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The Effects of Natural Disasters on Long-Run Economic Growth

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I. Introduction

On January 12, 2010, a catastrophic earthquake struck Haiti, greatly damaging the undeveloped country. One estimate reports that this disaster killed more than 230,000 people and rendered 1.2 million homeless.[1] There is no doubt that a natural disaster such as the one that occurred in Haiti has a negative impact on the economy in the short run. However, there are mixed and inconclusive understandings regarding the effects of natural disasters on the long-run economy. One of the first influential studies regarding the relationship between natural disasters and long-run economic growth was conducted by Skidmore and Toya in 2002. In their cross country study of 89 countries, Skidmore and Toya found a surprising result: countries that were subjected to disasters showed faster economic growth. At first glance, this finding hardly seems conceivable. Given the damage inflicted on affected areas, how can natural disasters ever be positive economic events? To further explore the relationship between disasters and economic growth, this paper tests Skidmore and Toya's finding for the period 1990-2004.This study also identifies the channels whereby disaster risks affect economic growth.

II. Definitions

People have dealt with disasters throughout history and in every part of the globe. A disaster can be defined as a situation or event, which overwhelms local capacity, necessitating a request to national or international level for external assistance.[2] Disasters that are caused by nature are called natural disasters, examples of which include avalanches, earthquakes, floods, forest fires, hurricanes, lightning, tornados, tsunamis, and volcanic eruptions. Of course, not all disasters are caused by nature; some disasters have human origins. Such disasters include wars,

[1] See BBC report: http://news.bbc.co.uk/2/hi/8522732.stm.
[2] This is the official definition of a disaster by EM-DAT: http://www.emdat.be/glossary/9.

terrorist attacks, nuclear incidents, epidemic diseases, industrial accidents, and transportation accidents.[3]

III. Literature Review [4]

The economics of natural disasters is a nascent field. Cavallo and Noy state that "compared to the vast amount of research done in natural sciences and other social sciences, economic research on natural disasters and their consequences is fairly limited".[5] The book *The Economics of Natural Disasters: Implications for Federal Policy* by Dacy and Kunreuther (1969) is often regarded as the field's pioneering work, but there have been few subsequent studies. However, recent major catastrophes including the Southeast Asian tsunami and Hurricane Katrina heightened interest in this field.

The body of research in the literature of economics of natural disasters can be categorized into two groups. One group considers the short-run effects of disasters on GDP[6] while the second examines the long-run effects of disasters on economic growth. The short-run studies include: Albala-Bertrand (1993), Kahn (2005), Anbarci et al. (2005), Bluedorn (2005), Raddatz (2007), Strobl (2008), Loayza et al. (2009), Noy (2009), Rodriguez-Oreggia et al. (2009), Leiter et al. (2009), Mechler (2009) and Hochrainer (2009); while long-run studies include: Skidmore and Toya (2002), Noy and Nualsri (2007), Cuaresma et al. (2008), Jaramillo (2009), Raddatz (2009)

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[3] Due to lack of reliable data, human related disasters are excluded from the discussion of this paper.
[4] The literature review draws heavily on Cavallo and Noy (2009).
[5] Cavallo and Noy 2009, 6.
[6] Abbreviations for this paper include:
GDP: Gross Domestic Product
CRED: Center For Research on Epidemiology of Disasters
TFP: Total Factor Productivity
GNI: Gross National Income

and Hallegatte and Dumas (2009).[7] Compared to the many short-run studies there have been fewer long-run studies conducted in the literature.

Among the few long-run studies is an article by Skidmore and Toya (2002), which is regarded as the first piece of empirical research on the subject.[8] In their cross-sectional study, Skidmore and Toya use the number of natural disasters normalized by land area in each of the 89 countries included in the sample during the period 1960-1990. They reach a somewhat counterintuitive conclusion that disaster risks may promote long-run economic growth. Specifically, they find that the frequency of climatic disasters is positively correlated with human capital accumulation, growth in total factor productivity (TFP) and per capita GDP growth.[9]

Interestingly, Noy and Nualsri's (2007) results supported the opposite conclusion. Using a panel of five-year country level data, they find a negative correlation between disaster effects and the long-run economic growth rate. The work of Jaramillo (2009) and Raddatz (2009) also supports the conclusion reached by Noy and Nualsri (2007). For example, Raddatz, using panel time series techniques, finds that "in the long run, a climate related disaster is linked to reductions in real GDP per capita by at least 0.6 percent".[10]

The Schumpeterian "creative destruction" process is one of the key explanations for the conclusions reached by Skidmore and Toya (2002). They explain that "disasters may provide an opportunity to update the capital stock, thus encouraging the adoption of new technologies".[11] Cuaresma et al. (2008) and Hallegatte and Dumas (2009) test this creative destruction hypothesis.

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[7] This paper focuses on the long-run effects. For a comprehensive survey of the literature, see Cavallo and Noy (2009).

[8] For example, Cuaresma et al. (2008) state that "To our knowledge, the article by Skidmore and Toya (2002) is the only piece of empirical research that assesses directly the long-run economic impact of natural disasters" (p.1).

[9] See figures 1 and 2 for some initial evidence regarding the relationship between the number of disasters and economic growth.

[10] Raddatz 2009, 9.

[11] Skidmore and Toya 2002, 665.

The former study utilizes an empirical approach and reaches the conclusion that "creative destruction only occurs in developed countries".[12] The latter study makes use of a calibrated endogenous growth theoretical model and concludes that "disasters do not have positive effects on the economy and large disasters can lead to poverty traps".[13]

The study by Skidmore and Toya (2002) has inspired several pieces of subsequent research, the majority of which find contrary results. This paper serves as a robustness test for their study. Specifically, I extend their work to a more recent period, from 1990 to 2004, to see if the same relationship between growth and disaster frequencies can be found. Note that compared to 1960-1990, the recent period is marked by considerable improvements in the recording of minor disasters. In the Emergency Events Database (EM-DAT), despite the shorter time span, the total number of counted natural disasters is twice as large over the period 1990-2007 than 1960-1990.[14] Given the absence of agreement regarding the long-run effects of disasters in literature, it would be valuable to explore if Skidmore and Toya's findings hold in the recent period characterized by improved data recording.

IV. Disaster Data

Disaster data for this paper come from the Emergency Events Database (EM-DAT), the best available and most widely used database for research on disasters.[15] This database is maintained by the Center for Research on the Epidemiology of Disasters (CRED) at the Catholic

[12] Cuaresma, Hlouskova and Obersteiner 2008, 9.
[13] Hallegatte and Dumas 2009, 783.
[14] In the database, the total number of natural disasters from 1960 to 1990 is 3,065, whereas the total number of natural disasters from 1990 to 2007 is 6,665. Regina Below, a database manager at CRED, explains that this increase was mainly due to a better recording of minor disaster events (email to the author).
[15] A less extensive source is the Munich Re dataset at: http://mrnathan.munichre.com/.

University of Louvain, Belgium. Since its establishment in 1973, CRED has compiled data on global disasters from 1900 to the present.

CRED uses a standardized method in data compilation and it has not changed its criteria for recording a disaster since its establishment. For a disaster to be entered into the CRED database, at least one of the following criteria must be fulfilled: (1) 10 or more people are reported killed; (2) 100 or more people are reported affected/injured/homeless; (3) a state of emergency is declared; (4) a call for international assistance is issued.[16]

EM-DAT reports information on the frequency of disaster events, the number of people killed, the number of people affected[17], and the estimated damage costs in U.S. dollars. However, Skidmore and Toya (2002) use only the frequency data in their study. They give three reasons for not using the damage and casualties data. First, damage and casualties data are not always available and sometimes predictions for missing values are not very accurate (2002, p.670). Second, they are more likely to be endogenously determined by the level of income whereas disaster frequency is exogenously determined regardless of income level. For example, wealthy countries intrinsically face higher economic damage since they have more physical capital at risk when faced with a natural disaster. On the other hand, wealthier countries are less likely to entail human life loss since they have better medical care and rigorous regulations on building codes, engineering, and other safety precautions (2002, p.670). Finally, Skidmore and Toya (2002) argue that disaster damage is sometimes exaggerated in developing countries in order to secure international assistance (p.670).[18]

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[16] http://www.emdat.be/criteria-and-definition

[17] By CRED definition, the affected people are those who require immediate assistance during the period of emergency. See CRED glossary for more definitions: http://www.emdat.be/glossary/9

[18] This phenomenon is widely recognized in the literature. See for example, Albala-Bertrand (1993) and Yang (2008).

The number of disaster events is indeed the most exogenous information that can be found in the CRED database. Whenever a natural event satisfying one of the four criteria occurs in a country, it gets recorded in the database regardless of the income level of the country. However, it is questionable whether frequencies alone can reflect actual disaster risks. By the CRED criteria, a local storm that killed 10 people is assigned the same frequency value as Hurricane Katrina. Table 1 lists the top 5 deadliest natural disasters that occurred in the U.S. from 1990 to 2009. It shows that there is a great deal of variation in terms of intensity even among the top 5 deadliest disasters. In fact, Hurricane Katrina alone left more casualties than the other four combined. Skidmore and Toya acknowledge that frequency alone does not reveal the actual disaster risk that countries face and comment that "more accurate data on disaster risk would be a valuable contribution".[19]

V. Theory of Disaster Effects on Long Run Growth

In the long run, disaster risks can affect the aggregate economy through its factors of production. Altered decisions on the factors of production eventually shape the output level and thus the standard of living for the economy. In this section, I propose two hypotheses and a model that explain how disaster risks can change the level of investment on the factors of production.

First, the effect of disaster risks on the long-run physical capital investment is obscure. One might conclude that higher risk of physical capital destruction due to disasters reduces the investment on physical capital. This can be true if a country faces a constant risk of a certain

[19] Skidmore and Toya 2002, 682.
There have been some efforts to come up with reliable data for disaster risks. For example, Yang (2008) uses data on storm intensity measured by wind speed to develop the "Mean Storm Index".

disaster.[20] However, disasters can also provide an opportunity to update and upgrade the capital stock, "allowing the adoption of new technology that is apt for the skilled labor".[21]

Second, disaster risks, especially the climatic ones, can lead to increased human capital investment. Climatic disasters can be regarded as a proxy for risk to physical capital rather than human capital; severe weather conditions are more likely to pose major threats to physical capital while forecasting abilities make human capital less vulnerable to climatic disasters. In an endogenous growth framework where individuals choose their level of investment between physical and human capital, higher climatic disaster risks reduce the expected return to physical capital, which in turn increase the relative return to human capital. Skidmore and Toya claim that "The higher relative return to human capital may lead to an increased emphasis on human capital investment." [22]

To offer insights on the effects of a climatic disaster on long-run growth, I utilize the Solow model (Solow, 1956) framework employed by Dacy and Kunreuther (1969) and Okuyama (2003). Also, I conceptualize Skidmore and Toya's conjecture that higher climatic disaster risks can lead to more investment in human capital using the Solow model.

Consider the constant returns to scale production function of an economy with no technological progress:[23]

$$Y = F(K, L) \tag{1}$$

[20] Jack Hirshleifer shows how continuing recurrences of plague lead to a period of depression in the century following the Black Death (1966, p.28). Although plague is substantially different from a climatic disaster in that it is a major threat to human capital rather than physical capital, his study shows that continuing recurrences can shatter a factor of production.
[21] Skidmore and Toya 2002, 677.
[22] Skidmore and Toya 2002, 665.
[23] This assumption of no technological progress will be relaxed later in this section.

where Y denotes the total output, K, the level of capital accumulation, and L, the amount of labor input. With the property of constant returns to scale, the production function can be converted into the per-capita form:

$$y = f(k) \tag{2}$$

where y is per-capita output and k is per-capita capital stock. Let s denote the saving rate, δ, the depreciation rate, and n, the population growth rate. Then the steady state level of capital stock k^* satisfies the following condition:

$$\Delta k = s \cdot f(k) - (n + \delta) \cdot k = 0\,. \tag{3}$$

Arranging terms,

$$s \cdot f(k^*) = (n + \delta) \cdot k^*. \tag{4}$$

This steady state situation is described at point A of Figure 3. Now suppose that a climatic disaster occurs and damages physical capital but leaves the human population unharmed. The amount of per-capita capital stock decreases from k^* to k_d, and the economy's output per-capita decreases from the steady state level y^* to y_d.

In the aftermath of the disaster, the economy is assumed to go through a recovery period. In the recovery period, resources are allocated toward the reconstruction of the damaged capital stock. Moreover, there might also be international aid that can further stimulate physical capital accumulation. Hence the economy experiences a short period of higher saving s_r , which in turn accelerates the speed of recovery. As the economy recovers from the damage, the saving rate goes back to the original saving rate, s. The economy returns back to the steady state per-capita capital stock, k^*, (movement from D to A) and the steady state per-capita output level, y^*.

The same point can be made using the growth rate of per capita capital stock. Dividing both sides of the equation (3), the growth rate of k, γ_k , can be written as :

$$\gamma_k = \frac{\Delta k}{k} = \frac{s \cdot f\,(k)}{k} - (n + \delta)\ . \tag{5}$$

In the steady state, there is no change in γ_k , so the economy is initially at point A of Figure 4 where

$$\frac{s \cdot f\,(k)}{k} = (n + \delta)\,. \tag{6}$$

With the climatic disaster, the level of capital stock decreases to k_d and output falls because of the shock caused by the disaster. Now, as the economy goes through the recovery period, the saving rate increases due to the massive reconstruction effort and foreign aid, accelerating the speed of recovery. As the reconstruction progresses, the saving rate eventually returns to the previous level and the capital growth rate returns back to the steady state level of zero. (movement from D to A)

Now I relax the assumption of no technological progress. Suppose an economy with initial technology level $A(t)$ has a constant technology growth rate of x. This economy now experiences the same climatic disaster described above. As Skidmore and Toya (2002) point out, there might be a "creative destruction" effect on the reconstruction process - old capital stock that needed replacement before the disaster is updated with newer technologies. Therefore, during the recovery period, the technology growth rate increases temporarily from x to x_r as shown in Figure 5. The technology growth rate eventually returns to its original level once the recovery is complete since the replacement itself cannot induce technological progress. Using a labor augmenting technological progress model (Barro and Sala-I-Martin, 1995) Equation (1) becomes:

$$Y = F[\,K,\ L{\cdot}A(t)\,] \tag{7}$$

where $L \cdot A(t)$ denotes the amount of effective labor (defined to be $\hat{L}$), a measure that reflects productivity of each worker. The capital per effective worker, $\hat{k}$, can be written as:

$$\hat{k} = \frac{K}{L \cdot A(t)} = \frac{k}{A(t)} \quad , \tag{8}$$

and the output per effective worker can be written as:

$$\hat{y} = \frac{Y}{\hat{L}} = f(\hat{k}) \quad . \tag{9}$$

The change in per-capita capital stock becomes:

$$\Delta k = s \cdot f[k, A(t)] - (n + \delta) \cdot k \, , \tag{10}$$

which can be further reduced to:

$$\Delta \hat{k} = s \cdot f(\hat{k}) - (x + n + \delta) \cdot \hat{k} \quad . \tag{11}$$

Dividing both sides of (11) by $\hat{k}$, growth rate of capital per effective worker is:

$$\gamma_{\hat{k}} = \frac{s \cdot f(\hat{k})}{\hat{k}} - (x + n + \delta) \quad . \tag{12}$$

Since there is no change in capital per effective worker at the steady state, the following condition should apply (point A of Figure 6):

$$\frac{s \cdot f(\hat{k}^*)}{\hat{k}^*} = (x + n + \delta) \quad . \tag{13}$$

When a disaster occurs, the capital stock per effective worker decreases from the steady state level to $\hat{k}_d$. At this point, the growth rate of capital per effective worker is B-C. As was the case with the economy which featured no technological progress, the reconstruction effort coupled with foreign aid raises the saving rate from s to s_r, contributing to the increase in the growth rate of capital per effective worker. However, as shown in Figure 5, the economy whose capital stock is upgraded during the recovery period also experiences a higher rate of technological growth, x_r. With the "creative destruction" process in effect, the growth rate of capital per effective worker is now D-E, which is lower than the capital growth rate with no technological replacement, D-C (Figure 6). To further justify this effect, Okuyama (2003) explains that "a higher rate of technological progress leads to a faster growth of the effective labor".[24] Compared to the period of the regular technological growth rate, x, more resources are spent on making each worker more productive in the period of the higher technological growth rate, x_r. That is, during the reconstruction process, the technology-replacing economy directs more resources towards human capital rather than physical capital than the economy with no technology replacement. This model suggests that climatic disasters can induce human capital investment for an economy that experiences creative destruction during the recovery period.

VI. Methodology

To test the proposed theory and examine the relationship between natural disasters and growth rate, I use the frequency data from EM-DAT and apply the method employed by Skidmore and Toya in 2002 for the period 1990 to 2004. One important strategy they use is the categorization of natural disasters into two groups; the climatic disaster group and the geologic disaster group. I adopt their categorization but I employ slightly different definitions of the two categories in order to be more consistent with the definitions used by CRED. Specifically, I define climatic events to be the events caused by atmospheric processes (meteorological) plus the events caused by deviations in the normal water cycle (hydrological). By the CRED

[24] Okuyama 2003, 19.

classification, the climatic disaster group consists of storms, including thunderstorms, blizzards, sandstorms, generic storms, tornados, and orographic storms among others, and also includes flood and wet mass movement. Also, I define the geologic disaster events to be the events originating from solid earth. Earthquakes, volcanic eruptions, rock falls, avalanches, landslides, subsidences and other dry mass movements fall into this category.[25]

The rationale behind this separation is that climatic and geologic risks may influence factors of production differently and may thus have different effects on the long-run economy. Compared to geologic disasters, climatic disasters are more frequent, often occurring in a particular period of time during a year. Climatic disasters are also more predictable, hence it is possible for people to evacuate the affected region beforehand. On the other hand, geologic disasters are less frequent and more irregular in their occurrence. They are also less predictable, which impedes the population's ability to evacuate. Therefore, as Skidmore and Toya claim, "climatic disasters are a reasonable proxy for risk to physical capital while geologic disasters may be perceived as a threat to both human and physical capital".[26]

VII. Results and Analysis

A) Disasters and economic growth

Table 2 reports the results from a simple semi-logarithmic regression. The dependent variable is per capita GDP growth rate and the explanatory variables include the number of per land disasters. The relevant time period for columns (1) and (2) is 1960-1990 and the time period

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[25] In my data for example, if Haiti had exactly 4 storms and 1 earthquake in 1980, I add 4 to its climatic disasters variable and 1 to its geologic disasters variable for that year. For specific classification of each disaster type, see http://www.emdat.be/classification.

[26] Skidmore and Toya 2002, 671-672.

For more information about the variables, see Appendix tables A and B.

for columns (3) and (4) is 1990-2004.[27] Consistent with Skidmore and Toya (2002), I find a positive and statistically significant relationship between the growth rate and the number of total (climatic + geologic) disasters normalized by land area for the period 1960-1990. I also find a similar relationship between the growth rate and disaster frequencies in the recent period, 1990-2004, though the relationship is not as significant as was the case in the previous period.[28]

In the first period (1960-1990), there is a stronger correlation between per capita GDP growth and the number of per land climatic disasters (heteroskedasticity-robust t statistic=2.97) but there is no statistically significant relationship between the growth rate and the number of per land geologic disasters (t= -0.63). However, in the second period (1990-2004), the relationship between climatic disasters and the growth rate gets weaker (t=1.65) compared to the relationship between total disasters and the growth rate (t=2.17).

Clearly, there seems to be less of a distinction between the climatic disasters and geologic disasters in terms of their relevance to the growth rate in the recent period. One possible explanation for this is the potential difference in disaster recording over time; as discussed previously, the CRED database has only recently started to record minor disasters. The minor disasters, which were not counted in the earlier period, may make each disaster group less distinct from each other and serve to mitigate the relationship between disaster risk and economic growth for the later period. Another reason presented by Skidmore in a personal communication to the author on April 2, 2010 is the difference in forecasting ability and communication level in the two periods. He suggests that there was an important interaction

[27] Columns (1) and (2) is a replication of Skidmore and Toya (2002, p.671). The slight differences in t statistics come from a different disaggregation of climatic and geologic disasters. See p.671 for their definition of the two disaster groups.

[28] This positive relationship between the growth rate and disaster frequencies can be also found in figures 1 and 2. Note the slope of the fitted values is flatter in the recent period.

between disaster propensity and improvements in communication in the earlier period, 1960-1990. During this period, improving accuracy in weather forecasting became increasingly beneficial for people in the disaster-prone area. In the short run, they could evacuate from the afflicted region, and in the long run, they could make better long-term investments. After the 90's; however, the communication revolution had already run its course, so the benefit from improving communication also decreased and one no longer observes any relationship between climatic disasters and investment decisions.

Table 3 reports the results from a growth regression that includes some of the control variables that are typically considered to be key determinants of economic growth for the period 1960-1990.[29] Skidmore and Toya (2002) use the following multiple linear regression (MLR) model:

$$G_t = \alpha + \beta I_t + \gamma O_t + \delta K_t + \vartheta Y_{t\,i} + \varepsilon_t \qquad (14)$$

where G_t represents the average growth rate of real GDP per capita during the period t, I_t, the average ratio of investment to GDP in period t, O_t, the level of openness during the period t, K_t, the average annual growth rate of physical capital stock per capita in t, and $Y_{t\,i}$, the log of initial income in the initial year i for the period t.[30]

As explained by many growth theoretical models, an economy that allocates a greater proportion of its output to investment grows faster, so I_t is expected to be positively correlated with the growth rate. A country with greater degree of openness is more likely to adopt new technology and improve institutions that are critical for economic development, hence the

[29] This is a replication of the regression done by Skidmore and Toya (2002, p.673) included here for comparison.

[30] Log in this paper means the natural logarithmic function (log of base e). I take a natural log of a variable in order to stabilize the variance of a sample, linearize the relationship between the independent variables and the dependent variables, and to normalize positively skewed distributions of the variables (Bland, 2000). Also, for the disaster variables, I add one to the frequency before I take a natural log in order to avoid arithmetic error.

coefficient for O_t is expected to be positive. Also, since capital stock is essentially one of the factors of production, countries with faster growing capital stock are assumed to experience a faster growing output level. However, the coefficient for the initial income level depends greatly on the period of consideration and the number of observations. For the particular period 1960-1990, the world by and large observed a rapid increase in GDP compared to other periods.[31] The countries that initially started with low income levels are more likely to show higher growth rates, making it plausible to expect a negative coefficient for the initial income variable.

Table 3 reports the estimated coefficients and heteroskedasticity-robust t statistics (in brackets) from an ordinary least squares (OLS) regression. Column (1) of the table shows that all the estimates for the explanatory variables are statistically significant at the one percent level. Consistent with Skidmore and Toya (2002), after accounting for the investment ratio to GDP, openness, growth in capital stock and initial income, I find a positive and statistically significant relationship between the number of total disasters normalized by land area and per capita GDP growth (Column 2).[32] As Column (3) shows, the positive relationship is even stronger for the number of climatic disasters (t=2.43). However, I find no statistical significance with which to reject the null hypothesis that there is no relationship between the number of geologic disasters and per capita GDP growth for this period (t= -0.34). In all cases the semi-logarithmic regression equations fit the data moderately well, explaining more than 70% of the variation in per capita GDP growth rate.

[31] For example, in my sample of 88 countries, the mean GDP growth rate is 0.02 (2%) for the period 1960-1990, while the mean GDP growth rate is 0.0167 (1.67%) for the period 1990-2004. See Appendix table B for the summary statistics.

[32] Similar relationships can be found even without the normalization by land area. (Skidmore and Toya, 2002) But it is more reasonable to normalize the frequency by the land area because large countries are more likely to have more disasters.

Table 4 lists the results of a similar regression for the recent period, 1990-2004. I use major components of GDP, such as consumption, investment and government spending as the explanatory variables.[33] While one would expect to find positive coefficients for other components of GDP, the robust positive relationship between government spending and growth is noteworthy.[34] I also add the disaster variables that are not normalized by land area to explore the effects of normalization.

Controlling for investment, government spending, consumption and gross domestic savings, I find a positive and statistically significant relationship between the number of per land total disasters and per capita GDP growth in the period 1990 to 2004. The relationship is not very significant unless I normalize the number of total disasters by land area (t=1.34). For the geologic disasters, I find no significant relationship whether I use the total number or the number normalized by land area. For the climatic disasters, I find a positive and significant relationship between the number of climatic disasters and per capita GDP growth rate regardless of the normalization.

In summary, Skidmore and Toya's findings (2002) continue to hold for the recent period of enhanced disaster recording. The regression analysis suggests a robust positive correlation between the frequency of disasters and long-run economic growth in both periods of consideration. The major difference between the two periods is that the number of per land climatic disasters reveals a weaker correlation than the number of per land total disasters in the later period.

[33] The gross domestic savings variable is also added to increase the explanatory power. The correlation between this variable and the investment ratio variable is 0.5490.
[34] Skidmore and Toya (2002) find a robust negative relationship between government consumption and growth rate for the period 1960-1990 (p.673).

B) Disasters and physical capital investment

In an attempt to identify the channels through which disasters affect economic growth, I first investigate the relationship between measures of physical capital and the number of disasters. The measures of physical capital include investment ratio to GDP, growth in capital stock, and the ratio of gross capital formation to GDP. Columns (1) and (2) of Table 5 show the relationship between investment ratio to GDP and the disaster variables from a simple semi-logarithmic regression. Consistent with Skidmore and Toya (2002, p.679), for the period 1960-1990, no significant relationship is found between investment and disasters. This is also the case after controlling for initial income and the level of secondary schooling (Columns 3 and 4).

Table 6 lists similar regression results for the earlier period using growth in capital stock as the dependent variable. With a simple regression, I find a significant relationship at the ten percent level (t=1.72) between climatic disasters and growth in capital stock (Column 2). However, after including additional explanatory variables and regional dummies, this relationship disappears (Column 4).

The same results are found for the recent period, 1990-2004. In Table 7, I find no significant relationship between the investment to GDP ratio and disasters of any kind. In Table 8, I use the ratio of gross capital formation to GDP as my dependent variable but still find no relationship, regardless of the inclusion of control variables. The physical capital regressions show that disaster coefficients are generally negative. However, statistically insignificant coefficients suggest that physical capital is not a good candidate for the route whereby disasters affect economic growth.

C) Disasters and human capital investment

The conjecture proposed by Skidmore and Toya (2002) together with the theoretical model presented in this paper suggest that climatic disaster risk can promote human capital investment. Provided that a society can choose its level of investment in the factors of production, more climatic risk to physical capital makes human capital relatively attractive, which in turn induces the society to invest more in human capital than physical capital (Skidmore and Toya, 2002). Human capital accumulation, which by nature enjoys the benefit of knowledge spillover, fosters economic growth as emphasized by many endogenous theoretical models (Lucas, 1988). This section explores the relationship between human capital investment and disaster risks empirically.

As in other studies, since human capital can be ambiguous in definition, I employ some proxies for human capital investment such as educational expenditure, secondary and tertiary school enrollment ratio, and the annual growth rate of secondary schooling year. I start with a replication of Skidmore and Toya's study (2002, p.680). Table 9 reports the regression results of the first independent variable, the average annual growth rate of secondary schooling year for the period 1960-1990. After accounting for initial income, initial years of secondary schooling, fertility rate and the investment rate, I find a robust positive relationship between growth in secondary schooling years and per land climatic disasters (Column 4). This result is consistent with that of Skidmore and Toya's (2002, p.680), except that the negative relationship between geologic disasters and the dependent variable disappears after incorporating additional explanatory variables such as fertility rate (1960-1985, average) and investment ratio.

Table 10 shows the results of the same regression except that this time, the dependent variable is the average gross secondary school enrollment ratio for the period 1960-1985. Again, the positive relationship between climatic disasters and the dependent variable is weaker (10%

significance level) than that of Skidmore and Toya's (2002 p.680) after the inclusion of the other explanatory variables. The secondary school enrollment ratio also shows a similar positive correlation with the climatic disasters for the recent period, 1990-2004 (Column 4, Table 11).

In Columns (1) and (2) of Table 12, I present regression estimates of the tertiary school enrollment ratio that include the explanatory variables discussed previously.[35] After accounting for initial income, investment ratio and regional dummies, I find no significant relationship between the tertiary school enrollment ratio and the frequency of climatic disasters. However, I find a negative and statistically significant relationship between tertiary school enrollment and the geologic disasters (Column 2). One possible explanation may be that the geologic disasters induced emigration of educated people to countries that were not included in this sample.

In Columns (3) and (4) of Table 12, I list the results of a similar regression with average educational expenditure (% of GNI, 1990-2007) as the dependent variable. Similar to my results from the previous regression, I only find a negative relationship between geologic disasters and educational expenditure (t=-2.59). Compared to the enrollment ratio variables, educational expenditure reflects the direct interest of a society in its human capital investment. One explanation for the negative relationship may be that the geologic disasters in this period posed a threat that was serious enough to lower the expected return to human capital investment.

VIII. Conclusion

The empirical evidence found in this paper suggests that there is a positive correlation between long-run economic growth and the frequency of the disasters. The positive correlation is consistent in both periods of consideration: the period studied by Skidmore and Toya, 1960-1990

[35] Since data are not readily available, I use tertiary school enrollment ratio of 1999 to maximize the number of observations for the sample. This can be viewed as a crude measure of the average ratio from 1990 to 2004.

and the recent period, 1990-2004. This study also explored the channels whereby disasters affect economic growth, both theoretically and empirically. For the period 1960-1990, Skidmore and Toya (2002) find that “human capital accumulation and technological development spurred by climatic disasters are the main routes through which disasters affect economic growth. The empirical study for the recent period shows weaker evidence for climatic disasters inducing human capital accumulation, but stronger evidence for geologic disasters leading to human capital destruction.

One should keep in mind that the empirical analysis in this paper was conducted by using disaster frequency data in isolation. As discussed previously, the frequency data are indeed the most exogenous information that can be found in the EM-DAT database. However, there surely is a price for excluding casualties and damage costs data in the analysis; disaster frequency alone may fail to fully represent the level of actual disaster risk.[36] Further study on this subject should explore measures that are not predetermined by the income level but are at the same time reasonably representative of the actual disaster risk. The absence of such a measure may be one important source of the disagreement in the current long-run studies. Nevertheless, the evidence found in this study suggests that risks associated with natural disasters provide substantial implications regarding a society’s investment decisions on its factors of production.

[36] Using a more endogenous measure that takes into account the casualties and damage data can lead to a very different conclusion than using the frequency data alone. One such measure is the Climate Risk Index (CRI). For more information about CRI, see figures 7 (a), (b) (Appendix) and Harmeling (2008).

<Figures and Tables>

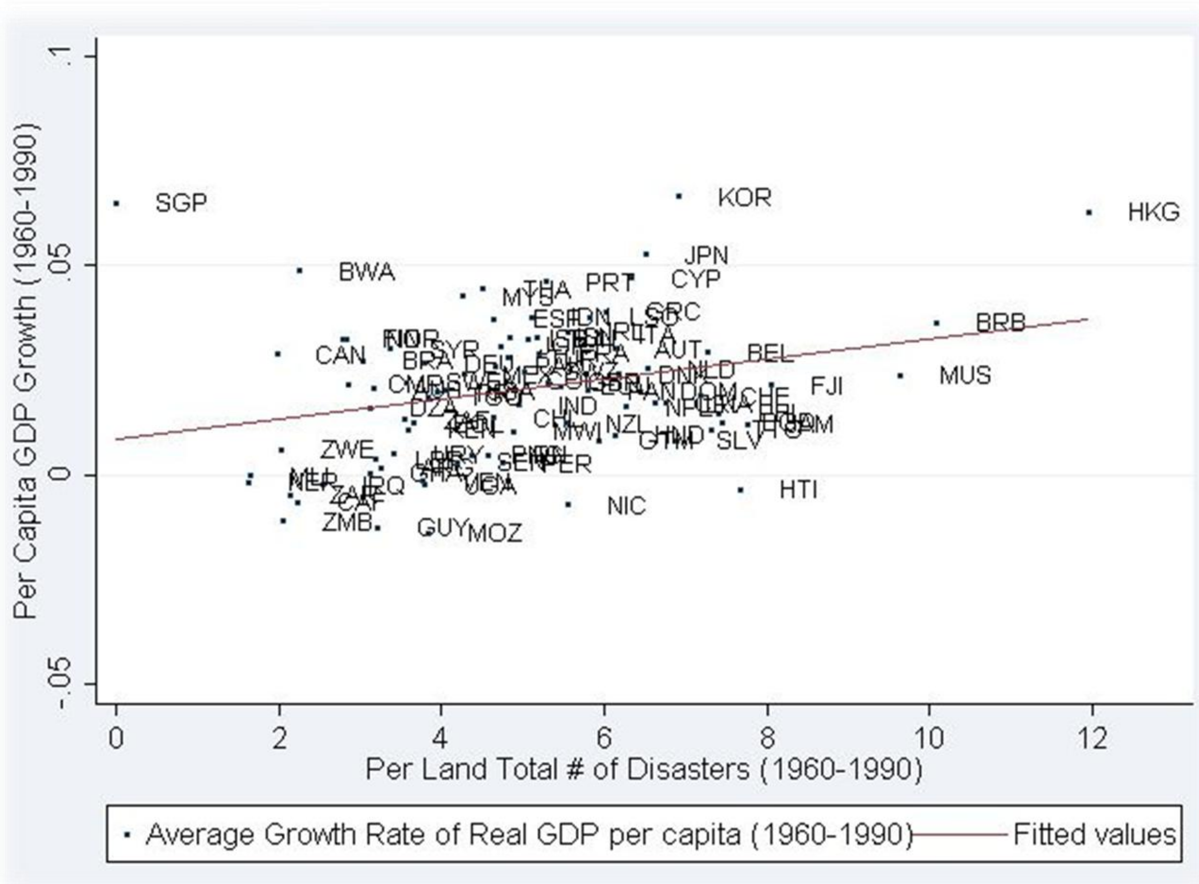


Figure 1. Relationship between the number of disasters and GDP growth rate: 1960-1990.
Source: Skidmore and Toya (2002, p.667), EM-DAT

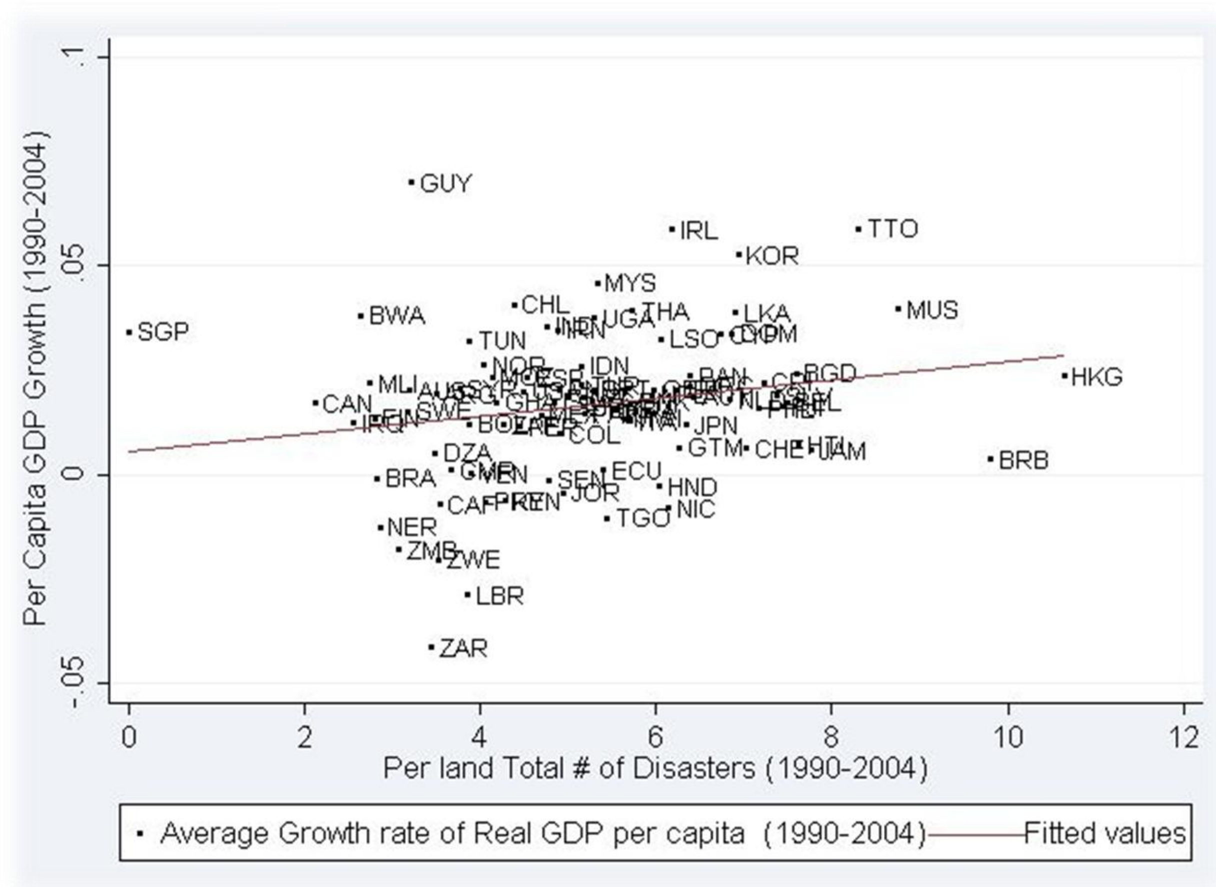


Figure 2. Relationship between the number of disasters and GDP growth rate: 1990-2004.
Source: EM-DAT

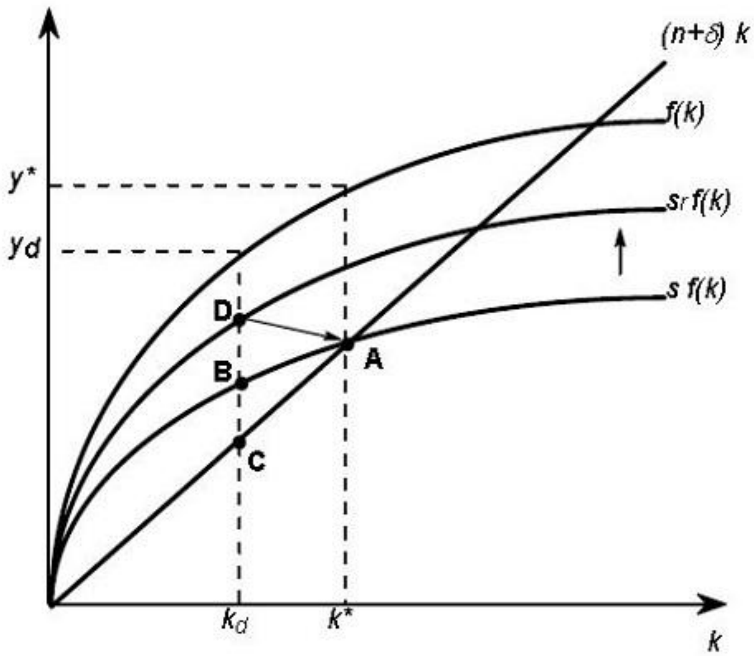


Figure 3. Solow Model with a Disaster.
Source: Okuyama (2003, p.15)

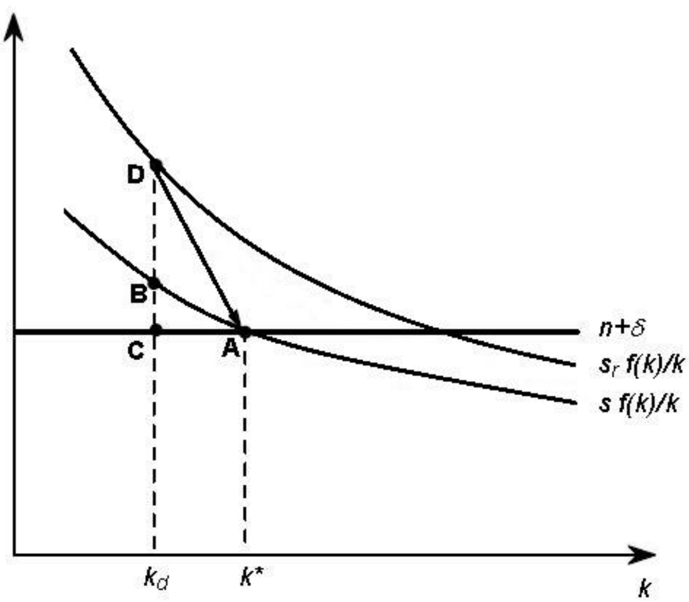


Figure 4: Dynamics of Recovery.
Source: Okuyama (2003, p.16)

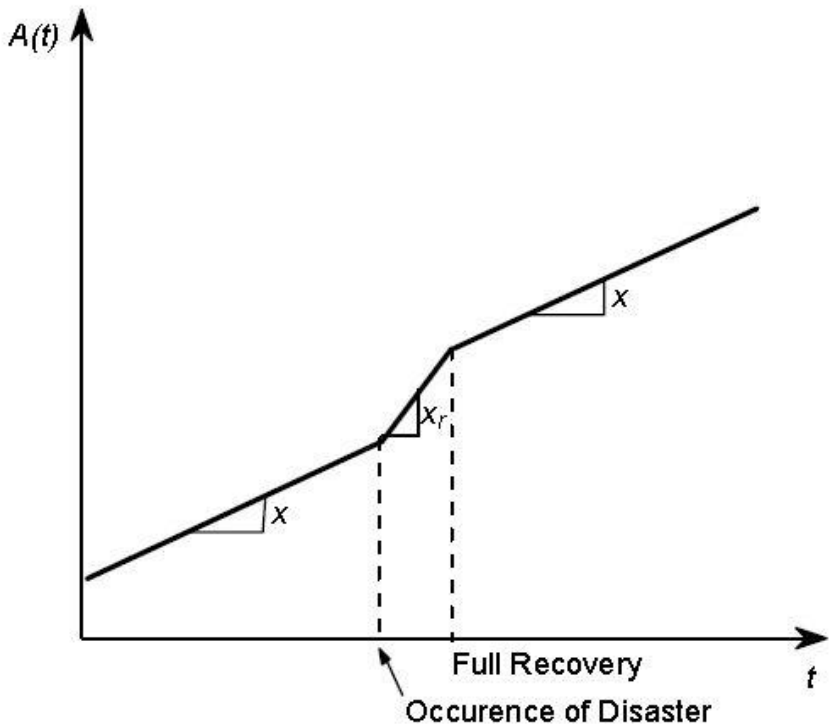


Figure 5. Technological Progress and a Disaster.

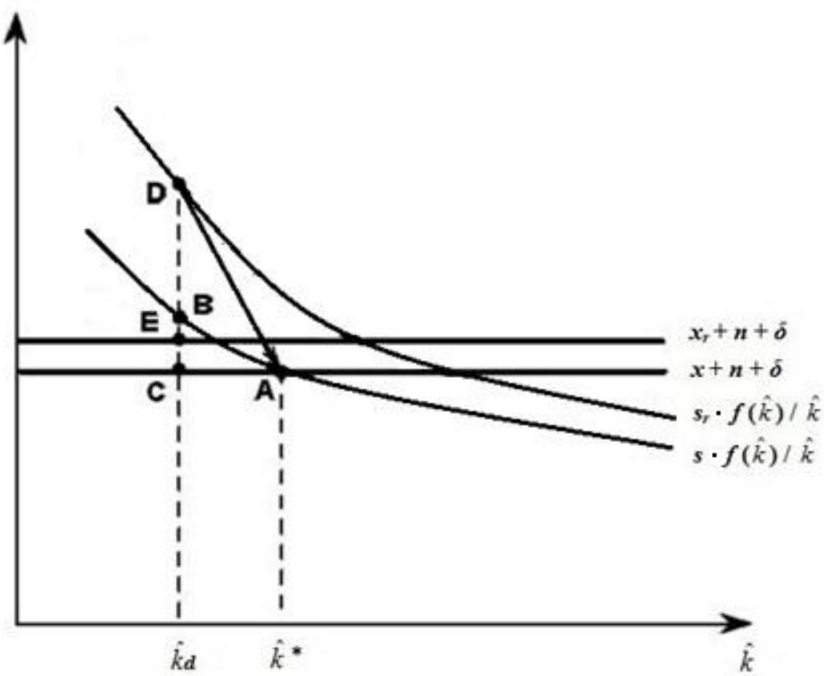


Figure 6. Transitional Dynamics with Technological Progress.
Source: Okuyama (2003, p. 17, 19).
Note: Some changes in notation were made by the author for Figure 6.

Table 1. Top 5 Deadliest Natural Disasters: USA 1990-2009

Rank	Dates		Disaster		Numbers		
	Start	Type	Sub type	Name	Killed	Total affected	Damage ($ Mil.)
1	Aug 2005	Storm	Tropical cyclone	Katrina	1833	11,000,148	10000
2	Jul 1995	Extreme temperature	Heat wave		670	5,000,000	11000
3	Mar 1993	Storm			270	3,000,010	7000
4	Jul 1999	Extreme temperature	Heat wave		257	2,100,000	7000
5	Jul 2002	Epidemic	Infectious Diseases	West Nile Fever	214	640,064	2500

Source: EM-DAT: The OFDA/CRED International Disaster Database.
www.emdat.be - Université Catholique de Louvain - Brussels – Belgium.

Table 2. Regression table with dependent variables GDP Growth Rates

	(1)	(2)	(3)	(4)
Dependent Variables	Per Capita GDP Growth Rate (1960-1990)		Per Capita GDP Growth Rate (1990-2004)	
Per Land Total Disasters (1960-1990)	0.00230*** [2.61]			
Per Land Climatic Disasters (1960-1990)		0.00242*** [2.97]		
Per Land Geologic Disasters (1960-1990)		-0.000521 [-0.63]		
Per Land Total Disasters (1990-2004)			0.00235** [2.17]	
Per Land Climatic Disasters (1990-2004)				0.00186* [1.65]
Per Land Geologic Disasters (1990-2004)				0.00118 [1.27]
Constant	0.00885* [1.91]	0.00978** [2.29]	0.00451 [0.76]	0.00495 [0.86]
Observations	88	88	88	88
R-squared	0.08	0.11	0.04	0.06

*** p<0.01, ** p<0.05, * p<0.1

Notes: The estimates are obtained from a semi logarithmic regression model. The regressions are done with SUR (Seemingly Unrelated Regression) method. Columns (1) and (3) show the results of one set of SUR, columns (2) and (4) present the results of the other set.

The robust z statistics are reported in brackets.

*** indicates that the estimate is statistically significant at the one percent level.

** indicates that the estimate is statistically significant at the five percent level.

* indicates that the estimate is statistically significant at the ten percent level.

See Skidmore and Toya (2002, p.671) for their results for column (1) and (2).

Table 3. Regression table with the dependent variable GDP Growth Rate: 1960-1990

	(1)	(2)	(3)
Dependent Variable: Per Capita GDP Growth Rate (1960-1990)			
Investment / GDP (1960-1990)	0.0650*** [3.18]	0.0810*** [4.15]	0.0816*** [4.00]
Openness (1965-1990)	0.0169*** [5.05]	0.0147*** [5.00]	0.0143*** [4.56]
Growth in Capital Stock (1960-1985)	0.0142*** [5.34]	0.0134*** [5.01]	0.0134*** [4.95]
Log of Initial Income (1960)	-0.00512*** [-3.62]	-0.00601*** [-4.37]	-0.00610*** [-4.36]
Per Land Total Disasters (1960-1990)		0.00147** [2.36]	
Per Land Climatic Disasters (1960-1990)			0.00153** [2.43]
Per Land Geologic Disasters (1960-1990)			-0.000162 [-0.34]
Constant	0.0293*** [2.93]	0.0273*** [2.96]	0.0284*** [3.08]
Observations	82	82	82
R-squared	0.73	0.76	0.76

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: The estimates are obtained from a semi logarithmic regression model.

Robust t statistics are reported in brackets.

*** indicates that the estimate is statistically significant at the one percent level.

** indicates that the estimate is statistically significant at the five percent level.

* indicates that the estimate is statistically significant at the ten percent level.

This regression is a replication of Skidmore and Toya (2002, p.673).

Table 4. Regression table with dependent variable Average Per Capita GDP Growth Rate : 1990-2004

	(1)	(2)	(3)	(4)	(5)
Dependent Variable: Per Capita GDP Growth Rate (1990-2004)					
Investment / GDP (1990-2004)	0.00110*** [4.44]	0.00102*** [4.13]	0.00105*** [4.22]	0.00108*** [4.38]	0.00108*** [4.38]
Government Spending /GDP (1990-2004)	0.00111*** [3.64]	0.00118*** [3.79]	0.00119*** [3.80]	0.00113*** [3.68]	0.00115*** [3.73]
Consumption /GDP (1990-2004)	0.000913*** [3.84]	0.000814*** [3.43]	0.000827*** [3.50]	0.000909*** [3.84]	0.000930*** [3.83]
Gross Domestic Savings /GDP(1990-2007)	0.00133*** [4.70]	0.00132*** [4.96]	0.00132*** [4.92]	0.00133*** [4.67]	0.00137*** [4.59]
Per Land Total Disasters (1990-2004)		0.00231** [2.49]			
Per Land Climatic Disasters (1990-2004)			0.00206** [2.06]		
Per Land Geologic Disasters (1990-2004)			0.000516 [0.67]		
Total Disasters (1990-2004)				0.0000192 [1.34]	
Climatic Disasters (1990-2004)					0.0000354** [2.58]
Geologic Disasters (1990-2004)					-0.00013 [-1.32]
Constant	-0.109*** [-4.19]	-0.115*** [-4.53]	-0.116*** [-4.55]	-0.109*** [-4.21]	-0.112*** [-4.22]
Observations	88	88	88	88	88
R-squared	0.4	0.44	0.45	0.4	0.41
*** p<0.01, ** p<0.05, * p<0.1					

Notes: The estimates are obtained from a semi logarithmic regression model.

The gross domestic savings ratio to GDP variable is relevant for the period 1990 to 2007.

All the other variables including the CRED disaster variables are relevant for the period 1990 to 2004.

Robust t statistics are reported in brackets.

*** indicates that the estimate is statistically significant at the one percent level.

** indicates that the estimate is statistically significant at the five percent level.

* indicates that the estimate is statistically significant at the ten percent level.

Table 5. Regression table with dependent variable Investment/ GDP :1960-1990

	(1)	(2)	(3)	(4)
Dependent Variable: Investment/ GDP (1960-1990)				
Log of Initial Income (1960)			0.0400*** [2.87]	0.0406*** [2.91]
Log of Secondary schooling (1960)			0.0174 [1.51]	0.0169 [1.47]
Per Land Total Disasters (1960-1990)	0.000255 [0.054]		-0.00522 [-1.44]	
Per Land Climatic Disasters (1960-1990)		0.00194 [0.45]		-0.00408 [-1.20]
Per Land Geologic Disasters (1960-1990)		-0.00269 [-0.62]		-0.00192 [-0.58]
Constant	0.193*** [7.51]	0.189*** [7.70]	-0.0651 [-0.56]	-0.0728 [-0.63]
Observations	88	88	88	88
R-squared	0	0.01	0.44	0.44
*** p<0.01, ** p<0.05, * p<0.1				

Notes: The estimates are obtained from a semi logarithmic regression model.

Robust t statistics are reported in brackets.

*** indicates that the estimate is statistically significant at the one percent level.

** indicates that the estimate is statistically significant at the five percent level.

* indicates that the estimate is statistically significant at the ten percent level.

This regression is a replication of Skidmore and Toya (2002, p.679).

Table 6. Regression table with dependent variable Growth in Capital Stock :1960-1985

	(1)	(2)	(3)	(4)
Dependent variable : Growth in Capital Stock (1960-1985)				
Log of Initial Income (1960)			-0.138 [-1.17]	-0.142 [-1.19]
Log of Secondary schooling (1960)			-0.0355 [-0.65]	-0.0352 [-0.64]
Openness (1965-1990)			0.387 [1.49]	0.379 [1.46]
Sub-Saharan Africa			-0.556*** [-2.75]	-0.563*** [-2.72]
Latin America			-0.147 [-0.96]	-0.145 [-0.92]
NIEs and ASEAN			0.607* [1.76]	0.607* [1.75]
OECD			-0.077 [-0.31]	-0.0684 [-0.27]
Per Land Total Disasters (1960-1990)	0.0431 [1.28]		-0.00984 [-0.38]	
Per Land Climatic Disasters (1960-1990)		0.0548* [1.72]		-0.0083 [-0.33]
Per Land Geologic Disasters (1960-1990)		-0.0229 [-0.84]		-0.00495 [-0.21]
Constant	0.444** [2.28]	0.440** [2.34]	1.689* [1.72]	1.714* [1.74]
Observations	88	88	82	82
R-squared	0.02	0.05	0.42	0.42
*** p<0.01, ** p<0.05, * p<0.1				

Notes: The estimates are obtained from a semi logarithmic regression model.

Robust t statistics are reported in brackets.

*** indicates that the estimate is statistically significant at the one percent level.

** indicates that the estimate is statistically significant at the five percent level.

* indicates that the estimate is statistically significant at the ten percent level.

This regression is a replication of Skidmore and Toya (2002, p.679).

Table 7. Regression table with dependent variable Investment/ GDP: 1990-2004

	(1)	(2)	(3)	(4)
Dependent Variable: Investment/ GDP (1990-2004)				
Log of Initial Income (1990)			4.638*** [4.92]	4.627*** [4.70]
Log of Secondary school enrollment (1990)			1.398 [1.05]	1.405 [1.00]
Per Land Total Disasters (1990-2004)	0.107 [0.17]		-0.308 [-0.69]	
Per Land Climatic Disasters (1990-2004)		0.157 [0.22]		-0.251 [-0.49]
Per Land Geologic Disasters (1990-2004)		-0.0473 [-0.11]		-0.0574 [-0.18]
Constant	15.58*** [4.37]	15.44*** [4.40]	-19.88** [-2.26]	-20.00** [-2.19]
Observations	88	88	88	88
R-squared	0	0	0.53	0.53
	*** p<0.01, ** p<0.05, *	** p<0.05, p<0.1	* p<0.1	

Notes: The estimates are obtained from a semi logarithmic regression model.

Robust t statistics are reported in brackets.

*** indicates that the estimate is statistically significant at the one percent level.

** indicates that the estimate is statistically significant at the five percent level.

* indicates that the estimate is statistically significant at the ten percent level.

Table 8. Regression table with dependent variable Gross Capital Formation / GDP : 1990-2004

	(1)	(2)	(3)	(4)
Dependent variable : Gross Capital Formation / GDP (1990-2004)				
Log of Initial Income (1990)			-0.602 [-0.50]	-0.658 [-0.51]
Log of Secondary school enrollment (1990)			1.179 [0.93]	1.184 [0.93]
Openness (1990-2004)			3.781** [2.38]	3.752** [2.40]
Sub-Saharan Africa			-3.177 [-1.23]	-3.368 [-1.39]
Latin America			-1.6 [-0.98]	-1.597 [-0.97]
NIEs and ASEAN			4.923** [2.21]	4.898** [2.22]
OECD			-1.358 [-0.57]	-1.32 [-0.54]
Per Land Total Disasters (1990-2004)	0.577 [1.34]		0.0461 [0.13]	
Per Land Climatic Disasters (1990-2004)		0.641 [1.33]		0.074 [0.19]
Per Land Geologic Disasters (1990-2004)		-0.123 [-0.36]		-0.0731 [-0.27]
Constant	18.62*** [7.53]	18.62*** [7.63]	12.7 [1.31]	13.33 [1.34]
Observations	88	88	88	88
R-squared	0.02	0.03	0.28	0.28
*** p<0.01, ** p<0.05, * p<0.1				

Notes: The estimates are obtained from a semi logarithmic regression model.

Robust t statistics are reported in brackets.

*** indicates that the estimate is statistically significant at the one percent level.

** indicates that the estimate is statistically significant at the five percent level.

* indicates that the estimate is statistically significant at the ten percent level.

Table 9. Regression table with dependent variable Growth in Secondary Schooling Year :1960-1990

	(1)	(2)	(3)	(4)
Dependent Variable: Growth in Secondary Schooling Year (1960-1990)				
Log of Initial Income (1960)			0.00631** [2.12]	0.00661** [2.23]
Log of Secondary schooling (1960)			-0.0275*** [-10.1]	-0.0274*** [-10.5]
Fertility (1960-1985)			-0.00082 [-0.45]	-0.00026 [-0.15]
Investment/ GDP (1960-1990)			0.144*** [3.88]	0.144*** [3.90]
Per Land Total Disasters (1960-1990)	-0.00117 [-0.89]		0.00247*** [3.23]	
Per Land Climatic Disasters (1960-1990)		-0.00098 [-0.91]		0.00261*** [4.13]
Per Land Geologic Disasters (1960-1990)		-0.00106 [-0.77]		-0.00116 [-1.62]
Constant	0.0468*** [5.35]	0.0474*** [5.65]	-0.0692** [-2.60]	-0.0718*** [-2.79]
Observations	88	88	88	88
R-squared	0.01	0.01	0.78	0.79
*** p<0.01, ** p<0.05, * p<0.1				

Notes: The estimates are obtained from a semi logarithmic regression model.

Robust t statistics are reported in brackets.

*** indicates that the estimate is statistically significant at the one percent level.

** indicates that the estimate is statistically significant at the five percent level.

* indicates that the estimate is statistically significant at the ten percent level.

This regression is a replication of Skidmore and Toya (2002, p.680).

Table 10. Regression table with dependent variable Secondary School Enrollment Ratio: 1960-1985

	(1)	(2)	(3)	(4)
	Dependent Variable : Secondary School Enrollment Ratio (1960-1985)			
Log of Initial Income (1960)			0.101*** [4.40]	0.102*** [4.37]
Log of Secondary Schooling (1960)			0.00785 [0.64]	0.00775 [0.65]
Fertility (1960-1985)			-0.0529*** [-3.48]	-0.0511*** [-3.25]
Investment/ GDP (1960-1990)			0.950*** [5.35]	0.956*** [5.38]
Per Land Total Disasters (1960-1990)	0.0289** [2.33]		0.0108* [1.69]	
Per Land Climatic Disasters (1960-1990)		0.0339*** [3.00]		0.0122* [1.96]
Per Land Geologic Disasters (1960-1990)		-0.0104 [-0.84]		-0.00178 [-0.31]
Constant	0.254*** [3.67]	0.255*** [3.92]	-0.366* [-1.69]	-0.378* [-1.74]
Observations	88	88	88	88
R-squared	0.05	0.08	0.84	0.84
	*** p<0.01, ** p<0.05, * p<0.1			

Notes: The estimates are obtained from a semi logarithmic regression model.

Robust t statistics are reported in brackets.

*** indicates that the estimate is statistically significant at the one percent level.

** indicates that the estimate is statistically significant at the five percent level.

* indicates that the estimate is statistically significant at the ten percent level.

This regression is a replication of Skidmore and Toya (2002, p.680).

Table 11. Regression table with dependent variable Secondary School Enrollment Ratio: 1990-2004

	(1)	(2)	(3)	(4)
Dependent Variable: Secondary School Enrollment Ratio (1990-2004)				
Log of Initial Income (1990)			0.198*** [6.61]	0.189*** [5.79]
Investment / GDP (1990-2004)			0.00631* [1.68]	0.00626 [1.66]
Sub-Saharan Africa			-0.0951 [-1.55]	-0.123* [-1.87]
Latin America			-0.0124 [-0.22]	-0.0123 [-0.22]
NIEs and ASEAN			-0.211*** [-2.87]	-0.217*** [-2.69]
OECD			0.0576 [0.86]	0.0649 [0.91]
Per Land Total Disasters (1990-2004)	0.0294 [1.63]		0.012 [1.22]	
Per Land Climatic Disasters (1990-2004)		0.0312* [1.78]		0.0172* [1.68]
Per Land Geologic Disasters (1990-2004)		-0.0005 [-0.032]		-0.0101 [-1.09]
Constant	0.532*** [4.88]	0.528*** [4.99]	-1.102*** [-5.18]	-1.029*** [-4.39]
Observations	88	88	88	88
R-squared	0.02	0.03	0.81	0.82
*** p<0.01, ** p<0.05, * p<0.1				

Notes: The estimates are obtained from a semi logarithmic regression model.

Robust t statistics are reported in brackets.

*** indicates that the estimate is statistically significant at the one percent level.

** indicates that the estimate is statistically significant at the five percent level.

* indicates that the estimate is statistically significant at the ten percent level.

Table 12. Regression table with dependent variables Tertiary School Enrollment Ratio (1999) and Educational Expenditure (1990-2007)

	(1)	(2)	(3)	(4)
Dependent Variables	Tertiary School Enrollment Ratio (1999)		Educational Expenditure (1990-2007)	
Log of Initial Income (1990)	0.0820*** [4.13]	0.0690*** [3.49]	0.956*** [3.30]	0.793** [2.60]
Investment / GDP (1990-2004)	0.00222 [0.74]	0.0018 [0.65]	0.0239 [0.52]	0.0244 [0.57]
Sub-Saharan Africa	-0.0794** [-2.50]	-0.118*** [-3.23]	0.639 [0.98]	0.12 [0.17]
Latin America	0.0264 [0.67]	0.0284 [0.73]	-0.806* [-1.73]	-0.77 [-1.65]
NIEs and ASEAN	0.0748 [1.02]	0.0666 [0.99]	-2.313*** [-2.81]	-2.417*** [-3.04]
OECD	0.198*** [3.23]	0.214*** [3.79]	-0.979 [-1.66]	-0.827 [-1.39]
Per Land Total Disasters (1990-2004)	-0.0112 [-1.36]		-0.091 [-0.83]	
Per Land Climatic Disasters (1990-2004)		-0.00329 [-0.42]		-0.0158 [-0.14]
Per Land Geologic Disasters (1990-2004)		-0.0142** [-1.99]		-0.213** [-2.59]
Constant	-0.443*** [-2.82]	-0.336** [-2.15]	-3.204 [-1.55]	-1.749 [-0.79]
Observations	81	81	87	87
R-squared	0.79	0.8	0.29	0.34

*** p<0.01, ** p<0.05, * p<0.1

Notes: The estimates are obtained from a semi logarithmic regression model.

Robust t statistics are reported in brackets.

For countries for which no tertiary school enrollment data are found for 1999, data for the next available year are used (mostly 2002). Countries that are excluded for the first two regressions (columns 1 and 2) are Ecuador, Germany, Haiti, Kenya, Singapore, Sri Lanka and Syrian Arab Republic. The country with no educational expenditure data is Papua New Guinea.

Appendix Table A. Definitions and Sources of Variables

Variables	Definition	Source
Per Capita GDP Growth Rate (1960-1990)	Average annual growth rate of real per capita GDP for the period 1960-1990.	SH1
Per Capita GDP Growth Rate (1990-2004)	Average annual growth rate of real GDP per capita (Constant Prices) for the period 1990-2004.	SH2
Log of Initial Income (1960)	Logarithm of real GDP per capita in 1960.	SH1
Log of Initial Income (1990)	Logarithm of real GDP per capita in 1990.	WMP
Government Spending /GDP (1990-2004)	Average Government Share of CGDP (% of GDP) for the period 1990-2004.	SH2
Consumption / GDP (1990-2004)	Average Consumption Share of CGDP (% of GDP) for the period 1990-2004.	SH2
Gross Domestic Savings / GDP (1990-2007)	Average Growth Domestic Savings (% of GDP) (1990-2007)	WDI2
Fertility (1960-1985)	Average net fertility rate for the period 1960-1985.	BL1
Openness (1965-1990)	The fraction of years during the period 1965-90 in which the country is rated as an open economy according to the criteria in Sachs and Warner (1995).	SW
Openness (1990-2004)	Logarithm of average openness in current prices for the period 1990-2004 where openness is defined to be exports plus imports divided by real GDP.	SH2
Total Disasters (1990-2004)	Logarithm of 1+ number of total disaster events (climatic plus geologic) for the period 1990-2004.	CRED
Climatic Disasters (1990-2004)	Logarithm of 1+ number of climatic disaster events for the period 1990-2004.	CRED
Geologic Disasters (1990-2004)	Logarithm of 1+ number of geologic disaster events for the period 1990-2004.	CRED
Per Land Total Disasters (1960-1990)	Logarithm of 1+ number of total disaster events per million square miles for the period 1960-1990.	CRED
Per Land Climatic Disasters (1960-1990)	Logarithm of 1+ number of climatic disaster events per million square miles for the period 1960-1990.	CRED
Per Land Geologic Disasters (1960-1990)	Logarithm of 1+ number of geologic disaster events per million square miles for the period 1960-1990.	CRED
Per Land Total Disasters (1990-2004)	Logarithm of 1+ number of total disaster events per million square miles for the period 1990-2004.	CRED
Per Land Climatic Disasters (1990-2004)	Logarithm of 1+ number of climatic disaster events per million square miles for the period 1990-2004.	CRED
Per Land Geologic Disasters (1990-2004)	Logarithm of 1+ number of geologic disaster events per million square miles for the period 1990-2004.	CRED
Investment / GDP (1960-1990)	Average ratio of real domestic investment to real GDP for the period 1960-1990.	BL1
Investment/ GDP (1990-2004)	Average Investment Share of CGDP (% of GDP) for the period 1990-2004.	SH2
Growth in Capital Stock (1960-1985)	Average annual growth rate of physical capital stock per capita constructed by Kind and Levine (1994) for the period 1960-1985.	KL
Gross Capital Formation / GDP (1990-2004)	Average Gross Capital Formation (% of GDP) for the period 1990-2004.	WDI2

Continued

Variables	Definition	Source
Growth in Secondary Schooling Year (1960-1990)	Average annual growth rate of secondary schooling year for the period 1960-1990.	BL2
Log of Secondary schooling (1960)	Logarithm of secondary schooling years in the total population aged 15 and over in 1960.	BL2
Log of Secondary school enrollment (1990)	Logarithm of gross secondary school enrollment ratio in 1990.	WDI2
Secondary School Enrollment Ratio (1960-1985)	Average gross secondary school enrollment ratio for the period 1960-1985.	WDI1
Secondary School Enrollment Ratio (1990-2004)	Average gross secondary school enrollment ratio for the period 1990-2004.	WDI2
Tertiary School Enrollment Ratio (1999)	Gross tertiary school enrollment ratio in 1999.	WDI2
Educational Expenditure (1990-2007)	Educational expenditure (% of GNI) for the period 1990-2007.	WDI2
Sub-Saharan Africa	Dummy for Sub-Saharan African countries.	ST
Latin America	Dummy for Latin-American countries.	ST
NIEs and ASEAN	Dummy for NIEs and ASEAN member countries.	ST
OECD	Dummy for OECD member countries.	ST

Sources:

BL1: Barro and Lee (1994).

BL2: Barro and Lee (1996).

CRED: EM-DAT. (2009).

KL: King and Levine (1994).

SH1: Summers and Heston (1994).

SH2: Summers and Heston (2006).

ST: Skidmore and Toya (2002).

SW: Sachs and Warner (1997).

WDI1: World Development Indicators (1998).

WDI2: World Development Indicators (2009).

WMP: World Mapper. [37]

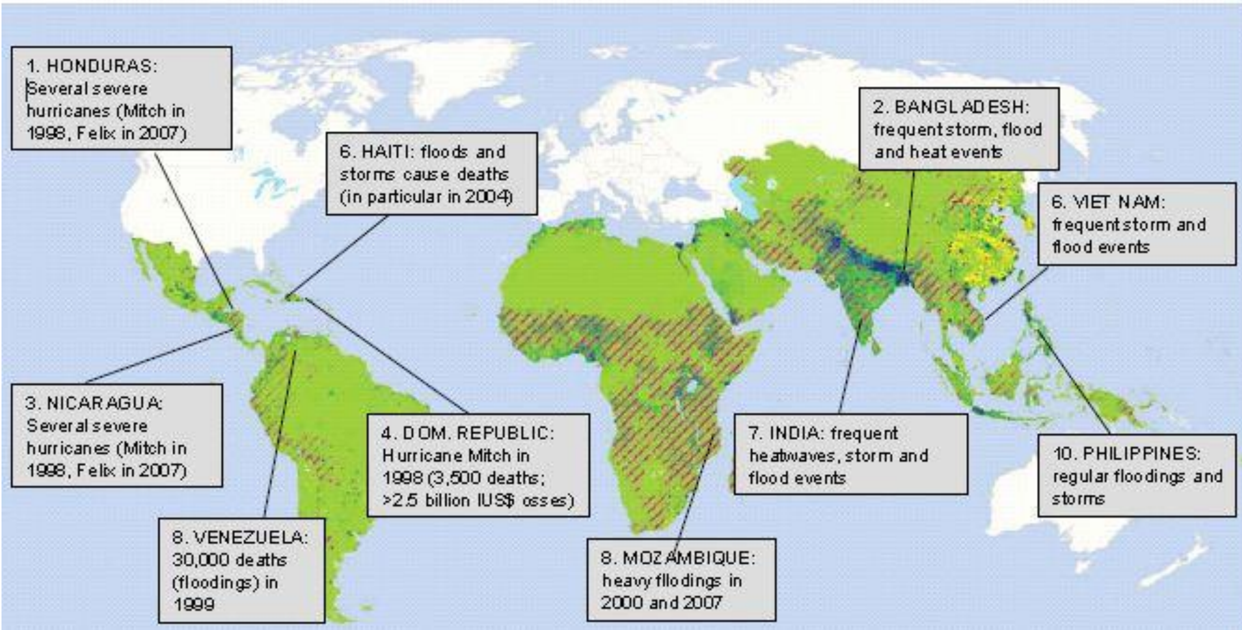
[37] Available at http://www.worldmapper.org/display.php?selected=163.

Appendix Table B. Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Per Capita GDP Growth Rate (1960-1990)	88	0.0200814	0.017229	-0.013893	0.066633
Per Capita GDP Growth Rate (1990-2004)	88	0.0167112	0.0183582	-0.041503	0.07
Log of Initial Income (1960)	88	7.518449	0.863173	5.7462	9.19979
Log of Initial Income (1990)	88	8.333317	1.087383	6.324359	10.05195
Government Spending /GDP (1990-2004)	88	19.9873	7.614395	5.413169	47.7575
Consumption / GDP (1990-2004)	88	67.34843	13.30569	38.84288	110.3162
Gross Domestic Savings / GDP (1990-2007)	88	18.18114	11.78566	-27.556	47.389
Fertility (1960-1985)	88	4.35379	1.515995	1.85302	7.20038
Openness (1965-1990)	82	0.4165665	0.4482854	0	1
Openness (1990-2004)	88	4.160218	0.5738483	2.773231	5.866682
Total Disasters (1990-2004)	88	29.48864	44.71879	0	330
Climatic Disasters (1990-2004)	88	25.38636	40.82664	0	317
Geologic Disasters (1990-2004)	88	4.102273	8.292137	0	55
Per Land Total Disasters (1960-1990)	88	4.871978	1.991405	0	11.96559
Per Land Climatic Disasters (1960-1990)	88	4.615195	2.113321	0	11.96559
Per Land Geologic Disasters (1960-1990)	88	1.668894	2.041804	0	6.12503
Per Land Total Disasters (1990-2004)	88	5.198774	1.762258	0	10.63993
Per Land Climatic Disasters (1990-2004)	88	5.066141	1.758786	0	10.63993
Per Land Geologic Disasters (1990-2004)	88	1.974229	2.090313	0	6.918795
Investment / GDP (1960-1990)	88	0.1938256	0.0813297	0.019997	0.37825
Investment/ GDP (1990-2004)	88	16.13562	8.024189	2.9409	37.74832
Growth in Capital Stock (1960-1985)	88	0.6542348	0.5543822	-0.71858	2.32263
Gross Capital Formation / GDP (1990-2004)	88	21.61807	6.500118	7	54.07
Growth in Secondary Schooling Year (1960-1990)	88	0.0410966	0.0313567	-0.022233	0.22163
Log of Secondary schooling (1960)	88	-0.9623909	1.380523	-6.90776	1.50452
Log of Secondary school enrollment (1990)	88	-0.7382054	0.715637	-2.813411	0.1739533
Secondary School Enrollment Ratio (1960-1985)	88	0.3944913	0.2521885	0.025833	0.91
Secondary School Enrollment Ratio (1990-2004)	88	0.6852423	0.3295576	0.071111	1.394
Tertiary School Enrollment Ratio (1999)	81	0.2648839	0.2207905	0.0029	0.8242
Educational Expenditure (1990-2007)	87	4.202805	1.645327	0.944	7.722
Sub-Saharan Africa	88	0.2272727	0.4214718	0	1
Latin America	88	0.2613636	0.4418956	0	1
NIEs and ASEAN	88	0.0681818	0.2535021	0	1
OECD	88	0.2613636	0.4418956	0	1

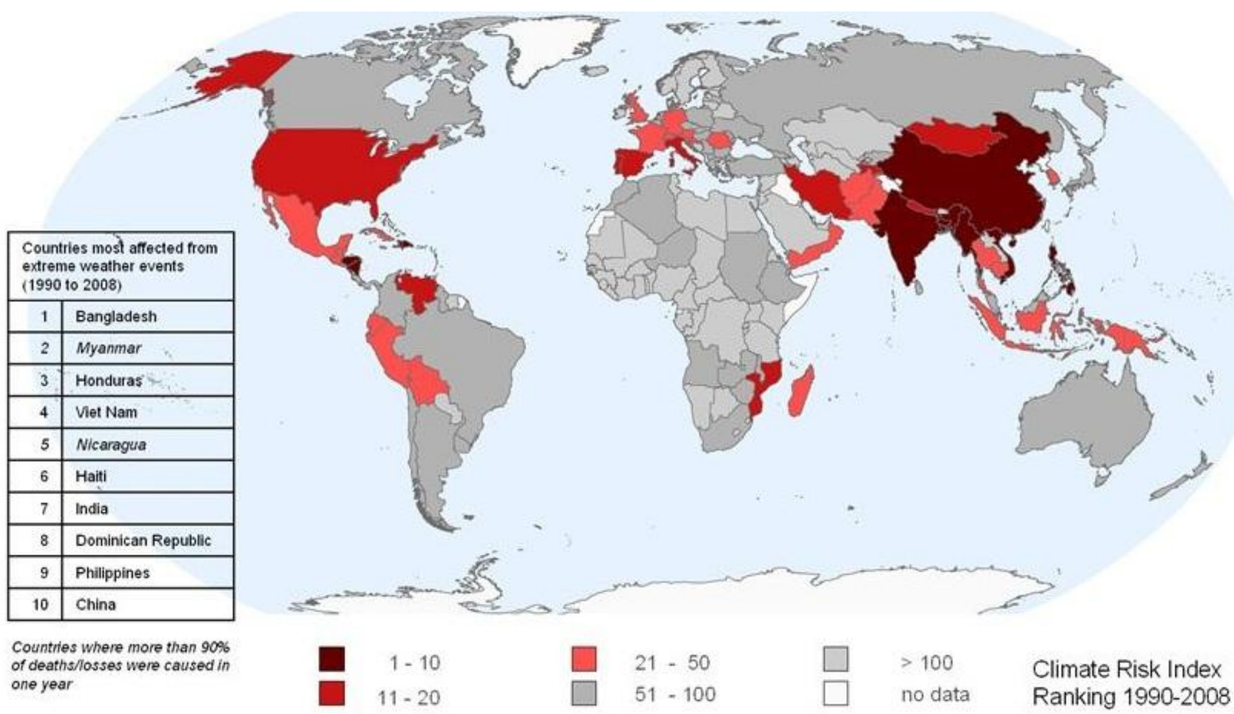
Appendix Table C. List of Countries

Algeria	DZA	Kenya	KEN
Argentina	ARG	Korea, Rep.	KOR
Australia	AUS	Lesotho	LSO
Austria	AUT	Liberia	LBR
Bangladesh	BGD	Malawi	MWI
Barbados	BRB	Malaysia	MYS
Belgium	BEL	Mali	MLI
Bolivia	BOL	Mauritius	MUS
Botswana	BWA	Mexico	MEX
Brazil	BRA	Mozambique	MOZ
Cameroon	CMR	Nepal	NPL
Canada	CAN	Netherlands	NLD
Central African Republic	CAF	New Zealand	NZL
Chile	CHL	Nicaragua	NIC
Colombia	COL	Niger	NER
Congo, Dem. Rep.	ZAR	Norway	NOR
Costa Rica	CRI	Pakistan	PAK
Cyprus	CYP	Panama	PAN
Denmark	DNK	Papua New Guinea	PNG
Dominican Republic	DOM	Paraguay	PRY
Ecuador	ECU	Peru	PER
El Salvador	SLV	Philippines	PHL
Fiji	FJI	Portugal	PRT
Finland	FIN	Senegal	SEN
France	FRA	Singapore	SGP
Germany	DEU	South Africa	ZAF
Ghana	GHA	Spain	ESP
Greece	GRC	Sri Lanka	LKA
Guatemala	GTM	Swaziland	SWZ
Guyana	GUY	Sweden	SWE
Haiti	HTI	Switzerland	CHE
Honduras	HND	Syrian Arab Republic	SYR
Hong Kong, China	HKG	Thailand	THA
Iceland	ISL	Togo	TGO
India	IND	Trinidad and Tobago	TTO
Indonesia	IDN	Tunisia	TUN
Iran, Islamic Rep.	IRN	Turkey	TUR
Iraq	IRQ	Uganda	UGA
Ireland	IRL	United Kingdom	GBR
Israel	ISR	United States	USA
Italy	ITA	Uruguay	URY
Jamaica	JAM	Venezuela	VEN
Japan	JPN	Zambia	ZMB
Jordan	JOR	Zimbabwe	ZWE



<Figure 7 (a): World map of hazard hotspots and countries most affected from 1998-2007 according to CRI>
The underlying map is taken from CARE 2008
Note: on the map, blue areas with striped overlay represent risk hotspots with predicted significant increase in population density. The darker the underlying color, the higher is the expected increase in population density.

Source: Harmeling (2008, p.8)



<Figure 7 (b): World map of Climatic Risk Index Ranking 1990-2008>

Source: Harmeling (2009, p.8)

References

Albala-Bertrand, J. M. *Political economy of large natural disasters*. Oxford, United Kingdom: Clarendon Press, 1993.

Anbarci, N., M. Escaleras, and C. A. Register. “Earthquake Fatalities: The Interaction of Nature and Political Economy.” *Journal of Public Economics* 89 (2005): 1907–1933.

Barro, Robert J., and Xavier Sala-I-Martin. *Economic Growth*, New York, NY: McGraw-Hill Inc, 1995.

Barro, R., and J. Lee. “Data Set for a Panel of 138 Countries.” 1994. Taken from the NBER web page. http://www.nber .org/ftp/barro.lee/.

_____. “International Measures of Schooling Years and Schooling Quality.” *American Economic Review,* 86 (1996): 218-23.

Bland M. *An Introduction to Medical Statistics* (3rd edition). New York: Oxford University Press, 2000.

Bluedorn, J. C. “Hurricanes: Intertemporal Trade and Capital Shocks.” Nuffield College Economics Paper 2005-W22. 2005.

Cavallo, E. and I. Noy. “The Economics of Natural Disasters- A survey.” Inter-American Development Bank Working Paper Series # IDB-WP-124, 2. 2009.

Cuaresma, J.C., J. Hlouskova, and M. Obersteiner. “Natural disasters as Creative Destruction? Evidence from Developing Countries.” *Economic Inquiry* 46 (2008): 214-226.

Dacy, D. C., and H.C. Kunreuther. *The Economics of Natural Disasters: Implications for Federal Policy*, New York, United States: The Free Press, 1969.

Davis, L. Natural Disasters*: From the Black Plague to the Eruption of Mt. Pinatubo*. New York: Facts on File, 1992.

Dorling, D. “World Mapper”. http://www.worldmapper.org/ (April.16.2010).

EM-DAT. 2009. The OFDA/CRED International Disaster Database. Université Catholique de Louvain, Brussels, Belgium. http://www.em-dat.net.

Hallegatte, S. and P. Dumas. “Can Natural Disasters have Positive Consequences? Investigating the Role of Embodied Technical Change.” *Ecological Economics* 68 (2009): 777-786.

Harmeling, Sven. “Global Climate Risk Index 2009: Weather-related loss events and their impacts on countries in 2007 and in a long-term comparison.” Gerold Kier and Thomas Spencer (eds.) Germanwatch e.V.: Bonn, Germany. 2008.

_____. “Global Climate Risk Index 2010: Who is most vulnerable? Weather-Related Loss Events since 1990 and how Copenhagen Needs to Respond.” Germanwatch e.V.: Bonn, Germany. 2009.

Hirshleifer, J. “Disaster and Recovery: The Black Death in Western Europe,” Rand Corporation Memorandum. 1996. http://www.rand.org/pubs/research_memoranda/2005/RM4700.pdf.

Hochrainer, S. “Assessing the Macroeconomic Impacts of Natural Disasters – Are there any?” World Bank Policy Research Working Paper 4968. Washington, DC, United States: The World Bank. 2009.

Jaramillo, C. R. H. *Do Natural Disasters Have Long-Term Effects On Growth?* Manuscript. Bogota, Colombia: Universidad de los Andes. 2009.

Kahn, M. E. “The Death Toll from Natural Disasters: The Role of Income, Geography, and Institutions”. *Review of Economics and Statistics* 87 (2005): 271–284.

King, R. and R. Levine. “Capital Fundamentalism, Economic Development, and Economic Growth.” *Carnegie-Rochester Conference Series on Public Policy*, 40 (1994): 259-92.

Leiter, A. M., H. Oberhofer, and P. A. Raschky. "Creative Disasters? Flooding Effects on Capital, Labor and Productivity within European Firms." *Environmental and Resource Economics* 43 (2009): 333–350.

Loayza, N., E. Olaberría, J. Rigolini, and L. Christiansen. "Natural Disasters and Growth-Going Beyond the Averages." World Bank Policy Research Working Paper 4980. Washington, DC, United States: The World Bank. 2009.

Lucas, R. "On the Mechanics of Economic Development." *Journal of Monetary Economics,* 22 (1988): 3-42.

Mechler, R. "Disasters and Economic Welfare: Can National Savings Help Explain Post-disaster Changes in Consumption?" World Bank Policy Research Working Paper 4988. Washington, DC, United States: The World Bank. 2009.

Noy, I. and A. Nualsri. "What do Exogenous Shocks tell us about Growth Theories?" University of Hawaii Working Paper 07-28. 2007.

Okuyama, Y. "Economics of natural disasters: A critical review." Research Paper 2003-12, Regional Research Institute, West Virginia University. 2003.

Raddatz C. "Are External Shocks Responsible for the Instability of Output in Low-Income Countries?" *Journal of Development Economics* 84 (2007): 155-187.

_____. "The Wrath of God: Macroeconomic Costs of Natural Disasters." Manuscript. 2009.

Rodriguez-Oreggia, E., A. de la Fuente, and R. de la Torre et al. "The Impact of Natural Disasters on Human Development and Poverty at the Municipal Level in Mexico." Manuscript. 2009.

Sachs, J., and A. Warner. "Fundamental Sources of Long-Run Growth." *American Economic Review Papers and Proceedings*, 87 (1997): 184-88.

Skidmore, Mark. “RE: Data from your paper: Do Natural Disasters Promote Long-run Growth? (2002),” email message to Chul-Kyu Kim, 2 April 2010.

Skidmore, M. and H. Toya. “Do Natural Disasters Promote Long-run Growth?” *Economic Inquiry*, 40 (2002): 664-687.

_____. 2007. “Economic development and the impacts of natural disasters.” *Economic Letters*, 94 (2007): 20-25.

Solow, Robert M. “A Contribution to the Theory of Economic Growth,” *Quarterly Journal of Economics*, 70 (1956): 65-94.

Strobl, E. “The Economic Growth Impact of Hurricanes: Evidence from U.S. Coastal Counties.” IZA Discussion Papers Series. 2008.

Summers, R., and A. Heston. 1994. “The Penn World Table (Mark 5.6).” http:// pwt.econ.upenn.edu/.

Summers, R., A. Heston, and B. Aten. 2006. Penn World Table Version 6.2, Center for International Comparisons of Production, Income and Prices at the University of Pennsylvania.

WDI. World Development Indicators on CD-ROM. The World Bank. 1998.

WDI. World Development Indicators on CD-ROM. The World Bank. 2009.

Yang, D. “Coping With Disaster: The Impact of Hurricanes on International Financial Flows.” *B.E. Journal of Economic Analysis and Policy* 8 (2008):13.