Impact of natural disasters on income inequality: Analysis using panel data during the period 1965 to 2004

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Abstract

Although natural disasters have been found to influence economic growth, their impact on income inequality has not yet been explored. This paper uses cross-country panel data during the period 1965 to 2004 to examine how the occurrence of natural disasters has affected income inequality. The major findings of this study are that although natural disasters have increased income inequality in the short term, this effect disappears in the medium term. These findings are observed even after the fixed effects of year and country are controlled for.

JEL classification: D63, Q54

Keywords: natural disasters, income inequality

1. Introduction

Human society has always been confronted with the possibility of natural disasters, which are defined as an exogenous shock that influences socio-economic conditions. For example, the Tsunami in Indonesia in 2004 and the Sichuan earthquake in China in 2008 caused a considerable amount of damage on these developing countries. Moreover, the Great East Japan earthquake that occurred in Japan in 2012 and Hurricane Katrina that occurred in the United States in 2005 demonstrate that devastating natural disasters are able to hamper economic activities even in highly developed countries. However, regardless of the country's stage of economic development, all of these natural disasters resulted in economic and human losses regardless of the stage of economic development. Since the end of the 20th century, natural disasters have become a major issue in social science (e.g., Horwich, 2000; Congleton, 2006; Shughart, 2006; Toya and Skidmore, 2007, Cavallo et al., 2010; World Bank).

A number of economic researchers have recently conducted empirical analyses of the impact of natural disasters and they have been able to provide evidence to draw policy implications (e.g., Skidmore and Toya, 2002 and 2013; Sawada, 2007; Sawada and Shimizutani, 2007 and 2008; Escaleras and Register 2012). Although a large number of studies have been concerned with the impact of natural disasters on economic growth, their findings vary according to the data set and estimation methods used (e.g., Skidmore and Toya 2002; Crespo-Cuaresma et al., 2008; Kellenberg and Mobarak 2008; Strobl, 2011).[1] On the other hand, averting an increase in income

[1] Natural disasters are observed to have had a significant impact on poverty level and human development (Rodriguez-Oreggia et.al. 2013).

inequality is also regarded to be an important issue when recovery from natural disaster is analyzed. This is partly because income redistribution from non-damaged areas to damaged areas is a practical political and economic problem that is experienced in the aftermath of many natural disasters. A natural disaster can cause a heightening of social unrest if income redistribution is not appropriately conducted, which can result in social turmoil or disturbance.[2] Such negative externalities of natural disasters can lead to additional economic and human losses. In order to consider the likelihood that this externality occurs, I have found it crucial to accumulate the evidence concerning the impact of disasters on income inequality. Despite the increasing number of studies examining the impact of natural disasters, few studies have attempted to deal with the relationship between a natural disaster and income inequality. For example, the study by Anbarci et al. (2005), which is regarded as an exceptional work in this debate, found that GINI increases the damage level in natural disasters; however, an inverse causality has not been assessed in this study. To date, no study that has scrutinized whether a natural disaster has an influence on income inequality. Investigating the association between the occurrence of natural disasters and income inequality is, therefore, a timely project.

To satisfy this requirement, this paper has used panel data covering 86 countries during the period 1965 to 2004 to probe how (and the extent to which) the occurrence of natural disasters have impacted on Gini coefficients of income. The major findings of this study are that income inequality is increased by the occurrence of natural disasters in the previous year but is not increased by the occurrence of natural disasters two or three years prior. This implies that the impact of natural disasters on income

[2] Inequality possibly increases the number of traffic fatalities (Anbarci et al., 2009).

inequality is observed in the short term, but does not persist into the medium term. The remainder of this paper is organized as follows. The testable hypotheses are proposed in Section 2. Meanwhile, Section 3 explains the data set and the empirical method used. Section 4 provides the estimation results and its interpretation. The final section offers some conclusions and raises the remaining issues to be addressed by future studies.

2. Hypothesis

Riverside areas are more inclined to suffer from flooding in comparison with areas of high ground. Similarly, seaside areas are more apt to suffer from tsunami in comparison with inland areas. In addition, typhoons take a similar path almost every year. Hence, disasters caused by typhoons, flooding, or tsunami can to a certain extent be predicted. Consequently, richer people will tend to reside in those areas that are less prone to these types of disasters. On the other hand, many poor people cannot choose to live in an area that is safe from these types of disasters. Consequently, they tend to be directly exposed to such disasters. In addition, prior to the occurrence of a disaster, poor people tend to be less able to invest in disaster-prevention measures because they are living under a daily severe budgetary constraint. Hence, natural disasters tend to cause an increase in poverty (Rodriguez-Oreggia et.al. 2013). Consequently, the damage caused by these types of disasters is greater for poor people than rich people, even if the disaster can (to a certain extent) be predicted.

There are, however, different types of disasters that are considerably less predictable. For example, before the earthquake that struck central Italy in 2009, Italian seismologists were predicting that there was a very low probability that a devastating earthquake could occur in the area. Despite their predictions, in April 2009 a massive earthquake took place in the city of Aquila, which is located in central Italy. This earthquake resulted in a large death toll and left large numbers of people homeless. It follows from this that accurate forecasts about the probability of earthquakes are likely to be inaccurate. However, people with a high income are more likely to be able to prepare for an unpredictable natural disaster by taking actions such as residing in an earthquake-proof building, even if it is difficult to predict in what area an earthquake will strike. Meanwhile, poor people are more likely to live in antiquated buildings that are prone to be damaged by an earthquake. Hence, when an earthquake strikes, the rich are less likely to be injured than the poor.[3] Considering the various types of disasters that can occur, natural disasters tend to have a larger impact on poor people than on rich people. Importantly, this effect does not depend on whether the disasters are predictable or not. Consequently, when a natural disaster strikes, poor people are more likely to be injured and left unable to work, leading to a reduction in their income. On the other hand, rich people are less likely to be injured and are more able to continue to work after a disaster, which means that their income level is not affected by natural disasters. Consequently, income inequality between rich and poor people is thought to widen in the wake of disasters.

Capital stock (such as plant and equipment) is also prone to damage when natural disasters occur. In particular, a natural disaster often reveals the fragility of building and production facilities of small- to medium-sized companies. Furthermore, people working in informal sectors are less likely to be insured, which tends to prevent

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[3] In the case of the Hanshin Awaji earthquake, there was a considerable difference in the damage incurred by antiquated wooden buildings and the damage to modern earthquake-proof buildings (Ministry of Land, Infrastructure, Transport and Tourism, 1996, 12).

them from coming back to work. One consequence of an unforeseen destructive shock is that people working in the informal sectors or in small businesses are thought to experience a marked decline in their income. In contrast, buildings in the formal sector or in established large companies tend to be less fragile. Furthermore, workers in the formal sector or in established large-sized companies are more likely to be insured. Therefore, they tend to experience less economic damage in comparison with those who work in the informal sector or in small- to medium-sized companies. The effect of natural disaster on income is, therefore, considered to diverge according to sector and type of company. Hence, a natural disaster can lead to an increase in income inequality through these factors.

From the macro-economic point of view, a natural disaster can hit a certain area and cause incomes to reduce, while it has no effect on the income levels in other areas. Inevitably, the impact of natural disasters on economic activities differs between the stricken area and other areas, thereby widening the difference of income between the two. All in all, a natural disaster is able to cause income inequality to increase at various levels: between areas, and between individuals of socio-economic statuses. Consequently, this study proposes the following hypothesis:

The occurrence of natural disasters increases the income inequality within a country.

3. Data and Methods

3.1. Data

Table 1 exhibits the definition and the source of each variable used in this paper. The dependent variable is the change of Gini coefficients from *t* year to *t+1* year, which is calculated as the difference of the Gini coefficient between these years (i.e. Gini in *t* year to Gini in *t+1* year). In this study, the Gini coefficients of income are collected from the Standardized Income Distribution Database (SIDD) that was developed by Salvatore (2008).[4] The key independent variable is the number of natural disasters, which has been gathered from the EM-DAT (Emergency Events Database).[5] These data comprise various types of disasters.[6] GDP (i.e. GDP per capita) was collected from the World Bank (2010). The available data for these variables include 86 countries (as exhibited in the Appendix) and cover the period 1965 to 2004. Hence, this paper used the Panel data covering this period.

It is evident that institutional, geographical and socio-economic conditions are closely related to outcomes of natural disasters (Kahn 2005; Toya and Skidmore 2007). Accordingly, the impact of natural disaster on income inequality depends in part on institutional conditions. Consequently, this paper controls for these conditions. In addition, legal origin and socio-economic heterogeneity are taken into account. Meanwhile, ethnic and religious heterogeneities are captured by the ethnic and

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[4] Data were obtained from http://salvatorebabones.com/data-downloads [accessed on 1 June 2011]. This paper has used SIDD-3 (which is an interpolated and extrapolated version of SIDD-2) incorporating in-sample and out-of-sample estimates for 1955 to 2005.
[5] Data were obtained from http://www.emdat.be [accessed on 1 June 2011].
[6] Types can be divided into drought, earthquake, extreme temperature, flood, mass movement dry, mass movement wet, storm volcano and wildfire.

religious polarization indexes, which have been extensively used to capture ethnic heterogeneity as developed by Montalvo and Reynal-Querol (2005a, 2005b)[7]. *French legal origin* is the dummy variable for the French legal origin, as defined by La Porta et al. (1999). If all other things are equal, it is predicted that areas of larger land size will experience more natural disasters. *Land* (i.e. land area) is used for controlling probability. Furthermore, area dummies (such as *Asia*, *Africa*, *South America* and *Absolute latitude*) are used to control for geographical locations that are closely related to the occurrence of natural disasters (Kahn, 2005).

Figure 1 demonstrates the relationship between the change of Gini coefficients and the number of natural disaster in the base year *t* after controlling for the Gini coefficients in the base year. A cursory examination of Figure 1 reveals that there is a positive association between the two. If a change of Gini coefficients is over 0, then income inequality widens from year *t* to year *t+1*. In particular, when the number of disasters is over 10, the change of Gini coefficients is likely to be over 0. This implies that income inequality tends to increase when natural disasters occur.

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[7] The ethnic (religious) polarization index can be defined as:

$$\text{Polarization} = 1 - \sum_{i=1}^{n} \left(\frac{0.5 - \pi_i}{0.5} \right)^2 \pi_i$$

where π_i is the proportion of the population who profess to belong to a given ethnic group i. This index measures the normalized distance of a particular distribution of ethnic groups within a bimodal distribution. Here, ethnic group is represented as i for country j. The index can be calculated for each country.

3.2. Econometric Model

To more closely test the hypothesis, a regression estimation should be conducted. The estimated model that was used in this study is:

$$Gini_{it+1} - Gini_{it} = \alpha_1 Gini_{it} + \alpha_2 Disasters_{it+1} + \alpha_3 Disasters_{i,t} + \alpha_4 Disasters_{i,t-1} + \alpha_5 Disasters_{i,t-2} + \alpha_6 Ln(GDP\ per\ capita)_{it} + \alpha_7 Land_{it} + u_i + k_t + \varepsilon_{it},$$

where $Gini_{it}$ represents Gini coefficients in country *i*, for year *t*. Hence, the dependent variable ($Gini_{it+1}$-$Gini_{it}$) suggests a change of Gini coefficients between year *t* and year *t+1* for country *i*. The initial level of income inequality is controlled by incorporating $Gini_{it}$. There seems to be different impact of natural disaster according to the date of occurrence within a year. For instance, the influence of a natural disaster that occurs at the beginning of a year might differ from the influence of a natural disaster that occurs at the end of the year (assuming that other things are equal). If the disaster occurred in the end of year *t+1*, disaster has hardly affect Gini coefficients in *t+1*. However, the data used in this paper can only provide the year when natural disasters occurred; they do not record the date and month when the disasters occurred. Here, I assume that natural disaster in *t+1* affects $Gini_{t+1}$, and the Gini coefficients change from *t* to *t+1* ($Gini_{t+1} - Gini_t$). On this assumption, $Disasters_{it+1}$ is also incorporated in addition to natural disasters in the base year (i.e., $Disasters_{it}$). The result of $Disasters_{it+1}$ possibly reflects only the correlation between disasters and income inequality, rather than the causality between the two. On the other hand, the result of $Disasters_{it}$ is thought to reflect the causality between disasters and income inequality. That is, $Disasters_{it}$ captures the impact of disasters in a certain year on income inequality in the next year. Hence, careful attention should be called for when the date of occurrence of disaster is considered. Furthermore, the short-term influence of natural disasters on economic growth is found to be negative (Raddatz 2007; Noy 2009). In contrast, the long-term influence of natural disasters on economic growth is found to be positive (Toya and Skidmore 2002). This suggests that whether the short-term impact of a natural disaster differs from medium-term or long-term impacts of a natural disaster is an empirical question. In order to assess this point, this paper has focused on the change of Gini coefficients in the period immediately following natural disasters and also in the period several years after natural disasters. To this end, the medium-term impact of natural disasters is captured by incorporating the number of natural disasters in the year *t-1* and also in *t-2*. In addition, in order to capture the level of economic development, the Log form of *GDP per capita* in the initial year *t* is incorporated. Furthermore, it is predicted that areas of larger land size will experience more natural disasters when other things are equal. Therefore, $Land_{it}$ is incorporated because the number of natural disasters is correlated with the error term when land size is not controlled. Various historical and institutional characteristics are found to influence the outcome of natural disasters (Kahn 2005). Consequently, u_i denotes the time invariant of the country's fixed effects, which captures various historical and institutional characteristics. In the simple OLS estimations, in order to control for u_i (as independent variables) this paper includes various variables capturing legal origin, socio-cultural polarization, and geographical location. In addition to OLS estimations as alternative specifications, this paper has also conducted the fixed effects estimation to control for u_i. Meanwhile, k_t denotes the unobservable year's fixed effects, which captures the macro-economic shock in year *t*. Year dummies are included in order to control for this. Furthermore, ε_{it} denotes the error term.

4. Estimation Results

The results of the OLS estimations are set out in Table 2, while the results of the fixed effects estimations are given in Table3. In each table, *Disasters (t+1)* and *Gini_t* are not incorporated in columns (1) and (5). On the other hand, columns (4) and (8) indicate the results of full model, which includes the initial level of *Gini_t* and the number of natural disasters in various points of time, such as *Disasters (t+1)*, *Disasters* *(t)*, *Disasters (t-1)*, and *Disasters (t-2)*. Furthermore, year dummies are not controlled for in columns (1) to (4) while they are controlled for in columns (5) to (8).

With respect to Table 2, various time invariant characteristics have already been captured as fixed effects, and therefore their estimations are not reported. In Table 2, coefficients of *Disasters (t+1)* and *Disasters (t)* have a positive sign and are statistically significant in all columns, which is in line with the hypothesis that was proposed earlier. On the other hand, the coefficients of *Disasters (t-1)* and *Disasters (t-2)* are not statistically significant in any columns, even though they have a positive sign. This means that the occurrence of natural disaster increases income inequality in the next year. However, the effect of natural disasters disappears if two or more years have passed. *Gini_t* has a positive sign and is statistically significant in all columns, implying that higher levels of income inequality in the initial year are more likely to increase income inequality in the next year. The other control variables that are used to capture the time invariant characteristics of the country are not found to be statistically significant in any of the columns.

The results exhibited in Table 3 show that the coefficients of *Disasters (t+1)* and *Disasters (t)* has continued to have a positive sign in all columns. It is interesting to observe that results of *Disasters (t)* are statistically significant in all columns while those of *Disasters (t+1)* are not statistically significant in any columns. This indicates, to a certain extent, the causal relationship between natural disasters and income inequality rather than the correlation between the two. Although the coefficients of *Disasters (t-1)* and *Disasters (t-2)* have a positive sign, they are not found to be statistically significant in any of the columns. Furthermore, the absolute value of *Disasters (t)* is about 0.01 (as shown in columns (2), (3), (4), (6), (7), and (8)), which means that the occurrence of a natural disaster results in 0.01 point increase of Gini coefficient in the next year. All in all, income inequality is widened by natural disasters only in the previous year and it is not affected afterwards. It follows from what has been reported in this paper that natural disasters have a detrimental effect on income inequality; however, this effect disappears within a few years. This leads to the conclusion that the *Hypothesis* proposed in the Section 2 is strongly supported in the short term but is not supported in the medium term. Although it is beyond the scope of this paper to scrutinize the reason why the impact of a natural disaster does not persist, one possible interpretation is that income redistribution policy is likely to be taken by the government under the emergent situation and owing to pressure from the stricken areas, which contributes to reducing income inequality.

5. Conclusions

Ascertaining the determinants of economic growth and income inequality is an important issue for researchers of economic policy. Since the turn of the 21st century, the outcomes of natural disasters have received considerable attention in the field of economics. Although an increasing number of researchers have studied the impact of natural disaster on economic growth, there seems to be little agreement among researchers. In addition, despite the increased attention that has been given to the relationship between natural disasters and economic conditions, little attention has been given to the impact of natural disasters on income inequality. This paper hopes to address this gap in our understanding of the impact of disasters on income inequality. Consequently, this paper used the panel data covering eighty-six countries during the period 1965 to 2004 to investigate how the large number of natural disasters that have occurred in this period have influenced changes of income inequality.

The major findings of this study are that natural disasters widen income inequality in the short term; however, this effect disappears in the medium term. These results continued to be observed even after allowing for the unobservable country's specific time invariant characteristics and year-specific effects. In my interpretation, the unforeseen and emergent situations that have followed natural disasters have prompted these governments to redistribute wealth from non-damaged areas to damaged areas, which reduces income inequality. Hence, the recovery from natural disasters is thought to be accompanied with the reduction of income inequality. According to existing studies, the long-term impact of natural disasters on economic growth is different from the short-term impact. This paper has found a similar tendency with respect to income inequality. There are a number of ways to reduce income inequality; for instance, the government can increase public spending on rebuilding the disaster stricken areas. In addition, the damage caused by natural disasters changes the industrial structure in the stricken areas, which results in economic growth.

However, the mechanism of the disappearance of the impact of natural disasters is not analyzed in this paper. For example, an inappropriate government policy for disaster relief can cause an unintended moral hazard problem (Shuie, 2004). In addition, it is necessary to probe how income inequality, which increases immediately after disasters, decreases within several years. Furthermore, the impact of disasters varies according to its characteristics. For instance, in some areas typhoons occur several times a year and they almost always follow the same course, a tsunami is likely to have the greatest impact on coastal areas, and flooding tends to damage riverside areas the most. In contrast, a landslide is predicted to occur in a mountainous area. Hence, people who reside in these disaster-prone areas are more likely to have prepared for a disaster beforehand. Furthermore, this tendency is likely to have influenced the location choice of many companies. If this is true, there is a possibility that the impact of a natural disaster on income equality will be attenuated. On the other hand, it is difficult to predict the area and date when an earthquake occurs. Hence, an earthquake tends to have a larger impact on income inequality when compared with more predictable natural disasters such as typhoons, flooding, or landslides. However, this paper does not scrutinize these differences in the impact of different natural disasters on income inequality because they are beyond scope of this paper and should be addressed in future studies.

References

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

Anbarci, N., Escaleras, M., Register, C. (2009). 'Traffic Fatalities: Does Income Inequality Create an Externality?' *Canadian Journal of Economics* 42(1), 244–266.

Cabinet Office, Government Of Japan., (2007). *A Disaster Prevention White Paper. (In Japanese) Cabinet Office,* Government of Japan. http://www.bousai.go.jp/hakusho/h19/index.htm.

Cassar, A., Healy, A., von Kessler, C. (2011). 'Trust, risk, and time preferences after natural disaster: Experimental evidence from Thailand,' Working Paper, University of San Francisco/

Carroll, N., Frijters, P., Shields, M.A. (2009). 'Quantifying the cost of drought: new evidence from life satisfaction data,' *Journal of Population Economics* 22, 445-461.

Cavallo, E., Powell, A., Becerra,O. (2010). 'Estimating the direct economic damages of the earthquake in Haiti', *Economic Journal* 120(546), F298-F312.

Chamlee-Wright, E. (2010). *The Cultural and Political Economy of Recovery: Social Learning in a Post-Disaster Environment.* Routledge: New York.

Crespo-Cuaresma, J., Hlouskova, J., Obersteiner, M. (2008). 'Natural Disasters as Creative Destruction? Evidence from Developing Countries,' *Economic Inquiry.* 46(2), 214–226.

Escaleras, M., Register, C. (2012). 'Fiscal decentralization and natural disaster risks,' *Public Choice* 151, 165-183.

Horwich, G.. (2000). 'Economic lessons from Kobe Earthquake,' *Economic Development and Cultural Change* 48, 521-542.

Ishino, T., Ogaki, M., Kameyasu, A., Murai, S. (2011). 'Effect of the great East Japan disaster on Happiness,' keio/Kyoto Global COE Discussion Paper Series, DP2011-38.

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

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

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

Luechinger, S., Raschky, P. A. (2009). 'Valuing flood disasters using the life satisfaction approach,' *Journal of Public Economics* 93(3-4), 620-633.

Ministry of Land, Infrastructure, Transport and Tourism. (1996). *White Paper on Disaster*

Management 1996. Ministry of Land, Infrastructure, Transport and Tourism: Tokyo.

Montalvo, J.G., Reynal-Querol, M. (2005 a). 'Ethnic polarization, potential conflict and civil war, ' *American Economic Review* 95(3), 796-816.

Montalvo, J.G., Reynal-Querol, M. (2005 b). 'Ethnic diversity and economic development,' *Journal of Development Economics* 76. 293-323.

Noy, I. (2009). 'The macroeconomic consequences of disasters,' *Journal of Development Economics* 88, 221-231.

Raddatz, C. (2007). 'Are external shocks responsible for the instability of output in low-income countries?' *Journal of Development Economics* 84, 155-187.

Rodriguez-Oreggia, E., De La Fuente, A., De La Torre, R., Moreno, H.A. (2013). 'Natural Disasters, Human Development and Poverty at the Municipal Level in Mexico, 'Journal of Development Studies 49 (3), 442-445.

Salvatore, B. (2008). 'Standardized income inequality data for use in cross-national research,' *Sociological Inquiry* 77, 3–22.

Sawada, Y., (2007). 'The impact of natural and manmade disasters on household welfare', *Agricultural Economics* 37, 59–73.

Sawada, Y., Shimizutani, S., (2007). 'Consumption insurance against natural disasters: evidence from the Great Hanshin-Awaji (Kobe) earthquake', *Applied Economics Letters* 14(4–6), 303–306.

Sawada, Y., and Shimizutani, S. (2008). 'How do people cope with natural disasters? Evidence from the great Hanshin-Awaji (Kobe) earthquake in 1995', *Journal of Money, Credit and Banking* 40(2–3), 463–488.

Shuie, C.H. (2004). 'Local granaries and central government disaster relief: Moral hazard and intergovernmental; finance in eighteenth- and nineteenth century China' *Journal of Economic History*, 64(1), 100-124.

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

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

Tierney, K and Goltz, J D. (1997), 'Emergency response: lessons learned from the Kobe earthquake', University of Delaware, Disaster Research Center, Preliminary Paper #260.

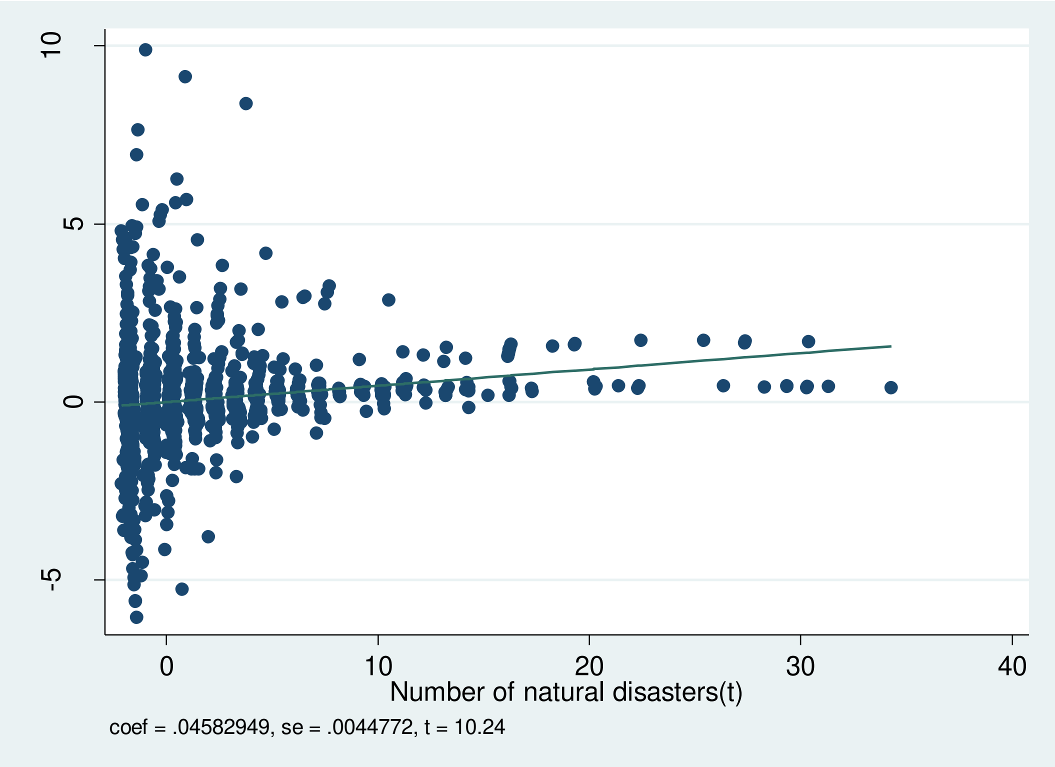
Toya, H., Skidmore, M. (2007). 'Economic development and the impacts of natural disasters', *Economics Letters* 94(1), 20-25.

Toya, H., and Skidmore, M. (2013). 'Natural Disaster Impacts and Fiscal Decentralization', *Land Economics* , 89, 101-117.

Whitt, S., and Wilson, R.K. (2007). 'Public Goods in The Field: Katrina Evacuees in Houston,' *Southern Economic Journal* 74(2), 377-387.

World Bank. (2010). *Natural Hazards, Un-natural Disasters: The Economics of Effective Prevention*. World Bank: Washington.

Figure 1. Association between the change of Gini coefficients and the number of natural disasters.



Note: The relations in Figure 1 are obtained after controlling for the initial level of Gini(t) and are illustrated using the avplot command in STATA 11.

Table 1 Basic statistics for the variables used in the estimation

	Source	Mean	Standard deviation
Gini_t	Gini coefficients of income in *t* year.	0.45	0.09
Change Gini_t+1	*Gini_t+1- Gini_t*	0.003	0.088
Disasters(t)	Number of disasters occurred in t year.	1.69	3.32
GDP per capita	GDP per capita (US$)	6,188	8,379
Land	Land size (million Km^2)	0.96	2.03
Ethnic polarization	Ethnic polarization index	0.50	0.23
Religious polarization	Religious polarization index	0.45	0.35
French legal origin	This is 1 if the country belongs to French legal origin; otherwise 0.	0.49	--
Asia	This is 1 if the country belongs to Asia; otherwise 0.	0.15	--
Africa	This is 1 if the country belongs to Africa; otherwise 0.	0.25	--
South America	This is 1 if the country belongs to South America; otherwise 0.	0.23	--
Absolute latitude	Absolute latitude where the country is located.	24.6	17.0

Table 2 OLS estimates (1965–2004): Dependent variable is Gini(t+1) to Gini(t)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gini_t		0.02**	0.02***	0.03***		0.02**	0.03***	0.03***
		(2.55)	(2.85)	(3.10)		(2.54)	(2.84)	(3.09)
Disasters(t+1)		0.01**	0.01**	0.01**		0.01*	0.01*	0.01*
		(2.22)	(2.22)	(2.21)		(1.83)	(1.87)	(1.91)
Disasters(t)	0.04***	0.02***	0.01***	0.01***	0.03**	0.01**	0.01**	0.01**
	(2.79)	(2.76)	(2.63)	(2.75)	(2.29)	(2.10)	(2.17)	(2.33)
Disasters(t-1)			0.008	0.006			0.006	0.004
			(1.58)	(1.53)			(1.04)	(1.13)
Disasters(t-2)				0.002				0.001
				(0.36)				(0.24)
Ln (GDP per capita)	0.018	0.004	0.002	0.0009	0.010	-0.003	-0.004	-0.004
	(0.38)	(0.10)	(0.06)	(0.02)	(0.22)	(-0.10)	(-0.10)	(-0.10)
Land	0.15	0.13	0.14	0.15	0.19	0.17	0.17	0.18
	(0.87)	(0.70)	(0.70)	(0.74)	(1.23)	(0.92)	(0.89)	(0.89)
Ethnic polarization	0.02	0.09	0.07	0.06	0.01	0.08	0.07	0.05
	(0.08)	(0.34)	(0.28)	(0.22)	(0.06)	(0.32)	(0.27)	(0.21)
Religious polarization	0.009	0.006	0.005	0.005	0.007	0.005	0.004	0.004
	(0.08)	(0.05)	(0.05)	(0.04)	(0.07)	(0.04)	(0.04)	(0.04)
French legal origin	0.06	0.08	0.09	0.09	0.06	0.09	0.09	0.09
	(0.46)	(0.67)	(0.69)	(0.70)	(0.47)	(0.69)	(0.71)	(0.72)
Asia	0.01	0.14	0.15	0.16	0.02	0.14	0.16	0.17
	(0.09)	(0.81)	(0.90)	(0.98)	(0.11)	(0.82)	(0.90)	(0.97)
Africa	0.05	-0.02	-0.03	-0.06	0.03	-0.04	-0.04	-0.05
	(0.58)	(-0.26)	(-0.31)	(-0.35)	(0.41)	(-0.43)	(-0.44)	(-0.44)
South America	0.07	-0.04	-0.05	-0.06	0.06	-0.04	-0.06	-0.07
	(0.47)	(-0.47)	(-0.36)	(-0.45)	(0.43)	(-0.31)	(-0.39)	(-0.47)
Absolute latitude	-0.001	0.004	0.005	0.006	-0.001	0.005	0.005	0.006
	(-0.28)	(0.82)	(0.97)	(1.08)	(-0.24)	(0.88)	(1.01)	(1.12)
Constant	-0.26	-1.55**	-1.67**	-1.78**	-0.37	-1.70**	-1.82**	-1.91**
	(-0.63)	(-2.08)	(-2.24)	(-2.36)	(-0.98)	(-2.30)	(-2.44)	(-2.55)
Year dummies	No	No	No	No	Yes	Yes	Yes	Yes
Observations	3208	3208	3128	3048	3208	3208	3128	3048

Note: "Yes" means that year dummies are included even though their results are not reported. Numbers in parentheses are *t*-statistics that are calculated based on the robust standard error clustered within a country. *is 10% significance, ** is 5% significance, and *** is 1% significance.

Table 3 Fixed effects estimates (1965–2004): Dependent variable is Gini(t+1) to Gini(t)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gini_t		0.03*	0.04**	0.06***		0.04	0.05**	0.06***
		(2.67)	(2.19)	(2.75)		(1.65)	(2.14)	(2.67)
Disasters(t+1)		0.01	0.008	0.005		0.01	0.006	0.004
		(1.41)	(1.22)	(1.01)		(1.27)	(1.02)	(0.75)
Disasters(t)	0.04***	0.01**	0.01**	0.01**	0.04**	0.01*	0.01*	0.01*
	(2.64)	(2.11)	(2.10)	(2.12)	(2.59)	(1.91)	(1.78)	(1.70)
Disasters(t-1)			0.005	0.002			0.006	0.002
			(1.22)	(0.73)			(1.14)	(0.72)
Disasters(t-2)				0.003				0.003
				(0.76)				(0.89)
Ln(GDP per capita)	0.12	0.10	0.07	0.05	0.03	0.03	0.01	-0.005
	(0.76)	(0.79)	(0.59)	(0.38)	(0.06)	(0.23)	(0.10)	(-0.04)
Land	-0.0002*	-0.0002*	-0.0002*	-0.0001*	-0.0002	-0.0001	-0.0001	-0.0001
	(-1.73)	(-1.89)	(-1.93)	(-1.93)	(-1.59)	(-1.61)	(-1.61)	(-1.58)
Year dummies	No	No	No	NO	Yes	Yes	Yes	Yes
Groups	86	86	86	86	86	86	86	86
Observations	3208	3208	3128	3048	3208	3208	3128	3048

Note: "Yes" means that the year dummies are included even though their results are not reported. Numbers in parentheses are *z*-statistics calculated based on the robust standard error clustered within a country. * is 10% significance, ** is 5% significance, and *** is 1% significance.

Appendix: List of countries used in the analysis

Number	Country name	Number	Country name
1	Argentina	44	Lesotho
2	Australia	45	Liberia
3	Austria	46	Luxembourg
4	Bahamas	47	Madagascar
5	Bangladesh	48	Malawi
6	Belgium	49	Malaysia
7	Bolivia	50	Mauritania
8	Brazil	51	Mexico
9	Burkina Faso	52	Nepal
10	Burundi	53	Netherlands
11	Cameroon	54	New Zealand
12	Canada	55	Nicaragua
13	Central African Republic	56	Niger
14	Chile	57	Nigeria
15	China	58	Norway
16	Colombia	59	Pakistan
17	Costa Rica	60	Panama
18	Cote d'Ivoire	61	Papua New Guinea
19	Denmark	62	Paraguay
20	Dominican Republic	63	Peru
21	Ecuador	64	Philippines
22	Egypt, Arab Rep.	65	Portugal
23	El Salvador	66	Puerto Rico
24	Fiji	67	Rwanda
25	Finland	68	Senegal
26	France	69	Seychelles
27	Gabon	70	Sierra Leone
28	Georgia	71	Singapore
29	Ghana	72	South Africa
30	Greece	73	Spain
31	Guatemala	74	Sri Lanka
32	Guyana	75	Sudan
33	Honduras	76	Sweden
34	Hong Kong, China	77	Switzerland
35	Hungary	78	Thailand
36	India	79	Trinidad and Tobago
37	Indonesia	80	Tunisia
38	Ireland	81	United Kingdom
39	Israel	82	United States
40	Italy	83	Uruguay
41	Japan	84	Venezuela, RB
42	Kenya	85	Zambia
43	Korea, Rep.	86	Zimbabwe