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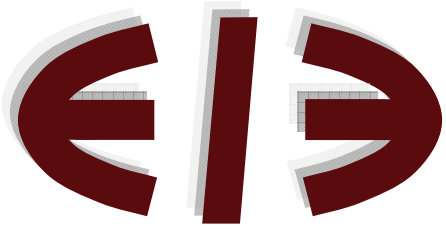

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Abstract

A growing number of studies 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

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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. Recently, institution has been found to be associated with the outcome of disasters (Kahn 2005). For instance, damage caused by natural disasters depends in part on public sector corruption (Escaleras et al., 2007).[1] The impact of disasters can be described as the probability that a disaster will occur and the degree of damage caused by a disaster. The expected impact of a disaster is small when the probability of a disaster is sufficiently low even if the damage is large. With respect to natural disasters, the probability of a natural disaster is not related to the degree of corruption within a government. To put it another way, corruption does not affect the probability of a natural disaster occurring because such a probability depends on natural conditions.[2] In contrast, where the magnitudes of disasters are equal, the economic outcome will vary according to institutional quality. Hence, corruption is important when we analyze how, and to what extent, to mitigate the damage caused by natural disasters. However, corruption is not relevant when we analyze how to prevent natural disasters.

When it comes to manmade technological disasters, institutional quality such as corruption seems to affect not only the level of damage caused by a disaster, but also the probability of disaster occurrence. 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.

Corruption is considered to affect the probability of accidents and manmade disasters via various 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

[1] 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 by public officials of resources that they are entrusted to administer, fraud in the form of manipulating information to further the personal interests of public officials, extortion, and favoritism (Andvig and Fjeldstad, 2001).

[2] 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.

required by law to obtain a pilot license. Airplane companies are obliged by public officials to employ only 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.[3]

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.[4] 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). Corruption reduces the incentive to train for positions in which technological devices are employed. 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 and Davoodi 1997; Vito 2002; Vito and Davoodi 2002). 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

[3] Intuitively, there is a wide range of causal factors through which corruption may increase the risk of failure. It is plausible that corruption decreases the incentive to adopt safety measures when the cost of obtaining a particular authorization with a bribe is lower than the cost of providing the safety measures.

[4] The licensing hypothesis requires that safety regulations be in place. However, corruption can reduce the level of regulation. This corruption effect appears dependent on the degree of democracy. As explained in the section 3, country dummies are included as independent variables to control the degree of democracy.

maintenance and operations, resulting in low-quality infrastructure (Vito and Davoodi 1997; Vito 2002; Vito and Davoodi 2002). In addition, corruption hampers economic growth (Mauro 1995) and therefore reduces per capital income, and as a result consumers purchase inferior products.[5] 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 hypothesis that a corrupt public sector raises the probability of technological accidents and therefore disasters. 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; 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. Related literature

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 have been used to suggest that economic growth rates fall, on average, by 0.45% points after a disaster, and that nearly 28% of the growth effect is due to 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).[6]

The level of damage caused by natural disasters has been explained not only by economic factors but also by political and institutional factors.[7] Low-quality governance and income inequality increase the death rate in a natural disaster, whereas democracy and social capital reduce the number of deaths (Anbarci et al. 2005; Kahn 2005; Escaleras et al. 2007; Yamamura

[5] In the regression estimations in this paper, per capita income is included as an independent variable and thus the income effect is controlled for. Hence, the indirect effect of corruption on disasters through income level is not captured in the coefficient of corruption.

[6] Kellenberg and Mobarak (2008) suggested that the relationship between GDP levels and the damage caused by natural disasters takes an inverted U shape, rather than being monotonically negative.

[7] Media is also considered to be a critical determinant of the damage caused by natural disasters (Eisensee and Strömberg 2007).

2010).[8] Government corruption is thought to be an important measure that captures the quality of governance and so plays a critical role when natural disasters occur.[9] Using China's 2008 earthquake in Sichuan as an example, the death toll from the earthquake reached approximately 70,000, with close to 10,000 school children confirmed dead after the collapse of 7,000 classrooms (Wong, 2008); for example, a government school built in 1975, and only renovated once in 1981, collapsed in the earthquake (Wong, 2008).[10] Parents of the deceased school children protested about the poor construction of the school. In response, local officials tried to buy the silence of the parents by offering them money if they signed a contract agreeing not to raise the construction issue again. In addition, Chinese news organizations have also been told by the central government not to conduct any reports on the schools. Chinese people suspect that government corruption is the reason behind the collapse of so many schools in the quake. Turning now to the recent natural disasters in Haiti and Japan, more than 200,000 lost their lives in Haiti's 2010 earthquake (The United Nations 2010), and approximately 15,000 people died in Japan's 2011 earthquake and tsunami (Sawada and Kodera 2011). According to the International Country Risk Guide (ICRG), Japan's corruption score sits around 4 and Haiti's at 1.5, which indicates that Japan's public sector is less corrupt than Haiti's. Therefore, the difference in the number of deaths in Haiti and Japan may be due, in part, to the degree of corruption in those governments.

Owing 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).[11] Seminal works from the 1990s (Mauro 1995), which empirically examined the effect of corruption, and the compilation of data on corruption have led the way for researchers to empirically investigate the political and economic outcomes

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[8] 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. Sobel and Leeson (2006) explored the outcome of Hurricane Katrina and argued that it is difficult for a centralized agency to make the best use of dispersed information to coordinate the demand for available supplies. The damage caused by Hurricane Katrina was magnified because of a massive governmental failure (Shughart II 2006). Congleton (2006) pointed out that the cause of the catastrophe that followed Katrina can be attributed to an interaction between the geographical features of New Orleans and the failure of the New Orleans levee system.

[9] The International Monetary Fund (IMF) has stated that corruption causes public finance to be ineffective in the enhancement of economic development (Hillman, 2004).

[10] Golden and Picci (2005) argued that the activities surrounding public works construction are the classic locus of illegal monetary activities between public officials and business. They also developed an objective measure of corruption. The measure calculates the difference between the physical quantities of public infrastructure and the cumulative price that the government pays for public capital stocks. Where the difference is greater between the money spent and the existing physical infrastructure—indicating that more money has been siphoned off in corrupt transactions—higher levels of corruption exist.

[11] Jain (2001) provided a literature review of classic research and introduced the current debate among researchers.

of public sector corruption (e.g., Glaeser and Saks 2006; Apergis et al. 2010; Dreher & Schneider 2010; Escaleras et al. 2010; Jong and Bogmans 2011, Johnson et.al. 2011; Swaleheen 2011).

3. Data and methods

3.1. Data

Data regarding the number of technological disasters from 1900 to 2010 were sourced from EM-DAT (Emergency Events Database).[12] 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 data from 1984 to 2010 on the number of technological disasters.[13] It is plausible that countries with greater corruption are less likely to provide information regarding technological disasters. This implies that there is the possibility for systematic measurement errors regarding the variables of technological disasters. Hence, special care is called for when using EM-DAT.

Definitions and the basic statistics for the variables used in this paper are presented in Table 1.[14] The mean value of the number of technological disasters is 1.70 and its standard deviation is 4.76, which is nearly three times larger than the mean value. The maximum and minimum values of the number of technological disasters are 71 and 0, respectively, indicating a significant gap. Table 2 shows more detailed statistics regarding the number of technological disasters and the frequency of technological disasters. Interestingly, 56.5% of technological disasters had a value of 0 and 18.4% just 1. Considering them jointly suggests that technological disasters are 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, an ICRG corruption index and World Bank corruption index are used. My primary measure of public sector corruption, the ICRG corruption index, was taken from the ICRG and contains data on 146 countries over a 27-year period (1984–2010). The ICRG is assembled by the Political Risk Service Group. The ICRG corruption index has the advantage of covering a longer period than the alternative measure (the World Bank corruption index). The ICRG corruption index values range from 0 to 6; larger values indicate less corruption. According to the ICRG, the most common form of business corruption is financial corruption in the form of demands for special payments and bribes connected with licenses. The ICRG corruption index captures financial corruption. With regard to the alternative measure of

[12] 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).
[13] The number of technological disasters was sourced from the International Disaster Database. http://www.emdat.be (accessed on June 1, 2011).
[14] In addition to data regarding the number of technological disasters, EM-DAT also provides various indexes for damage caused by disasters such as estimated damage costs (US$), number of homeless, number of injured, and number of deaths. This paper, however, focuses on the determinants of accidents rather than the determinants of damage. Hence, indexes for damage caused by disasters are not used in this paper.

corruption, the World Bank constructed World Governance Indicators, which provides data for the World Bank corruption index on 213 countries over a 14-year period (1996–2009).[15] In comparison with the ICRG corruption index, the World Bank corruption index has the advantage of including a larger number of countries, although over a shorter time period.[16] The World Bank corruption index 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 originally provided by the World Bank, the World Bank corruption index 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 the World Bank corruption index to have a value range of 0 to 6. This change enables me to compare the effect of the ICRG corruption index on the number of technological disasters, and that of the World Bank corruption index on the same. As exhibited in Table 1, the mean value and the standard deviation for the ICRG corruption index are 3.19 and 1.46, respectively. In addition, the mean value and the standard deviation for the World Bank corruption index are 3.17 and 1.83, respectively. This shows that the values for the ICRG corruption index are similar to those of the World Bank corruption index. As shown in Appendix 1, the countries used in the estimations change depending on whether the ICRG corruption index or the World Bank corruption index is used. According to EM-DAT, technological accidents can be classified as either industrial accidents, transport accidents, or miscellaneous accidents. Appendix 2 shows that the number of industrial accidents and transport accidents was essentially the same between 1965 and 1980. However, between 1996 and 2009, the number of transport accidents was more than 10 times that of industrial accidents. In contrast, the number of miscellaneous accidents was slightly larger than that of industrial accidents and transport accidents between 1965 and 1980, and then steadily increased throughout the study periods.[17]

GDP (GDP per capita), population, government size, openness, and rate of industry (value-added of industry/GDP) were 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 was unable to use 2009 data in the regression, although there were 2009 data available regarding the number of technological disasters, and in the ICRG corruption and World Bank corruption indexes.

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[15] Available from http://info.worldbank.org/governance/wgi/index.asp (accessed on June 1, 2011).

[16] Transparency International also provides the proxy for corruption. This data covers 1995 to 2010, which is a shorter period than the ICRG corruption index. The number of countries included in the data from Transparency International is smaller than in the World Bank corruption index. That is, the data from Transparency International are not as helpful. Therefore, this paper does not use those data in estimations.

[17] It is important to consider the difference between the accident categories to examine the influence of corruption. However, it is beyond scope of this paper to do so in detail. Future research could deal with this issue.

3.2. Basic methods

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

$$\textit{Number of disasters}_{it} = \alpha_0 + \alpha_1 \textit{ ICRG corruption (or World Bank corruption)}_{it} + \alpha_2 GDP_{it} + \alpha_3 Population_{it} + \alpha_4 Government\ size_{it} + \alpha_5 Openness_{it} + \alpha_6 \textit{ Rate of industry}_{it} + u_i + m_t + \varepsilon_{it}, \quad (1)$$

where the dependent variable is $\textit{Number of disasters}_{it}$ in country *i,* for year *t*. α represents the regression parameters, vu_i the unobservable time-invariant feature of country *i*, and m_t the unobservable year effects of year *t.*[18] The effects of u_i *are* controlled for by including country dummies, and the effects of m_t *are* controlled for by including year dummies. ε_{it} represents the error term. Therefore, the specification is considered to be a two-way fixed model. When *ICRG corruption* is used as the proxy for the degree of corruption, it includes data on 86 countries, from 1984 to 2008. In contrast, when *World Bank corruption* is used as a proxy for the degree of corruption, the data cover 92 countries, from 1996 to 2008. *Number of disasters* is count data and does not take a negative value. Compared with OLS or a Probit model, the Poisson model is more appropriate in this situation for the estimation. This is because the estimation results for count data will suffer bias in OLS where dependent values are allowed to take both negative and positive values.[19] Furthermore, the dependent variable must take 0 or 1 in a Probit model. A Probit model is more suitable to analyze qualitative data than count data.

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, *Number of disasters* 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 natural 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

[18] As indicated by Figure 1, there are some outliers. In this case, per capital technological disasters are a likely alternative measure and so could be used as a dependent variable. However, in all estimations, population has been already included as an independent variable. This means that the scale of each county has been controlled for. That is, the outlier bias is, to a certain extent, alleviated.

[19] When *y* is a dependent variable, "for strictly positive variables, we often use the natural log transformation, log(*y*), and use a linear model. This approach is not possible in interesting count data applications, where *y* takes on the value zero for nontrivial fraction of the population." (Wooldridge 2002, 645).

focuses on the number of technological disasters rather than the resulting damage.

If the hypothesis is supported, *ICRG corruption* (or *World Bank corruption)* will take the negative sign. Figures 1(a) and (b) demonstrate the relationship between a country's average *Number of disasters* from 1984 to 2008 and a country's average corruption (*ICRG corruption*) from 1984 to 2008. Figure 1(a) shows that *Number of disasters* 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 *Number of disasters* 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 *Number of disasters* and corruption continues to be observed. The findings demonstrated in Figures 1(a) and (b) are congruent to the hypothesis. In addition, I divided the sample into less corrupt countries whose *ICRG corruption* is larger than 3 (*ICRG corruption* $\geq$ 0) and more corrupt countries whose *ICRG corruption* is smaller than 3 (*ICRG corruption* $<$ 0). The incidence rate of less corrupt countries is 1.17, whereas that of more corrupt countries is 2.58. I defined the exposed group as the less corrupt countries. Accordingly, the incidence rate ratio is 0.45, which means that technological disasters are less likely to occur in less corrupt countries compared with more corrupt countries. Furthermore, I divided the sample into larger countries with populations over 100 million and smaller countries with populations under 100 million. The incidence rate ratio is 0.47 for larger countries and 0.58 for smaller countries. It follows then that technological disasters are less likely to occur in less corrupt countries, which is observed not only in the smaller countries sample but also in the larger countries sample. A closer examination of the influence of corruption on *Number of disasters* is explored using a regression analysis in section 4.

With regard to control variables, and following Kahn (2005) who examined the determinants of deaths from technological disasters, *GDP* and *Population* are included to capture basic economic conditions. *GDP* is considered to reflect the degree of economic development within a country. 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. 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.

As illustrated in Figure 1, China and India experience a far larger number of disasters and can be considered as outliers. The number of technological disasters appears to depend on country size because the frequency of using technology depends on the size of the demand for that technology. *Population* is included to capture the effect of country size. The predicted sign of

the coefficient of population is positive because the demand for technology is positively associated with population when all other things are considered equal. Further, country dummies and year dummies are included to address the outlier problem. For the purpose of controlling for the different effects caused by the economic structure, *Rate of industry* (value-added of industry/GDP) is used. Higher rates of industry lead to higher rates of technological disasters. Thus, *Rate of industry* is predicted to take the positive sign.

The presence of government is captured by *Government size.* Even after controlling for quality of government with *ICRG corruption* (or *World Bank corruption*), 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 profits. As a result, private firms make various investments 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 *Government size* increases the probability of disasters and so takes the positive sign. *Openness* is considered to reflect the importance of technology via trade. *Openness* appears to have the opposite effect as follows: importing technology increases the frequency of using technology, thus raising the probability of disasters. In contrast, imported technology is accompanied by disaster prevention measures, reducing the possibility of disasters. Therefore, the sign for *Openness* depends on whether the positive effect outweighs the negative.

3.3. Estimation based on 5-year-average data

Potential time series issues should be taken into account. There is a simultaneous relationship between corruption and disasters when yearly data with no lags are used to predict disasters. A simultaneous relationship is not consistent with the causality suggested earlier. Serial autocorrelation is often a problem in panel regressions of this type and would be expected to bias the estimated standard errors downwards (Bertand et al., 2004). To alleviate these problems, I also conducted estimations of alternative specifications in which 5-year-average data were used. ICRG corruption data cover 27 years, while the World Bank corruption data only cover 14 years. Hence, the period covered by the World Bank data is too short to be used for the 5-year-average estimation. Therefore, only ICRG corruption data are used. Five-year-average disasters are calculated in each period: 1984–1988, 1989–1993, 1994–1998, 1999–2003, and 2004–2008.

3.4. IV Poisson 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, *ICRG corruption* (or *World Bank corruption*) 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 *ICRG corruption* (or *World Bank corruption*) (Wooldridge 2002, 265–266). That is, the inclusion of country dummies attenuates the endogeneity bias. In addition, for the purpose of controlling for bias, I used the Instrumental Variables Poisson Model (IV Poisson model)[20]. The first-stage regression, in the form of Equation (2), is estimated with *ICRG corruption* as the dependent variable:

$$ICRG\ corruption_{it} = \beta_0 + \beta_1\ French\ legal\ origin\ dummy_{\ i} + \beta_2\ British\ legal\ origin\ dummy_{\ i} + \beta_3\ Share\ of\ Catholic_{\ i} + \beta_4\ GDP_{it} + \beta_5\ Population_{it} + \beta_6\ Government\ size_{it} + \beta_7\ Openness_{it} + \beta_8\ Rate\ of\ industry_{it} + m_t + s_{it}. \quad (2)$$

Kahn (2005) used historical settler mortality rates as an instrument for institutional quality when he explored the determinants of damage from natural and technological disasters. I use a similar strategy for my choice of instrumental variables. However, the size of the sample reduced dramatically when historical morality rates are used because the data are only available for 36 of the sample countries included in this paper. Hence, I used other historical data as instrumental variables so as to not reduce the sample size. 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; Becker et al., 2009).[21] In this paper, I use *French legal origin dummy* and *Share of Catholic* (percentage of the population that is Catholic in 1980) as instrumental variables.[22] *French legal origin dummy* and *Share of Catholic* were sourced from earlier research (La Porta et al. 1999).[23]

It has been observed in previous studies (Treisman 2000; Serra 2006) that the public sector is inclined to be corrupt in countries of French legal origin that are now regarded as civil law countries. According to La Porta et al. (1999, 231–232), civil law has been largely used as an instrument of the State to expand its power and has been used to discover a just solution to a dispute rather than to protect individuals against the State. These characteristics of civil law have led to the establishment of institutions that further the power of the State. Thus, I assume that in civil law countries, the ability of citizens to monitor and criticize collusion between

[20] An instrumental variables negative binominal model is more appropriate. However, a method such as this has not been developed. The IV Poisson model is considered to be the second-best model and so is used in this paper. For the estimation, I used the IV Poisson model procedure outlined in Stata. I thank a referee for his/her suggestion to use the IV Poisson model.

[21] Freille et al. (2007) suggested that political and economic influences on the media were strongly related to corruption.

[22] Previous works generally used the percentage of Protestants to examine corruption. In this paper, however, these data are not used because they did not create a good fit with the estimated model when used as an independent variable.

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

bureaucrats and the business world is somewhat reduced. The extreme power of the State possibly corrupts the bureaucracy. I assume then that *French legal origin dummy* is negatively related to *ICRG corruption*.

Nearly half a millennium ago, the Protestant reformation occurred in reaction to the moral decay of the Catholic Church (Paldam 2001). The Protestant church has traditionally been separate from the state and has openly opposed abuse of government (Pellegrini and Gerlagh 2008, 249). In contrast, the Catholic Church is considered to have a more hierarchical structure when compared with other churches (Pellegrini and Gerlagh 2008). Furthermore, the Catholic Church tends to show a greater tolerance toward abuses of power and corruption.[24] Thus, Paldam (2001) suggested that the public sector is more likely to be corrupt in the countries where Catholics are dominant. If this holds true, then *Share of Catholic* is negatively associated with *ICRG corruption*. 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 although year dummies are included in all estimations. In addition to Equation (2), an alternative specification is provided to check for robustness, expressed as:

$$\textit{ICRG corruption} \text{ (or } \textit{World Bank corruption)}_{it} = \eta_0 + \eta_1\, \textit{GDP}_{it} + \eta_2\, \textit{Population}_{it} + \eta_3\, \textit{Government size}_{it} + \eta_4\, \textit{Openness}_{it} + \eta_5\, \textit{Rate of industry}_{it} + \eta_1\, \textit{French legal origin dummy}_{i} * m_t + \gamma_2\, \textit{Share of Catholic}_{i} * m_t + u_i + s_{it}. \quad (3)$$

In Equation (3), η represents the scalar while γ is the vector. Legal origin dummy and Share of *Catholic* disappeared in the equation (because time-invariant features such as *French Legal origin dummy* and *Share of Catholic* are controlled by m_t) although those that interacted with the country dummies are included.

While *French Legal origin* and *Share of Catholic* are time-invariant, the dependent variables in the first and second stages vary with time. Choosing time-invariant variables as instruments cannot be justified if the time-variation in the predicted corruption stems from the potentially endogenous time-varying variables. However, more appropriate instruments with time-variant feature are not available. Empirical work has provided evidence to support the assertion that the higher the transitory income, the higher the corruption, indicating that corruption expands in good economic conditions and shrinks in bad conditions (Gokcekus and Suzuki 2011). That is to say, macroeconomic conditions influence the degree of corruption. Thus, I infer that the impact of the determinants of corruption will change according to macroeconomic conditions. Hence, time-invariant characteristics are considered to have different influences on corruption between different years. Socioeconomic circumstances appear to change over long-term periods rather than in the short term. Therefore, in the estimation based on 5-year-average data, I attempted to control for potentially endogenous time-varying variables by including time-invariant

[24] In contrast to Catholics, "Protestantism leads to a civil society that more effectively monitors the state" (Gocekus 2008, 59).

instrumental variables that interact with period dummies.[25] More precisely, there are five periods in the ICRG corruption data: 1984–1988, 1989–1993, 1994–1998, 1999–2003, and 2004–2008. Instrumental variables interact with period dummies such as 1989–1993 dummy, 1994–1998 dummy, 1999–2003 dummy, and 2004–2008 dummy. The base period is 1984–1988. The ICRG corruption index data cover 27 years, and therefore socioeconomic circumstances are considered to have changed during this period. Hence, the ICRG corruption data, from which the 5-year-average disasters are calculated, are suitable for the IV Poisson estimation. In contrast, the World Bank corruption data are not used in the IV Poisson estimation because the data span only 14 years.

As argued above, the choice of instrumental variables is based on evidence provided by previous studies. However, it is possible that the estimation results will vary according to the sets of variables used. In other words, probably thanks to some arbitrary combination of instrumental variables, the expected results are likely to be obtained. For a robustness check, it is necessary to conduct estimations using various combinations of instrumental variables. In this paper, three combinations were used in the estimations.

4. Results

4.1. Results of negative binominal model

The estimation results of the negative binominal model are set out in Table 3. Columns (1) and (2) show the results when the ICRG corruption index is used as a dependent variable, and columns (3) and (4) show the results when the World Bank corruption index is used. In columns (1) and (3), country dummies are included as independent variables. In columns (2) and (4), both country and year dummies are included.

I will now discuss the results shown in Table 3. Consistent with my prediction, the coefficients of *ICRG corruption* take the negative sign in columns (1) and (2) and are statistically significant at the 1% level. The absolute values of the coefficients are between 0.13 and 0.09 in columns (1) and (2), respectively. The coefficients of *World Bank corruption* also take the negative sign and are statistically significant at the 1% level in columns (3) and (4). The absolute values of the coefficients are 0.22. The effects of World Bank corruption index are approximately two times larger than those of ICRG corruption index. However, both results are in line with the prediction, implying that the effects of corruption are robust with an alternative index. With respect to control variables, *GDP* yields a significant negative sign in all columns. This result implies that economic development reduces the possibility of technological disasters after controlling for institutional factors captured by country dummies. As for the results of the

[25] One would think that institutional factors may matter and should be included as independent variables in Equation (1) rather than used as instruments in Equation (2). However, in Equation (1) the time-invariant features are captured by country dummies, and therefore instrumental variables such as the legal origin dummies and the proxy for religion are removed.

other control variables, *Population, Government size, Openness* and *Rate of industry,* in most cases they exhibit statistical significance in columns (1) and (2). In contrast, they are not statistically significant in columns (3) and (4). This may be explained by the sample size of columns (3) and (4), which at 1,035 is approximately half that of columns (1) and (2). The focus of the results is on the country and year dummies shown in column (2). The coefficients of *Government size* and *Openness* take the negative sign and are statistically significant. This implies that *Government size* and *Openness* reduce the incidence of technological disasters. In contrast, the sign of the coefficient of *Rate of industry* is positive and statistically significant at the 1% level. Thus, a rise in the rate of industry leads to an increase in technological disasters.

I now turn to the results for the 5-year-average disasters presented in Table 4. *ICRG corruption* continues to take the negative sign and be statistically significant in columns (1)-(4). A change in socioeconomic condition is thought to have a significant effect on the results. Accordingly, focus is given to those results in column (2), where both country and year dummies are included. The absolute value of *ICRG corruption* is 0.21, which is more than two times larger than column (2) in Table 3. *GDP* and *Government size* also continue to yield a significant negative sign in column (2). In addition, *Rate of industry* continues to take the positive sign and be statistically significant in column (2). Columns (3) and (4) show the results where the instruments from the IV Poisson model such as *French legal origin* and *Catholic* are used as independent variables. *French legal origin* and *Catholic* are controlled when country dummies are included and so country dummies are not included in columns (3) and (4). *French legal origin* and *Catholic* produced the negative sign; however they were not statistically significant. Hence, *French legal origin* and *Catholic* do not directly influence the dependent variable.

The results from Tables 3 and 4 show that both *Corruption* and *GDP* reduce the number of disasters, and that these results did not vary using the different data sets.

4.2. Results of IV Poisson model

The results of the IV Poisson estimation are exhibited in Table 5. In columns (1)–(3), where country dummies are included to control for unobservable country specific characteristics,[26] the instrumental variables are the interactions between the institutional variables and period dummies as follows: column (1), interaction term between *French* and period dummies, and interaction term between *Share of Catholic* and period dummies; column (2), interaction term between *French* and period dummies; and column (3), interaction term between *Share of Catholic* and period dummies.

In column (4), institutional variables are used as instrumental variables. Country dummies are not included, while period dummies are. In this specification, institutional effects are not captured by country dummies and so can be used as instrumental variables. The sets of

[26] Period dummies are not included because the estimation does not reach convergence if period dummies are included.

instrumental variables are as follows: column (4), *French Legal Origin dummy* and *Share of Catholic* are a set of institutional variables. An over-identification test provides a method of testing for the exogeneity of instrumental variables. Test statistics are not significant in columns (1)–(4) of Table 5 and thus do not reject the null hypothesis that the instrumental variables are uncorrelated with the error term. This suggests that the instrumental variables are valid.

Table 5 shows that *ICRG corruption* yields the predicted negative sign and is statistically significant in all estimations. This suggests that the results of corruption exhibited in Tables 3 and 4 are robust even after controlling for endogeneity bias. In addition, its absolute values in columns (1)–(3) are larger than those in columns (4). This may be explained in part by the fact that controlling country-specific effects increases the effects of corruption on the number of disasters. Furthermore, the absolute values in columns (1)–(3) are 7–10 times larger than the results of *ICRG corruption* presented in column (2) of Table 4. This shows that controlling for endogeneity bias increases the magnitude of the corruption effects.

With respect to the other control variables, the coefficient of *GDP* takes the negative sign in columns (1)–(3), while it takes the positive sign in columns (4). In all columns, *GDP* is statistically significant. I interpret the results for *GDP* as suggesting that *GDP* captures the level of technology required to prevent accidents when unobservable country-specific effects are controlled. This is consistent with the results for *GDP* shown in Tables 3 and 4. *Population* yields the positive sign in all columns and is statistically significant at the 1% level in columns (3) and (4). This implies that, as predicted, an increase in demand for technology leads to an increase in the frequency of using technology. As a consequence, the number of technological disasters increased. It is surprising to observe that *Government size* yields the negative sign and is statistically significant at the 1% level in columns (1)–(3), and it produces the positive sign in columns and is statistically significant in columns (4). Size of government reduces the probability of technological accidents when public sector corruption and country fixed effects are controlled for. In other words, *Government size* contributes to the reduction of technological accidents when the degree of public sector corruption and other time-invariant features are controlled for. From this, I derive the argument that a large government is positively associated with public sector corruption and that *Government size* increases the number of technological disasters through public sector corruption. The coefficients of *Openness* take the negative sign in all estimations and are statistically significant in column (4). Hence, the effect of *Openness* is not as obvious. As discussed earlier, there are both positive effects (e.g., imported technology accompanied by disaster prevention measures) and negative effects (e.g., imports increase the frequency of technology use). My interpretation of this situation is that the negative effect is considered to neutralize the positive effect. *Rate of industry* yields the positive sign and is statistically significant in columns (4). In contrast, it yields the negative sign in columns (1) - (3) even though it is not statistically significant. Controlling for country-specific features removes

the influence of *Rate of industry,* which is not consistent with the results of Table 3 and 4. Hence, the effect of *Rate of industry* is not conclusive.

The results shown in Tables 3–5 and discussed so far strongly support the hypothesis that corruption increases the probability of technological disasters. Thus, 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 technological 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 have done so. 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;).

As noted earlier, the measurement errors of EM-DAT could possibly cause estimation bias. It is

important to deal with this problem. Technological accidents can be classified into various types such as industrial accidents, transport accidents, and miscellaneous accidents. The occurrence of accidents depends on the characteristics of each accident type. Hence, it is worthwhile to compare the effect of corruption among accident type. What is more, 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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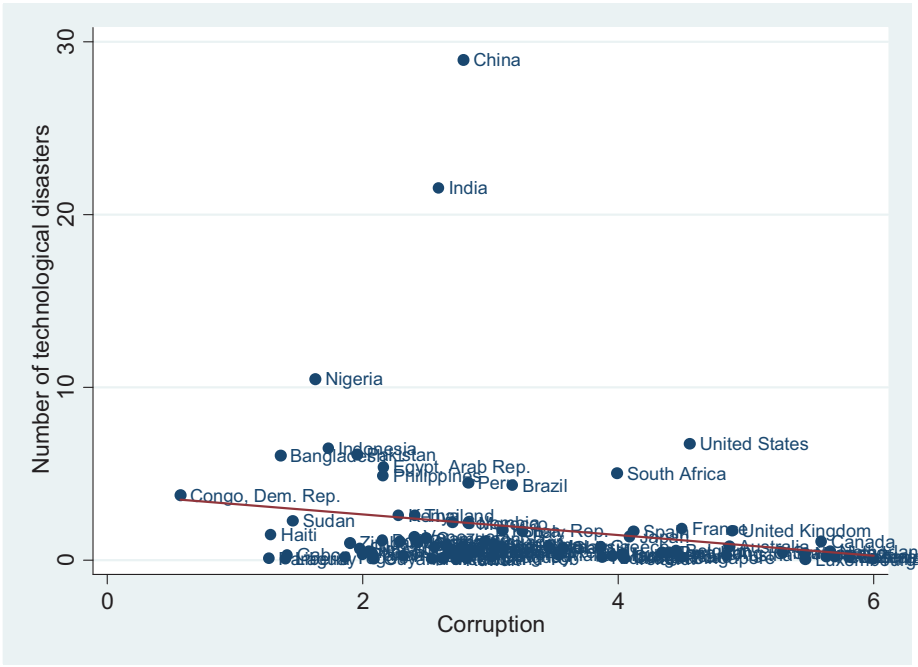
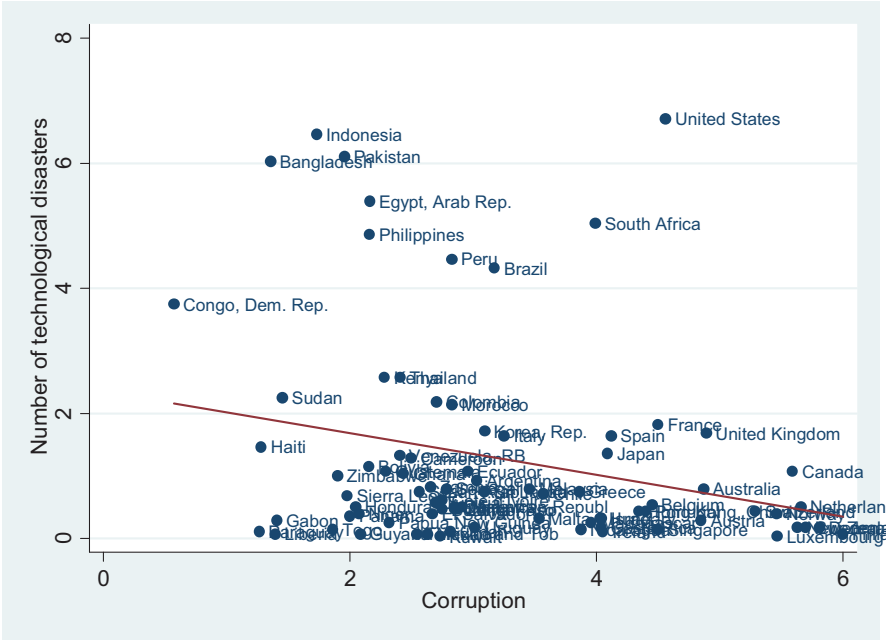


(a) Full sample



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

Figure 1. Association between corruption index (ICRG corruption index) and number of

technological disasters

Table 1. Variable definitions and basic statistics

Variable	Detailed definition	Mean	Standard deviation	Maximum	Minimum
Number of disasters	Number of technological disasters	1.70	4.76	71	0
	Independent variables				
ICRG corruption index	Corruption index of international country risk guide (ICRG).	3.19	1.46	6	0
World Bank corruption index	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
Population	Population (million)	44.3	151.1	1300	0.06
Government size	Government consumption expenditure/GDP	0.15	0.06	0.76	0.02
Openness	Trade/GDP	0.77	0.51	4.56	0.11
Rate of industry	Value-added of industry/GDP	0.30	0.10	0.78	0.01
	Instrumental variables				
French legal origin dummy	---	---	---	---	---
British legal origin dummy	---	---	---	---	---
Share of Catholic	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 disasters	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 ('annual disasters' is a dependent variable)

	(1)	(2)	(3)	(4)
ICRG corruption	-0.13***	-0.09***		
	(-4.28)	(-4.28)		
World Bank corruption			-0.22***	-0.21***
			(-3.42)	(-3.10)
GDP	-0.04***	-0.13***	-0.14***	-0.19***
	(-2.97)	(-8.18)	(-4.64)	(-5.32)
Population	0.003***	-0.001	0.003	-0.002
	(3.63)	(-1.35)	(0.24)	(-1.44)
Government size	-3.70***	-3.40***	-0.80	-1.51
	(-3.33)	(-3.16)	(-0.46)	(-0.84)
Openness	0.51**	-0.58**	0.33	0.10
	(2.58)	(-2.46)	(1.04)	(0.36)
Rate of industry	0.007	0.02***	0.008	0.01
	(0.60)	(2.91)	(0.72)	(1.34)
Constant	0.27	0.84*	0.40	0.41
	(0.60)	(1.94)	(0.76)	(0.72)
Country dummies[3]	Yes	Yes	Yes	Yes
Year dummies[3]	No	Yes	No	Yes
Wald test (p-value)	0.00***	0.00***	0.00***	0.00***
Observations	1873	1873	1035	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 dummies are not included and "Yes" means dummies are included.

Table 4. Negative binominal estimation ('5-year-average disasters' is a dependent variable)

	(1)	(2)	(3)	(4)
ICRG corruption	-0.11** (-1.97)	-0.21*** (-3.43)	-0.19*** (-3.62)	-0.11* (-1.90)
GDP	-0.02 (-1.28)	-0.13*** (-7.27)	0.01 (1.46)	-0.001 (-0.14)
Population	0.004** (2.59)	-0.0007 (-0.74)	0.002*** (12.9)	0.002*** (11.7)
Government size	-4.13** (-2.33)	-3.55** (-2.46)	-3.30** (-2.55)	-2.93** (-2.52)
Openness	0.59** (2.18)	-0.55 (-1.48)	-1.12*** (-6.77)	-1.54*** (-7.17)
Rate of industry	-0.002 (-0.25)	0.02** (2.46)	0.007 (1.40)	0.01** (2.44)
French legal origin			-0.02 (-0.20)	-0.15 (-1.17)
Catholic			-0.002 (-1.49)	-0.001 (-1.16)
Constant	0.57 (1.02)	1.14** (2.43)	1.64*** (6.64)	1.96*** (7.84)
Country dummies[3]	Yes	Yes	No	No
Year dummies[3]	No	Yes	No	Yes
Wald test (p-value)	0.00***	0.00***	0.00***	0.00***
Observations	449	449	449	449

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 dummies are not included and "Yes" means dummies are included.

Table 5. IV Poisson estimation ('5-year-average disasters' is a dependent variable: instruments interacted with time dummies)

	(1)	(2)	(3)	(4)[4]
ICRG corruption	-2.11***	-2.31***	-1.35***	-0.90***
	(-4.17)	(-3.94)	(-3.59)	(-3.10)
GDP	-0.19**	-0.21**	-0.13**	0.08***
	(-2.42)	(-2.49)	(-2.03)	(3.42)
Population	0.005	0.005	0.003***	0.002***
	(0.12)	(0.12)	(6.43)	(6.00)
Government size	-23.6***	-22.9***	-21.9***	3.77*
	(-3.53)	(-3.27)	(-3.93)	(1.65)
Openness	-0.43	-0.53	-0.24	-1.19***
	(-0.65)	(-0.72)	(-0.51)	(-6.70)
Rate of industry	-0.002	0.001	-0.007	0.03**
	(-0.10)	(0.05)	(-0.33)	(2.19)
Constant	21.6***	10.1***	7.02***	0.93
	(3.41)	(3.79)	(3.94)	(0.99)
Country dummies[3]	Yes	Yes	Yes	No
Period dummies[3]	No	No	No	Yes
Instrumental variable	(1) French legal origin dummy* period dummy (2) Share of Catholic* period dummy	(1) French legal origin dummy* period dummy	(1) Share of Catholic* period dummy	(1) French legal origin dummy (2) Share of Catholic
Over-identification test[5]	8.71	4.00	1.66	0.40
	$p = 0.46$	$p = 0.40$	$p = 0.88$	$p = 0.52$
Wald test (p-value)	0.00***	0.00***	0.00***	0.00***
Observations	449	449	449	449

1. Numbers in parentheses are z-statistics.

2. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.
3. “No” means dummies are not included and “Yes” means dummies are included.
4. In column (4), Africa and Asia region dummies are included to control for area-specific effects. However, the results for the year dummies and area dummies are not reported to save space.
5. A Sargan test is used to test the null hypothesis regarding over-identification. I used the command “override” after ivreg (2SLS) Stata 11 because I was unable to conduct an over-identification test for the IV Poisson method.

Appendix 1. List of countries used in the analysis

Number	Name	ICRG corruption	World Bank corruption
1	Argentina	#	#
2	Australia	#	#
3	Austria	#	#
4	Bangladesh	#	#
5	Belgium	#	#
6	Belize		#
7	Benin		#
8	Bolivia	#	#
9	Brazil	#	#
10	Burkina Faso	#	#
11	Burundi		#
12	Cameroon	#	#
13	Canada	#	#
14	Central Africa		#
15	Chad		#
16	Chile	#	#
17	China	#	#
18	Colombia	#	#
19	Congo, Dem.	#	#
20	Congo, Rep.	#	
21	Costa Rica	#	#
22	Cote d'Ivoire	#	#
23	Denmark	#	#
24	Dominican Rep	#	#
25	Ecuador	#	#
26	Egypt	#	
27	El Salvador	#	#
28	Fiji		#
29	Finland	#	#

Number	Name	ICRG corruption	World Bank corruption
51	Liberia	#	#
52	Libya	#	#
53	Luxembourg	#	#
54	Madagascar	#	#
55	Malawi	#	#
56	Malaysia	#	#
57	Malta	#	#
58	Mauritania		#
59	Mexico	#	#
60	Morocco	#	#
61	Nepal		#
62	Netherlands	#	#
63	New Zealand	#	#
64	Nicaragua	#	#
65	Niger	#	#
66	Nigeria	#	#
67	Norway	#	#
68	Oman	#	#
69	Pakistan	#	#
70	Panama	#	#
71	Papua New Guinea	#	#
72	Paraguay	#	#
73	Peru	#	#
74	Philippines	#	#
75	Portugal	#	#
76	Puerto Rico		#
77	Rwanda		#
78	Senegal	#	#
79	Seychelles		#

30	France	#	#	80	Sierra Leone	#	#
31	Gabon	#	#	81	Singapore	#	#
32	Georgia		#	82	South Africa	#	#
33	Ghana	#	#	83	Spain	#	#
34	Greece	#	#	84	Sri Lanka	#	#
35	Guatemala	#	#	85	Sudan	#	#
36	Guyana	#	#	86	Sweden	#	#
37	Haiti	#	#	87	Switzerland	#	#
38	Honduras	#	#	88	Syrian Arab Republic	#	
39	Hong Kong	#		89	Thailand	#	#
40	Hungary	#	#	90	Togo	#	#
41	India	#	#	91	Trinidad and Tobago	#	#
42	Indonesia	#	#	92	Tunisia	#	#
43	Ireland	#	#	93	United Kingdom	#	#
44	Israel	#	#	94	United States	#	#
45	Italy	#	#	95	Uruguay	#	#
46	Japan	#	#	96	Venezuela, RB	#	
47	Kenya	#	#	97	Zambia	#	#
48	S. Korea	#		98	Zimbabwe	#	#
49	Kuwait	#	#				
50	Lesotho		#				

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

Appendix 2. Types of technological disasters (number of accidents)

	(1) Industrial accidents	(2) Transport accidents	(3) Miscellaneous accidents	(4) Total number of Technological accidents
1965–1980	95	99	115	309
1981–1995	232	1048	285	1565
1996–2009	196	2100	810	3106
Total (1965–2009)	523	3247	1210	4980