b) *TECDIS* is smaller than 10

	(1)	(2)	(3)
CORR_ WD.	–1.21***	–3.17***	–2.50***
	(–4.36)	(–4.73)	(–4.11)
Wald Chi-square	585.3***	767.5***	716.0***
Observations	1108	1053	996

1. Numbers in parentheses are z-statistics calculated using robust standard errors.
2. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.
3. In each column, constant and control variables corresponding to Table 9 are included but not reported because of space limitations.

Appendix 1. List of countries used in the analysis

Number	Name	CORR_ICRG	CORR_WD	Number	Name	CORR_ICRG	CORR_WD
1	Argentina	#	#	51	Liberia	#	#
2	Australia	#	#	52	Libya	#	#
3	Austria	#	#	53	Luxembourg	#	#
4	Bangladesh	#	#	54	Madagascar	#	#
5	Belgium	#	#	55	Malawi	#	#
6	Belize		#	56	Malaysia	#	#
7	Benin		#	57	Malta	#	#
8	Bolivia	#	#	58	Mauritania		#
9	Brazil	#	#	59	Mexico	#	#
10	Burkina Faso	#	#	60	Morocco	#	#
11	Burundi		#	61	Nepal		#
12	Cameroon	#	#	62	Netherlands	#	#
13	Canada	#	#	63	New Zealand	#	#
14	Central Africa		#	64	Nicaragua	#	#
15	Chad		#	65	Niger	#	#
16	Chile	#	#	66	Nigeria	#	#
17	China	#	#	67	Norway	#	#
18	Colombia	#	#	68	Oman	#	#
19	Congo, Dem.	#	#	69	Pakistan	#	#
20	Congo, Rep.	#		70	Panama	#	#
21	Costa Rica	#	#	71	Papua New Guinea	#	#
22	Cote d'Ivoire	#	#	72	Paraguay	#	#
23	Denmark	#	#	73	Peru	#	#
24	Dominican Rep	#	#	74	Philippines	#	#
25	Ecuador	#	#	75	Portugal	#	#
26	Egypt	#		76	Puerto Rico		#
27	El Salvador	#	#	77	Rwanda		#
28	Fiji		#	78	Senegal	#	#
29	Finland	#	#	79	Seychelles		#
30	France	#	#	80	Sierra Leone	#	#
31	Gabon	#	#	81	Singapore	#	#

32	Georgia		#
33	Ghana	#	#
34	Greece	#	#
35	Guatemala	#	#
36	Guyana	#	#
37	Haiti	#	#
38	Honduras	#	#
39	Hong Kong	#	
40	Hungary	#	#
41	India	#	#
42	Indonesia	#	#
43	Ireland	#	#
44	Israel	#	#
45	Italy	#	#
46	Japan	#	#
47	Kenya	#	#
48	Korea, Rep.	#	
49	Kuwait	#	#
50	Lesotho		#
82	South Africa	#	#
83	Spain	#	#
84	Sri Lanka	#	#
85	Sudan	#	#
86	Sweden	#	#
87	Switzerland	#	#
88	Syrian Arab Republic	#	
89	Thailand	#	#
90	Togo	#	#
91	Trinidad and Tobago	#	#
92	Tunisia	#	#
93	United Kingdom	#	#
94	United States	#	#
95	Uruguay	#	#
96	Venezuela, RB	#	
97	Zambia	#	#
98	Zimbabwe	#	#

Note: # means that observations are included in the sample used for the estimation.

Appendix 2. First stage results for Table 7;
Two-limit Tobit estimation
(*CORR_ICRG* is a dependent variable): 1984–2008

	(1)	(2)	(3)
LEGA_FRE	–0.34***	–0.39***	–0.35***
	(–4.94)	(–5.65)	(–5.00)
CATHO	–0.005***	–0.002**	–0.003***
	(–5.05)	(–2.18)	(–3.63)
GDP	0.07***	0.06***	0.06***
	(21.9)	(18.4)	(17.2)
POP	–0.0001	–0.0002*	–0.0002*
	(–0.99)	(–1.79)	(–1.84)
GOVSIZ		4.73***	5.13***
		(8.14)	(7.67)
OPEN		–0.13***	–0.13**
		(–2.62)	(–2.41)
INDRAT			–0.37
			(–1.28)
AFRIC	–0.95***	–0.77***	–0.86***
	(–11.5)	(–8.80)	(–9.54)
ASIA	–1.05***	–0.68***	–0.74***
	(–10.1)	(–6.02)	(–6.37)
Constant	3.46***	2.76***	2.91***
	(36.7)	(21.0)	(18.7)
Log pseudo-likelihood	–3175	–2967	–2793
Left-censored observations (CORR_ICRG = 0)	40	35	35
Right-censored observations (CORR_ICRG = 6)	158	154	148
Observations	2077	1984	1873

1. Numbers in parentheses are z-statistics calculated using robust standard errors.
2. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.
3. Upper and lower bounds are 6 and 0, respectively.

Appendix 3. First stage results for Table 9;
Two-limit Tobit estimation
(*CORR_WD* is a dependent variable): 1996-2008

	(1)	(2)	(3)
LEGA_FRE	0.01 (0.18)	0.001 (0.02)	0.03 (0.48)
CATHO	–0.005*** (–4.40)	–0.002** (–2.07)	–0.002** (–2.41)
GDP	0.10*** (26.7)	0.09*** (23.6)	0.09*** (23.7)
POP	–0.0001 (–1.16)	–0.0007 (–0.56)	–0.0001 (–0.97)
GOVSIZ		6.96*** (10.1)	7.12*** (10.2)
OPEN		0.13** (2.12)	0.09 (1.41)
INDRAT			0.21 (0.53)
AFRIC	–1.06*** (–10.4)	–0.87*** (–8.10)	–0.90*** (–8.35)
ASIA	–0.59*** (–4.87)	–0.30** (–2.34)	–0.31** (–2.43)
Constant	2.84*** (25.9)	1.65*** (10.1)	1.64*** (8.71)
Log pseudo-likelihood	–1754	–1579	–1496
Left-censored observations (CORR_ICRG = 0)	4	3	3
Right-censored observations (CORR_ICRG = 6)	11	11	11
Observations	1157	1092	1035

1. Numbers in parentheses are z-statistics calculated using robust standard errors.
2. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.
3. Upper and lower bounds are 6 and 0, respectively.