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# DO NATURAL DISASTERS HAVE LONG-TERM EFFECTS ON GROWTH?<sup>1</sup>

#### CHRISTIAN R. JARAMILLO H.2

#### Abstract

Large natural disasters (LNDs) are ubiquitous phenomena with potentially large impacts on the infrastructure and population of countries and on their economic activity in general. Using a panel of 113 countries and 36 years of data, I examine the relationship between different measures of natural disaster impact and long-run economic growth. The sample is partitioned in two separate ways: according to the amount and type of disasters that countries have experienced and to the size of those disasters. For each partition, I present two sets of econometric estimations. The first regressions identify short-run and longer-lasting effects of LNDs. However, these first estimations do not distinguish between temporary but persistent effects and truly permanent ones. I thus estimate a structural model that allows me to identify permanent changes. The results of the first regressions show that for some of the groups of countries the disaster impact persists beyond the 2-5 years in which reconstruction and adaptation are expected to have an effect on the economy. However, the estimates using the structural model show that only for a very small number of countries which share a history of highly devastating natural disasters the negative effects are truly permanent.

Key words: Natural disasters, catastrophes, hurricanes, earthquakes, growth, panel data.

JEL Classification: O11, O19, Q54.

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# ¿TIENEN LOS DESASTRES NATURALES EFECTOS DE LARGO PLAZO SOBRE EL CRECIMIENTO?

#### CHRISTIAN R. JARAMILLO H.

#### Resumen

Los desastres naturales de grandes proporciones son fenómenos recurrentes que pueden tener un gran impacto en la infraestructura y la población de los países afectados y en su actividad económica. Este artículo examina la relación de largo plazo entre distintas medidas de impacto de los desastres naturales y el crecimiento económico usando un panel de 113 países para 36 años. Para realizar el análisis divido la muestra de dos formas: Según el tipo v la cantidad de desastres y según la magnitud de los desastres. Con cada partición de la muestra realizo dos ejercicios econométricos. Las primeras regresiones permiten distinguir entre efectos de corto plazo de los desastres naturales sobre el crecimiento y efectos de más largo plazo. Sin embargo, estas regresiones no permiten distinguir entre efectos temporales pero persistentes y efectos en verdad permanentes. Es por esto que también estimo un modelo estructural que sí me permite hacer esta distinción. Los resultados de las primeras regresiones indican que para ciertos grupos de países los desastres sí tienen un efecto más allá de los dos a cinco años en que el proceso de reconstrucción y adaptación debería afectar a la economía. No obstante, las estimaciones del modelo estructural muestran que sólo en un grupo muy reducido de países, los cuales comparten una historia de desastres naturales muy devastadores, el impacto de estos eventos puede ser considerado permanente.

Palabras clave: Desastres naturales, catástrofes, huracanes, terremotos, crecimiento, datos panel.

Clasificación JEL: O11, O19, Q54.

#### I. Introduction

That large natural disasters (LNDs) have economic effects is not very controversial. The loss of lives and capital plus the disruption in productive activities in the aftermath of a natural disaster are some of the mechanisms through which an event of this nature may affect the economy of a country. What is not so clear is how a disaster changes a country's GDP growth rate. Even less understood is the timing of such an impact. For how long should one expect to observe signs of the effect of natural disasters in macroeconomic statistics? Are we talking only about a short-term fluctuation in economic activity or do natural disasters have long-run effects on growth?

This paper provides answers to these questions using panel data on recorded disaster events and macroeconomic variables of 113 countries over a 36-year span. I run regressions using different disaster measures to explore the existence and direction of both short-run and long-run disaster effects on current GDP.

To study long-term effects one must define the meaning of "long run". How many years must pass before an effect can be considered a long-run effect? I use different definitions of "short-run" –two, three or five years— to check the robustness of the estimates. However, this does not allow me to distinguish between permanent effects and effects that are transitory but long-lived. For this I estimate a structural model which allows me to identify truly permanent effects.

The economic literature on natural disasters has two main strands: On the one hand, there are several case studies documenting the ways in which specific disasters have affected different countries. These case studies provide valuable insights on the mechanisms through which natural disasters may have an economic impact. Section II of this paper summarizes some of the main lessons that have been learnt from these works.

On the other hand, the availability of data on worldwide natural disasters has made possible several panel data studies on the macroeconomic consequences of these events. Some have found evidence of negative short-term effects (Auffret, 2003; Heger, Julca & Paddison, 2008; Noy, 2009), while others have found a positive long-run effect for certain types of disasters (Skidmore & Toya, 2002). The results of these papers are also discussed in Section II. To my knowledge, all of these studies have focused either on the short-term or on the long-term effects of disasters but have not incorporated both dimensions simultaneously, which is one of the contributions of my research.

The data on disasters that I use is the same one employed in these studies and comes from EM-DAT: The OFDA/CRED International Disaster Database. It contains records of people killed, injured, homeless and otherwise affected, estimated damages, dates of occurrence and the countries affected by natural, technological and political disasters. The data are a compilation from different sources, among them the UN, OFDA, reinsurance firms and several NGOs and humanitarian institutions, and it includes events starting 1900 through the present. The time series data on macroeconomic variables comes from the Penn World Tables 6.0.

These contain data from 1950-1998, albeit most countries start reporting in 1960. This period seems to coincide with the more reliable data in the EM-DAT database (Jaramillo, 2007).

The regressions show that there are indeed short-term, long-term but temporary, and permanent effects of LNDs. However, the direction and magnitude of those effects depends on the frequency and intensity of the disasters that affect the country. The results of this paper can therefore be interpreted as identifying a specific mechanism through which geography plays an important role in the process of economic development (Sachs, 2001).

The next section discusses the theory and evidence on the economic consequences of natural disasters, drawn mainly from case studies. Section III describes the data in detail, emphasizing aspects that require special attention. In Section IV, I i) present the methodology employed to partition the sample and the resulting groups of countries, ii) derive the empirical specifications for the econometric analyses from a simple growth model, iii) present the estimation results. Section V concludes.

## II. Theory and Evidence on the Economic Consequences of Natural Disasters

Why should a natural disaster have an effect on economic growth in either the short or long run? Specific natural disasters provide evidence on some of the mechanisms by which this type of event can affect the economic performance of a country. Figure 1 shows the usual sequence of events following a natural disaster. I have divided these consequences into four main categories: Immediate consequences, short-term, medium-term and long-term effects. A similar classification is proposed by Otero & Martí (1995), who use the names "emergency", "rehabilitation and immediate recovery" and "reconstruction", where the first two periods fall into what I have called the short run, while reconstruction corresponds to what I have called the medium run.

What happens right after a natural disaster occurs? As can be seen in Figure 1, a natural disaster kills people, harms other people in a way that requires aid (injured, homeless, etc.) and damages or destroys buildings, roads, crops, etc. Horwich (2000) reports that 6,500 people died as a result of the Kobe earthquake, almost 400,000 buildings were damaged or destroyed and over 300,000 people lost their houses. Likewise, Auffret (2003) writes that hurricanes David and Frederick killed 2,000 people in a span of five days, left 100,000 families without a roof and generated damages equivalent to one third of that year's GNP in the Dominican Republic. These figures illustrate the destructive potential of natural disasters.

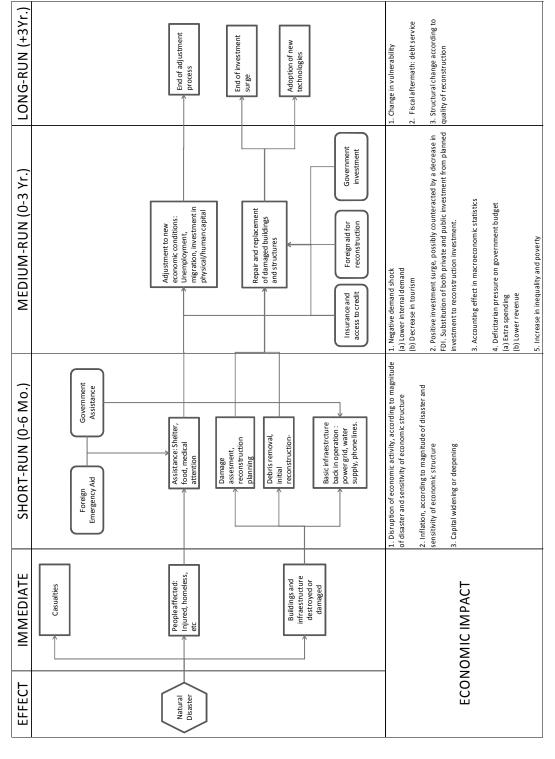
Any indirect economic effects that natural disasters may have are mainly consequences of their direct and immediate impact, which tends to vary according to the type of disaster. Otero & Martí (1995) identify the effects on infrastructure and agriculture of different types of disasters and suggest, for example, that earthquakes are extremely harmful for infrastructure but have almost no effect on agriculture, while droughts have the opposite effect, being very bad for agriculture without significantly affecting infrastructure.

As shown in Figure 1, the first six months after a disaster has occurred can be characterized by three simultaneous events. To begin with, humanitarian assistance is provided to the people affected by the natural disaster. Injured people receive medical treatment, while the homeless are given food and shelter. Usually, it is the local government who provides aid to affected regions, backed by foreign governments and other organizations. The extent to which emergency aid is provided from abroad is likely to depend on the income level of the affected country, the magnitude of the disaster and on other factors, including international political considerations. Second, regarding material damages, it is likely that in the first couple of months following a natural disaster the main objective will be to reestablish some basic public services, such as electricity, water and communications, with success depending on the severity of damages and on the institutional capacity of the local government. In the case of Kobe, lifeline utility services were fully restored within three months of the earthquake (Horwich, 2000). Lastly, at this point the long-term reconstruction activities are likely to be just starting.

What could happen to the affected country's economy in these initial months following a disaster? In the very short run there will probably be a disruption of economic activity in the affected region. Whether this economic halt has an effect on economic statistics such as GDP growth depends on several factors, including the promptness and quality of the aid provided to the affected population. Assistance to the affected population is important because it will determine the speed with which productive factors are put back to use after a natural disaster. Quick and organized help to the affected population has other benefits, which include preventing the spread of disease among the injured and homeless.

Another important factor is the economic importance of the affected regions and industries. Albala-Bertrand (1993) suggests that inter-sectoral linkages, the internal composition of sectors and the types of capital stock damaged or lost are the main determinants of the economic significance of a natural disaster. For instance, a country whose economy depends to a large extent on oil exports might experience a significant decrease in economic growth if a natural disaster causes its main refineries to stop operating for a significant part of the year. Otero & Martí (1995) report that this was indeed the case after the 1987 earthquake in Ecuador, where damages to infrastructure in the oil sector caused a 2.7% contraction in GDP. More generally, Heger, Julca & Paddison (2008) claim that the economic structure of Small Island Developing States (SIDS) in the Caribbean (being highly dependent on agriculture, tourism and trade) intensifies disaster impact. On the other hand, if a natural disaster affects a remote province whose agricultural output adds little to the country's GDP, the effect might be none. This was not the case in the Dominican Republic in 1998, when the path followed by Hurricane Georges included more than 70% of the country (Auffret, 2003). By their sheer size, large industrial economies can more easily absorb output shocks from natural disasters originating in specific provinces or sectors in the economy (Auffret, 2003). Horwich (2000) suggests that the Kobe earthquake did not have significant impact on the Japanese economy because of substantial substitution of production from the affected region to other regions which had idle capacity due to Japan's discrete economic performance in the previous years.

Figure 1: The economic life-cycle of a natural disaster



Do natural disasters have a short-term effect on economic growth? Albala-Bertrand (1993) compares GDP growth rates before and after 28 major natural disasters and does not find evidence of a significant difference. Charvériat (2000) conducts a similar exercise using information on 35 natural disasters in Latin America and the Caribbean between 1980 and 1996 and finds a median decrease in real GDP growth rates of 2 percentage points in the year of the disaster, followed by a 3 percentage point increase in the two following years. On the other hand, Auffret (2003) finds a negative contemporary effect of damages due to natural disasters on GDP growth for a set of countries from Latin America and the Caribbean. For some small Caribbean islands, Heger, Julca & Paddison (2008) report evidence of a contemporary negative impact of natural disasters on GDP growth. Using a panel VAR model, Raddatz (2007) finds that geologic disasters have no significant effect on output, but that climatic and humanitarian (famines and epidemics) disasters have a negative and significant effect on GDP. More importantly for my purposes, the effect of climatic disasters is found to disappear after five years. Lastly, Noy (2009) observes a negative effect of natural disasters on contemporary GDP growth after controlling for several country characteristics.

A natural disaster may also have a short-run effect on local prices, insofar as there may be both a decrease in supply and an increase in demand for certain goods. In the aftermath of a disaster people usually rush to buy basic supplies such as bottled water, canned food, etc. Benson & Clay (2004) report how flooding of rice fields in Bangladesh in 1974 contributed to price volatility of foodstuffs and led to widespread famine. In the case of Dominica, these authors find that the food price index increased over 45% between 1978 (year in which hurricane David hit the island) and 1979. However, Albala-Bertrand (1993) reports having found no such increase in the price level following 28 major natural disasters.

The mixture of deaths and damages following a natural disaster also has an impact on the capital/labor ratio. The standard Solow growth model, which will be further discussed in Section IV, predicts that an economy's GDP growth rate depends fundamentally on the distance between a country's current capital/labor ratio and the steady-state value of that ratio. Countries near their steady state grow more slowly than countries farther away from the steady state, basically due to decreasing returns to capital. Within this framework, what may happen to a country after a natural disaster? The two broad possibilities are that the country experiences capital deepening (an increase in capital per worker) or capital widening (a decrease in capital per worker). In the first scenario, if the country is below its steady state it would be instantaneously moved closer to it, which would cause short-run growth to decrease. In the second scenario, the opposite would happen. In either case, all effects would be exclusively short-run effects. Okuyama (2003) and Loayza et al. (2009) provide diagrams discussing this effect, while Olaberría (2009) develops a three-sector model to analyze the differential impact of different types of natural disasters.

The medium run can be thought of as the initial couple of years following a natural disaster. As shown in Figure 1, most of the reconstruction and repair of damaged buildings and most of the adaptation by affected population take place at this time.

How the reconstruction process is funded has important economic consequences. Once again, the local government is likely to play an important role funding reconstruction investments, with some assistance by foreign governments. The Inter-American Development Bank has estimated that the percentage of disaster damages covered by the international community ranges from 6 percent to 25 percent, averaging 8.6 percent (Freeman, Keen & Muthukumara, 2003).

There may also be some degree of private funding of reconstruction projects. Particularly, insurance companies will fund repairs and reconstructions in accordance with the proportion of property insured. Insurance markets are important in this context because they determine the extent to which output volatility translates into consumption volatility (Auffret, 2003), and yet the share of insured property tends not to be very high. Skidmore & Toya (2002) report that in an industrialized city such as japanese Kobe only 3% of property was insured at the time of the 1995 earthquake. Even in Tokyo only 16% of property was insured at that time. Freeman, Keen & Muthukumara (2003) argue that insurance, both private and public, is likely to be particularly low in developing countries because people expect government to come in their help when disaster strikes, and the government expects similar assistance from the international community. This is known as the "Samaritan's dilemma". Other supply and demand factors affecting insurance coverage include difficulties in risk assesment due to the generally low probability of occurrence of natural disasters and low levels of development of the insurance market (Charvériat, 2000; Freeman, Keen & Muthukumara, 2003).

Access to credit can also be an important determinant of the reconstruction process, both at the micro and the macro level. For example, peasants whose crops are damaged due to natural disasters may find it very difficult to recover if they have no access to credit to invest in next season's crops. Similarly, the local government might need some additional funding in order to replace damaged infrastructure such as airports or roads.

The medium run is also the time when people adjust to the new circumstances brought about by the ocurrence of a natural disaster. For example, some people may decide to emigrate from affected regions. In the extreme case an entire area may end up being uninhabitable, as in Montserrat, where 70% of the population had to emigrate after the eruption of the Soufriere Hills volcano in 1995 (Auffret, 2003). After the Kobe earthqueake, it has been estimated that around 100,000 people left the affected region (Horwich, 2000). One of the reasons for emigrating may be increased unemployment in the affected region following a natural disaster. For example, peasants may be unable to find work in flooded fields. However, the tendency towards greater unemployment may be partially or totally counteracted by the job creation due to reconstruction projects.

In the medium run people also face different kinds of investment decisions. Changes in the labor market and in individual circumstances may make additional education more or less attractive. Business owners may be faced with the decision either to repair their damaged property, demolish and completely rebuild or simply relocate elsewhere. Both for the government and for individuals, access to credit will be an important constraint on investment decisions.

What macroeconomic effects can this medium-run adjustment process have? Significant changes in the labor market may occur during the first few years after a natural disaster due to fluctuations in aggregate demand, both internal and external. Areas in which tourism is an important source of income for a large part of the population can experience a severe economic downturn due to a significant decrease in the number of tourists visiting the area. This decrease in tourism may be due to the fact that people are afraid that another natural disaster may occur or because potential tourists think that it is not worthwhile to visit until reconstruction has finished. In the case of Dominica, Benson & Clay (2004) find that hurricane David in 1979 halted tourism growth for five years. Given that tourism represents around 35% of Dominica's external earnings, that was a serious blow to the country's economy. Crowards (2000) reports a sharp drop (averaging 13%) in tourist arrivals in a disaster year for caribbean islands between 1990 and 1998. Even though the number of tourists slowly picks up in subsequent years, Crowards finds that it takes a long time for it to return to its pre disaster level and that it may never do so.

The reconstruction phase implies an increase in investment, both public and private. This investment surge may offset the negative demand effect due to a decrease in private consumption and tourism. This was the case in Dominica, Bangladesh and Malawi, where Benson & Clay (2004) find that in the years following a natural disaster there was an increase in GDP growth. This may also help to explain Noy's (2009) finding of positive growth in the year that a disaster strikes. However, a particular fact about growth accounting may be responsible for this positive effect. Growth accounting is concerned with fluctuations in flows rather than stocks. Therefore, when a natural disaster occurs the losses are not incorporated into the national accounts while the investment surge due to reconstruction is (Jaramillo, 2007). As shown in Figure 2, at t<sub>0</sub> the natural disaster occurs and the country experiences a reduction in real GDP due to human and material losses. Afterwards, from t<sub>0</sub> to t<sub>T</sub> reconstruction takes place and the country experiences GDP growth due to more investment. The problem with growth accounting is that while the country is actually moving along path GDP<sub>R</sub>, the national accounts reflect a fictitious path GDP<sub>A</sub> in which only the positive investment effect is observed.

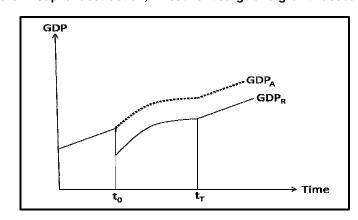


Figure 2: Capital destruction, investment surge and growth accounting

Even if total investment increases after a natural disaster, foreign direct investment (FDI) is likely to experience a negative shock in the years following a disaster. There are several possible explanations for this: first, foreign investors may perceive that damages to road and communications infrastructure pose significant obstacles to the normal operation of their businesses. Second, the economic downturn may make investors think that they will not make a sufficiently attractive profit. Third, investors may consider investment in disaster-stricken countries to be more risky than it was before the occurrence of the disaster, and opt to invest elsewhere (Charvériat, 2000).

These fluctuations in investment can have an effect on the affected country's external balance, even more if we consider the possibility of reduced exporting capability due to damaged infrastructure and assets. Rasmussen (2004) reports a median increase in current account deficit of 10.8 percent of GDP for the member countries of the Eastern Caribbean Currency Union (ECCU) following the 12 worst natural disasters since 1970. Also studying islands from the Caribbean, Crowards (2000) finds for the period 1990-1998 a mean widening of the trade deficit of 20 percentage points in the year of disaster occurrence. The balance of payments could also be affected by an increase in capital inflows due to foreign aid and by additional imports due to reconstruction projects. Heger, Julca & Paddison (2008) find that very specialized economies are more likely to see a substantial increase in their imports due to natural disasters. Additionally, there are likely to be presurres towards a depreciation of the exchange rate due to the deficitarian trade balance and the decrease in FDI (Freeman, Keen & Muthukumara, 2003).

Governments in affected countries will be faced with unexpected expenditures, which might push the government's budget towards a public deficit. However, Benson & Clay (2004) find that aggregate statistics on fiscal performance are not a good indicator of the fiscal impact of natural disasters, since governments tend to reallocate expenditures within a given budget rather than incur in additional expenses following a disaster. In fact, Raddatz (2007) finds for 40 low-income and predominantly African countries that government expenditure tends to decrease after a natural disaster. This may be a wise decision insofar as extra spending probably has to be funded via foreign credit, with the consequent increase in debt service in future years. Also, foreign aid programs may be conditioned on fiscal performance by the recipient country and so could be jeopardized by an increase in public deficit following a natural disaster (Otero & Martí, 1995). Rasmussen (2004) finds for ECCU members a median increase of 6.5 percentage points in the ratio of public debt to GDP over the three years following the 12 largest natural disasters since 1970.

How do governments manage to reallocate expenses in order to have funds available for reconstruction? Development and infrastructure projects are the ones from which resources are usually taken away to finance reconstruction activities (Benson & Clay, 2004). This may be a mechanism by which natural disasters affect long-run economic growth, since governments tend to postpone important investments in infrastructure and development programs with a potentially high expected return in terms of future economic growth and poverty reduction and invest the money in reconstruction projects with a lower long-term impact. Public finances can also be affected via a decrease in revenue due to the economic downturn in the aftermath of a

disaster. Otero & Martí (1995) report that in 12 case studies conducted by ECLAC on different natural disasters in Latin America there was always an increase in the public deficit after the disaster event.

The consequences of a natural disaster are not likely to be equally distributed among all strata of the population. Two main factors contribute to this post-disaster increase in inequality. First, it is the least well-off who are most likely to suffer large relative losses when a natural disaster occurs (Freeman, Keen & Muthukumara, 2003). For instance, poor people tend to build their houses in unstable areas and their foundations do not usually meet anti-seismic requirements (Charvériat, 2000). Second, it is the least well-off who are most likely to be uninsured and to lack access to credit, making recovery even more difficult for them. Otero & Martí (1995) report that 20 years after the 1972 earthquake in Nicaragua, the "precarious urban conformation" of the capital city of Managua still revealed the devastation caused by the earthquake. Benson & Clay (2004) find that foreign governments and aid agencies tend, just like local governments, to reallocate expenditure rather than to increase overall expenditure in the aftermath of a disaster, negatively affecting the possibilities of recovery of the affected population. This may explain Raddatz's (2007) finding of no significant effect of natural disasters on the overall amount of foreign aid received by 40 low-income countries in the period 1965-1997. There is also evidence of natural disasters having a more severe economic impact on women than men (Charvériat, 2000).

The effects of natural disasters on development have been thoroughly studied, particularly because developing countries suffer the overwhelming majority of the disaster burden. Between 1990 and 1998, 94 percent of the world's major disasters and 97 percent of disaster related deaths were in developing countries (Freeman, Keen & Muthukumara, 2003). It has generally been concluded that development provides implicit insurance against natural disasters. Kahn (2005) finds that poorer nations have a similar amount of natural disasters to their wealthier counterparts, but that the number of casualties is substantially higher. Anbarci, Escaleras & Register (2005) also report a negative effect of GDP on earthquake related deaths. They additionally find that countries with higher levels of inequality tend to have more casualties when an earthquake occurs. They explain this finding as the result of society being unable to resolve the collective action problem of implementing preventive and mitigating measures: wealthier members of society prefer to self-insure and the poor are left exposed to the destruction caused by natural disasters. Toya & Skidmore (2007) additionally find that countries with a more educated population, greater openness and more developed financial markets have fewer deaths and less damages due to natural disasters. Rasmussen (2004) reports that the percentage of population affected by natural disasters is strongly related to the countries' level of development.

However, Jaharudin & Habibullah (2008) find a non linear relation between development and the number of people killed by natural disasters in 17 asian countries in a 35 year period. Raschky (2008) reports similar findings of non linearities in the relation between development and disaster impact when the latter is measured in terms of damages as share of GDP.

The literature on natural disasters has found that most reconstruction activities take place in the couple of years following a disaster. The actual number of years can be longer or shorter in each case, depending on several factors: magnitude of disaster, availability of resources, public policy priorities, governance, macroeconomic situation, etc. After Hurricane Hugo wrecked almost all of Montserrat's infrastructure in 1989, the reconstruction process took nearly 5 years (Benson & Clay, 2004). On the other hand, only 15 months after the Kobe earthquake manufacturing in the affected area was at 98% of its pre earthquake level (Horwich, 2000).

The long run can be understood as what happens once the reconstruction process has ended and people have fully adapted to new circumstances. Should any further impacts on the economy be expected from natural disasters that occurred several years ago? In order to answer this question one must look at the disaster effects on technological change and vulnerability.

Regarding technological innovation, Okuyama (2003) suggests that reconstruction activities may allow the incorporation of new technologies into the affected economy. The employment of these new technologies may allow increased production with the same amount of inputs, thereby conducing to greater future growth. However, other research along this line has not found much supportive evidence: using a theoretical model, Hallegatte & Dumas (2009) find that the rapid replacement of old capital with newer one may indeed reduce the costs from the disaster but can in no way actually turn the disaster into a positive event. Using data for 49 developing countries between 1976 and 1990, Crespo, Hlouskova & Obersteiner (2008) find that natural disasters actually have had a negative effect on the absorption of new technologies by developing countries via international trade.

Hallegatte & Dumas (2009) and Benson & Clay (2004) both conclude that the quality of reconstruction is what determines whether the disaster has positive or negative long-run effects. In fact, the model employed by Hallegatte & Dumas (2009) shows that a higher quality reconstruction may take longer and be more expensive, thereby increasing the medium-run impact of the disaster, but it improves the economic performance in the long run. What determines then this quality of reconstruction? Planning is the first factor. A reconstruction plan that is elaborated after careful assessment of damages and priorities will probably yield better results than one consisting simply of 'Put it as it was before' instructions. The magnitude of the disaster, particularly its economic significance, is an important determinant of the quality of reconstruction. If the only road connecting the coastland with the interior of the country is damaged and there is a risk of famine there will not be much time to consider a new route or better materials. Availability of resources also plays an important role. If the government simply does not have the necessary resources to finance a higher quality project, either because of credit constraints or lack of foreign aid, it is impossible to take advantage of the opportunities for technical upgrade provided by the natural disaster.

Benson & Clay (2004) conclude that vulnerability is the key to understanding the links between natural disasters and the economy. The United Nations defines vulnerability as:

"The conditions determined by physical, social, economic and environmental factors or processes, which increase the susceptibility of a community to the impact of hazards." (Heger, Julca & Paddison, 2008)

Vulnerability is the disaster specific and time fluctuating capacity of a natural disaster to affect economic activity. It is determined by the geographic, economic and political characteristics of countries. Institutions play an important role via ex-ante risk management mechanisms, such as anti-seismic standards, and ex-post risk coping mechanisms, such as insurance markets (Auffret, 2003). Some policy interventions likely to ameliorate disaster impact include land-use planning, which prohibits settlements in disaster prone areas; building standards, which make buildings more resistant to earthquakes, hurricanes and the like; and engineering interventions such as dams and seawalls aimed at reducing disaster impact (Freeman, Keen & Muthukumara, 2003).

The fact that natural disasters have different impacts on different groups of the population has led some authors to examine the political economy of disaster impact, concluding that vulnerability is determined more by socio-economic conditions than by geography (Albala-Bertrand, 1993; Anbarci, Escaleras & Register, 2005). A consistent finding of several studies is that better institutions reduce disaster impact (Kahn, 2005; Toya & Skidmore, 2007; Raschky, 2008; Noy, 2009; the only exception is Raddatz, 2007). Among other things, these authors have argued that better institutions, understood for instance as more stable democratic regimes or greater security of property rights, enhance accountability and make for higher quality government assistance (Besley & Burgess, 2002). Better institutions also imply more effort in disaster prevention and mitigation.

Less developed countries with a large share of output and population depending on agriculture are probably more vulnerable to climatic natural disasters like hurricanes or floods than industrialized countries with densely populated cities, which could be more vulnerable to geological natural disasters like earthquakes or volcano eruptions. Loayza, Olaberría, Rigolini & Christiaensen (2009) find that different types of disasters have different impacts on different parts of the economy. For instance, they find that disasters such as droughts are particularly negative for agriculture. A series of papers have also discussed how SIDS in the Caribbean are particularly vulnerable to all natural disasters, due to their location and their economic dependence on agriculture, tourism and imports (Rasmussen, 2004; Heger, Julca & Paddison, 2008). Horwich's (2000) argument that the Kobe earthquake of 1995 did not have any significant impact on the Japanese economy because human capital did not suffer as much as physical capital can be interpreted as saying that the Japanese economy was not very vulnerable to capital losses.

Vulnerability may change through time due to adaptation to natural disasters. Certain types of disasters (like hurricanes) which seem to occur with a regular frequency are likely to provide incentives that once-in-a-lifetime disasters (like earthquakes or volcano eruptions) do not (Before 1995 it had been almost a millennium since the last earthquake in the Kobe region; the last volcano eruption in Montserrat had been almost 200 years before the 1995 one). Climate change could also be contributing to increased vulnerability in the coming years: global

warming is expected to cause more floods and droughts in Latin America, as well as increased intensity of weather storms worldwide (Freeman, Keen & Muthukumara, 2003). There is also evidence on how deforestation and environmental degradation has contributed to greater vulnerability to natural disasters, particularly landslides, wind storms and droughts (Albala-Bertrand, 1993; Charvériat, 2000).

The reconstruction process after a natural disaster can have a major effect on post-disaster vulnerability. For example, if reconstruction projects after an earthquake pay more attention to anti-seismic standards, then vulnerability to future earthquakes decreases. Benson & Clay (2004) found that Dominica's main crop, bananas, was very sensitive to high-speed winds, making the country's economic structure quite vulnerable to hurricanes. However, bananas were also able to grow very fast after a storm, therefore allowing for a quick recovery.

What does the data say on the possible implications of natural disasters for economic growth in the long run? Skidmore & Toya (2002) found that climatic natural disasters (floods, hurricanes, etc.) do have a statistically significant positive effect on the average GDP growth rates of 89 countries in the period 1960-1990, while geologic disasters (volcanic eruptions, earthquakes and the like) have a negative, but mostly statistically insignificant, effect. They interpret this result as providing evidence of long-term disaster effects and use the technological upgrading argument to justify their finding. They conduct some additional regression analyses which further confirm that this is the important mechanism at work. Relying instead on deviations from time series forecasts, Hochraimer (2009) finds that natural disasters have a negative effect on GDP even five years after their ocurrence.

Three main conclusions can be drawn from the economics literature on natural disasters: first, natural disasters can only be expected to have a negative impact on contemporary economic growth if they are economically significant. What this means is that a disaster's capacity to affect the economy depends not necessarily on the number of people killed and the amount of damages, but on the importance of such damages and losses for the country's economic structure. Second, natural disasters may have a negative effect on growth in the year in which they occur, but in the following years there will be a tendency towards greater growth due to the reconstruction process that usually takes place and to the accounting effect. However, this positive effect can be counteracted by things such as lack of access to credit and a decrease in aggregate demand. Third, long-run effects, if any, are likely to depend on the quality of the reconstruction process and on the way in which reconstruction affects vulnerability to future disasters.

#### III. The Data

The data for the yearly panel of countries comes from two sources. I use country macroeconomic time series from the Penn World Tables 6.0 (PWT).3 The data on disaster events comes from EM-DAT: The OFDA-CRED International Disaster Database.4 In the remainder of this section I describe the variables obtained or constructed from each data source.

#### **EM-DAT**

EM-DAT records the occurrence and effects of mass disasters in the world since 1900. It compiles data from several sources, and its main objective is to assist in humanitarian action in response and prevention of mass disasters. It has entries for approximately 12,800 events, and among its sources are UN agencies, non-governmental organizations, insurance companies, research institutes and press agencies.

The disaster-event entries in EM-DAT are individual occurrences in chronological order and include date, type of disaster, several measures of affected population, damage estimates and notes about the main sources of data for any particular event. EM-DAT groups disasters in three broad categories (natural, technological and conflict) with several types in each category. In order for an event to qualify for the registry, it must satisfy at least one of several minimum requirements: ten or more people killed; 100 or more people reported affected; declaration of state of emergency; or call for international assistance.

My focus is on events that can be unambiguously interpreted as exogenous. Thus, I concentrate on natural disasters and discard famines. I also discard insect infestations and epidemics for this reason: their onset may be exogenous but they need not become catastrophes unless the available institutions are unable to cope. Finally, I consider only those types of natural disasters that can be viewed as occurring at a point in time, rather than those that build up or develop through extended periods, so I also drop droughts from the sample.

The remaining disaster events are earthquakes (445 events), floods (1179), wild fires (136), wind storms (1178), waves and surges (18), extreme temperatures (127), volcano episodes (108) and slides (221). The amount and types of disasters that occur vary widely across regions, as can be seen in Figure 3. The graph is consistent with Kahn's (2005) finding of Africa having fewer disasters than the rest of the world and Asia being more disaster prone than the average. The graph can also explain why Raddatz (2007) finds only a small effect of natural disasters on output volatility, given that 32 of the 40 low-income countries in the sample are in Africa.

<sup>&</sup>lt;sup>3</sup> The PWT can be found at the Center for International Comparisons, University of Pennsylvania. http://pwt.econ.upenn.edu/

This data can be found at EM-DAT: The OFDA/CRED International Disaster Database - www.em-dat.net -

Université Catholique de Louvain - Brussels - Belgium. http://www.em-dat.net/ .

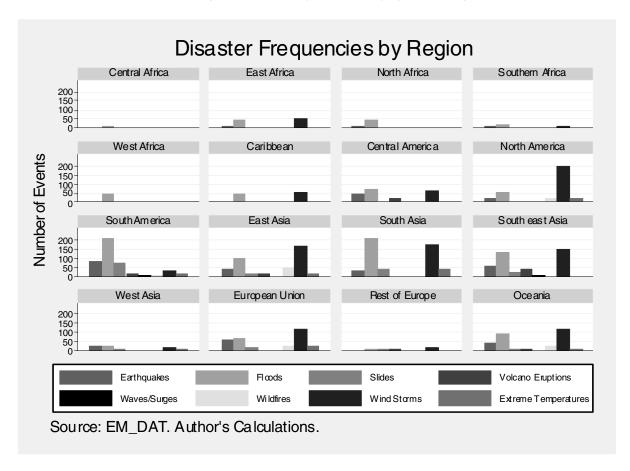


Figure 3: Frequency of Events by Type and Region

From the data in EM-DAT, I construct four types of measures of disaster impact normalized by the relevant country "size". Given that the focus of this paper is on the time dimension of disaster impact rather than on the differential impact of different types of disasters, all measures have been aggregated over the eight types of disasters for a given country in a given year. In accordance with the findings of section II, these measures concentrate on the disruptive effect of a natural disaster rather than its physical dimension:

AFFECTED: People affected by natural disasters in a given year as a fraction of

the current country population.

KILLED: People killed by natural disasters in a given year as a fraction of the

current country population.

DAMAGES: Damages due to natural disasters as a fraction of current GDP.

DISASTERS: Log (1 + number of natural disasters in a given year)

The correlations among these aggregate measures are reported in Table 1. Not surprisingly, they are positively correlated, although one would have perhaps expected a higher coefficient.

According to the pairwise correlation coefficients, the share of people affected is the most comprehensive measure of all. For a discussion of the limitations of these measures as indicators of disaster impact and country vulnerability, see Crowards (2000).

**Table 1: Correlation between Disaster Measures** 

	DAMAGES	KILLED	AFFECTED	DISASTERS
DAMAGES	1			
KILLED	0.2020	1		
AFFECTED	0.3076	0.3511	1	
DISASTERS	0.0969	0.0810	0.2032	1

If no disasters of any type are recorded for a given country in a certain year, *DISASTERS* has a value of zero for that observation. Whenever *DISASTERS* > 0, there is a recorded event that has a non-zero value in at least one of the other three variables. If, for example, *KILLED*> 0, the other two variables may be positive, zero or missing. Suppose that for a certain country in a given year KILLED>0 but *DAMAGES* is missing. There is no way to decide whether this is the result of misreporting of *KILLED*, unavailability of damage estimates or actual absence of significant capital losses. My approach to this is straightforward: I replace all missing values of the three variables *AFFECTED*, *KILLED* or *DAMAGES* with zeros. In the cases where missing values are present but the true value is positive, this approach will generate downward bias in the estimation. However, it is likely that in the vast majority of cases missing data values just reflect zero values, or at most very small ones.

I also calculate cumulative measures for country i at year t in the following way:

CUM\_AFFECTED: Cumulative fraction of people affected, since the first year in the data.

$$CUM \_AFFECTED_{it} = \sum_{\tau=0}^{t} AFFECTED_{i\tau}$$
.

CUM\_KILLED:

Cumulative fraction of people killed by natural disasters since the first year in the data. This measure and the previous one are based on the country's population in the year that the natural disaster occurs.

$$CUM \_KILLED_{it} = \sum_{\tau=0}^{t} KILLED_{i\tau}$$

CUM\_DAMAGES:

Cumulative damages as a fraction of GDP, based on GDP at the year of occurrence of each natural disaster.

$$CUM\_DAMAGES_{it} = \sum_{\tau=0}^{t} DAMAGES_{i\tau}$$

CUM\_DISASTERS: Cumulative log of 1 plus the number of disasters occurring each year in the data.

$$CUM\_DISASTERS_{it} = \sum_{\tau=0}^{t} DISASTERS_{i\tau}$$

Table 2 provides summary statistics for both the contemporary and cumulative disaster measures:

Disaster Measure	Mean	Std. Dev.	Median	Max.	Min.
AFFECTED*	63	431	0	10,409	0
CUM_AFFECTED*	875	2,600	27	37,897	0
KILLED*	0.10	1.53	0	50.65	0
CUM_KILLED*	2.28	8.87	0.05	79.65	0
DAMAGES**	0.01	0.08	0	3.89	0
CUM_DAMAGES**	0.09	0.26	0.002	5.18	0
DISASTERS***	0.82	1.76	0	18	0
CUM_DISASTERS***	12.06	27.44	3	272	0

**Table 2: Summary Statistics for Disaster Measures** 

### Multiple data sources

Several concerns besides the missing data must be addressed with EM-DAT. First, it is difficult to assess and compare the quality of the sources, especially for earlier events. The multiple sources also account for occasional repeated entries for events, and it is not always obvious whether two entries with small differences are indeed duplicates. Moreover, different sources emphasize different data: reinsurance firms likely provide better damage estimates, but they are based on claims, while UN agents have more encompassing assessments of damages and affected population. Thus, different data sources have different strengths (and perhaps systematic biases). Additionally, some data series may be more informative than others about the true dimension of the event. This is especially the case if measurement error differs across measures. Fortunately, this first type of concern, although difficult to address directly, is likely to be of less importance as the number and scope of international institutions that deal with LNDs

<sup>\*</sup> per million inhabitants

<sup>\*\*</sup> per million dollars of GDP

<sup>\*\*\*</sup> raw number of disasters before log

increases. For the time period of our panel, I am confident that this type of noise does not systematically affect the results.

A second concern, also related to the variety of the sources, is bias over time. The institutional infrastructure for disaster aid has evolved throughout the 20th century. It is reasonable to presume that events are more likely to be registered by the authorities in any given country later in the century, and conditional on this, they are also more likely to be reported to international agencies. Jaramillo (2007, p. 12) finds that a log-linear fit with country-specific intercepts shows a yearly increase of some 1.1% in the number of reported disaster events in the period 1960-1998. Since it is reasonable to believe that the actual number of cataclysmic events per year is roughly steady, the increase in events reported must come, at least in part, from these reporting biases. Another part of these numbers is certainly a result of increases in population and economic activity: other things equal, the more people in a country the higher the probability of having 10 deaths in an earthquake –and thus being recorded in EM-DAT–, and the higher the GDP the larger the expected damages from a given disaster. Jaramillo (2007, p.12) also reports that a log-linear fit for population growth yields a 2% yearly increase and that the correlation between the total number of disasters and per capita GDP is positive.

One must wonder whether the increased reporting is also a result of a strategic improvement in record-keeping. It seems that foreign aid as a response to LNDs has risen in the period of analysis. Could it be that the countries pay more attention to these events because it pays in terms of getting aid for disaster relief? Regressions by Jaramillo (2007, p.13) show that the odds ratio of a country reporting at least an event increases on average 0.063 each year. Even after controlling for per capita GDP and population, this effect is correlated strongly with the world being more generous the year before. However, it may simply be that reporting improved exogenously and is settling into a new, better standard of accuracy: the statistical significance of the lag of world aid vanishes when linear and quadratic trends are included. No definitive indictment is thus possible. The pattern is similar if one examines the number of disasters reported rather than the number of countries reporting.

Bias stemming from the failure of a country's authorities to observe and register a disaster is not likely a grave concern, since an unregistered event is probably one of little impact on economic activity to begin with. Natural disasters may be inaccurately measured, but it is difficult that they go unnoticed. Thus the trend in reporting, if due to better record-keeping, is not a major concern provided that one controls with a trend variable. To the extent that it is present, however, this usually downward error in *DISASTERS* is likely to generate upward bias in our estimates.

The failure to report an observed disaster to international agencies, on the other hand, may cause systematic bias and affect the results in unpredictable ways. One can conceive a number of reasons for some regimes to hide the extent of disasters or to exaggerate it; and the correlation of these incentives with the macroeconomic variables that I use is not at all clear. In this aspect, the variety of sources of the EM-DAT database is an advantage, as it minimizes the chances that a given event goes completely unrecorded, even if no official report is filed by the

affected country. Partly as a result of this possibility, I believe that any measurement error problem is likely to be less severe for the variable *DISASTERS* than it is for the other three measures.<sup>5</sup>

#### **Endogeneity of the disaster measures**

A third data concern includes endogeneity and timing. I partially address both issues by concentrating on events that are clearly exogenous (natural disasters) and punctual in time, i.e. they last a short time (less than a month) and give only short warning. Nevertheless, this does not completely deal with either issue, as (i) the measured impact of a given disaster is likely to vary with the economic characteristics of the country itself, and (ii) the consequences of a disaster need not be punctual or immediate, even if the disaster itself is. Insofar as this is the case, the disaster counter variable *DISASTERS* is arguably the least affected by this endogeneity.

This point about the way a natural disaster affects economic activity is complicated by the differences in the time aggregation of the macroeconomic and disaster time series. Suppose for instance that there is some delay in part of the impact of earthquakes. If an earthquake happens in May, its negative impact will be recorded in this year's national accounts. If it happens in November, most of that impact will show in next year's macroeconomic data. Suppose instead that the reconstruction activity after the earthquake occurs over a long period of time. In this case, it is the spurt of investment activity that may be recorded (positively) in different years depending on the exact month of occurrence. Of course, this pattern of impact is likely to vary by disaster and by country.

While the time pattern of the economic reaction to disasters is precisely what I want to inspect, this particular aggregation issue is an undesired source of error. For events that occur randomly throughout the year (like earthquakes), this error is most likely white noise and causes attenuation bias in some controls of the estimation. In contrast, events that occur consistently in a given moment of the year (like hurricanes) will bias the results in a systematic but unpredictable manner.

Finally, even after narrowing the set of events, one might wonder what exactly is exogenous about them. A country like Colombia, for instance, may not know when an earthquake will happen, but it certainly knows that it is prone to earthquakes; just as in the Caribbean region 2.5 storms are expected each year (Auffret, 2003). As discussed in Section II, this knowledge may affect vulnerability through time. Thus, it is the actual timing of the disaster that is exogenous, rather than the extent of destruction it causes. Again, this lends more credibility to the event count variable *DISASTERS*. It also calls for fixed country effects in the estimation.

<sup>&</sup>lt;sup>5</sup> Nevertheless, I do exclude from the panel the former communist countries that remain after merging the PWT and EM-DAT. They are Hungary, Romania, Poland and China.

#### IV. Estimation

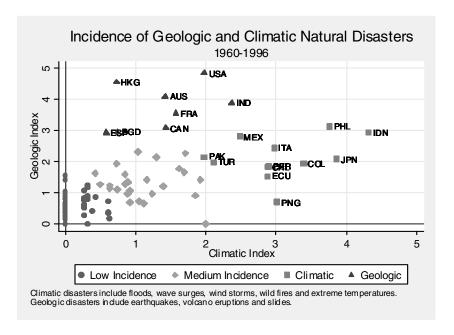
#### Not All Countries are Created Equal

The analysis in Section II showed that certain countries are particularly vulnerable to certain disasters at certain moments in time. Therefore, I divide the countries in the sample into smaller groups, employing as criteria the prevalent types of disasters in the country and the recorded impact of disasters. The idea behind this classification is that countries are affected differently, if at all, according to the type of disaster and the country's vulnerability. I use the following methodology to classify the countries in the sample.

The literature on the economic impact of natural disasters suggests that there are two main disaster families, each with unique characteristics: climatic and geologic (Skidmore & Toya, 2002). One of the main differences between these two disaster families is that while climatic disasters present a cyclical pattern of occurrence, geologic disasters tend to be more unpredictable. This difference can have a significant effect on the way in which people, firms and the government handle risk. I thus classify countries in terms of the prevalence of these two families of disasters. Following Skidmore & Toya (2002), extreme temperatures, floods, waves/surges, wind storms and wildfires are climatic disasters, while earthquakes, volcano eruptions and landslides are considered to be geologic disasters. Given Kahn's (2005) finding of no correlation between a country's national income and its amount of natural disasters, I use as an indicator of disaster prevalence the cumulative measures of disaster occurrence for each disaster in each country. I take logs of those totals, and employ principal components analysis to construct an index for each family of disasters. I then normalize these indices by subtracting the minimum value and dividing by the standard deviation.

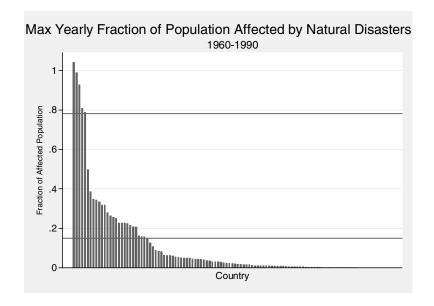
Having constructed the two variables representing the prevalence of climatic and geologic disasters in each country, I use cluster analysis (with the k-means algorithm) to group countries together according to the values of these two variables. Figure 4 shows the results of the cluster analysis. There appears to be a group of countries for which both indexes take low values, indicating that natural disasters of any type are not very common. I label these countries "Low Incidence" countries. There is a second group of countries, that I call "Medium Incidence" countries, which have higher values of both indices than the low incidence countries. These countries, despite not being labeled as low incidence, cannot be said to suffer large amounts of either type of natural disaster. It is precisely the main characteristic of the third and fourth families, labeled "Climatic" and "Geologic", that the countries belonging to each have relatively large index values for either climatic or geologic disasters. For example, in the climatic family we find Mexico, the Philippines and Indonesia, while the United States, India and Bangladesh belong to the geologic family. Table 6 in Appendix 1 shows the complete country classification according to disaster incidence.

Figure 4



I also use cluster analysis to classify countries in terms of their maximum yearly share of population affected by natural disasters. What I am trying to capture is differences between countries in terms of their economic vulnerability to natural disasters. The reason for using the variable on population affected to do this task is that it is not related to the level of economic development of a country (The correlation between GDP per capita and the maximum share of affected population is -0.1) and because it captures the differences in area, population and economic structure between countries. The reason for using the maximum is that I am interested in measuring how bad things can get when disaster strikes. Figure 5 shows for each country in the sample the maximum yearly percentage of affected population by natural disasters. The lines around the 80% level and the 15% level represent the cutoff points of the three clusters generated by the k-means algorithm I employ to group countries by this criterion. The figure shows that there is a small group of countries where disasters at some point in the sampled years managed to affect the overwhelming majority of the population. These are Bangladesh (1988, floods), Guatemala (1976, earthquake), Mauritius (1975, cyclone Gervaise), Dominica (1979, hurricane David) and Antiqua & Bermuda (1995, hurricane Luis). Countries in which less than 50% but more than 15% of the population were affected in the worse year belong to a second group, the medium impact group. The last group is made up by countries in which there was not a year in which more than 15% of the population was affected by natural disasters. Table 6 in Appendix 1 shows the complete country classification according to disaster impact.

Figure 5



#### A Growth Model to Guide the Estimations

Both of my econometric estimations are based on a simple adaptation of the Solow – Swann growth model, in the same spirit of Mankiw, Romer & Weil (1992) and Islam (1995).

Let a country's output at time t, denoted  $Y_t$ , be given by a Cobb-Douglas production function with constant returns to scale, which depends on capital  $(K_t)$ , labor  $(L_t)$  and technology  $(A_t)$ :

$$Y_t = F(K_t, A_t L_t) = K_t^{\alpha} (A_t L_t)^{1-\alpha}$$
[1]

The evolution of the capital stock is a function of the exogenous savings (s) and depreciation rates ( $\delta$ ):  $\dot{K}_t = sY_t - \delta K_t$ . Technology is assumed to grow exogenously at the rate g, while the labor force grows at the exogenous rate n, starting from initial levels  $A_0$  and  $A_0$ , respectively. Defining  $A_0$  and  $A_0$ , we obtain  $A_0$  and  $A_0$ , we obtain  $A_0$  and  $A_0$  are an analysis and  $A_0$  and  $A_$ 

This country's economy reaches a steady state when  $\dot{k}_t = 0$ . The steady state levels of capital per effective worker and output per effective worker are:

$$k^* = \left(\frac{s}{n+g+\delta}\right)^{\frac{1}{1-\alpha}}$$
  $y^* = \left(\frac{s}{n+g+\delta}\right)^{\frac{\alpha}{1-\alpha}}$ 

Taking logs of the steady state level of output per effective worker and approximating around the steady state it is possible to obtain an expression for the evolution of the log of output per effective worker towards its steady state value in terms of the country's rate of convergence  $(\lambda_i)$ :

$$\left[\frac{d \ln y_{i,t}}{dt}\right] = \lambda_i \left[\ln y_i^* - \ln y_{i,t}\right]$$
With  $\lambda_i = (1 - \alpha)(n_i + g_i + \delta_i)$ 

This is a first order lineal differential equation, which can be solved to obtain:

$$\ln y_{i,t} = (1 - e^{-\lambda_i}) \ln y_i^* - e^{-\lambda_i} \ln y_{i,t-1}$$
 [3]

This equation can be converted into per capita terms, instead of effective labor terms, using  $\ln y_{i,t} = \ln \left[ \frac{Y_t}{L_t} \right]_i - \ln A_{i,0} - g_{i,t}$ :

$$d \ln \left[ \frac{Y_t}{L_t} \right]_i = g_{i,t} + \left( 1 - e^{-\lambda_i} \right) \left[ \ln \left[ \frac{Y_{t-1}}{L_{t-1}} \right]_i^* - \ln \left[ \frac{Y_{t-1}}{L_{t-1}} \right]_i \right]$$
 [4]

The equation above shows that output grows at rate g in the steady state, since the term in brackets becomes equal to zero (In the steady state, output per capita in t-1 is by definition at its steady state level). The log of the steady state value of output per capita can be substituted to obtain:

$$d \ln \left[ \frac{Y_{t}}{L_{t}} \right]_{i} = g_{i,t}$$

$$+ \left( 1 - e^{-\lambda_{i}} \right) \left[ \frac{\alpha}{1 - \alpha} \ln s_{i} - \frac{\alpha}{1 - \alpha} \ln \left( n_{i,t} + g_{i,t} + \delta_{i} \right) + \ln A_{i,0} + g_{i,t} t - \ln \left[ \frac{Y_{t-1}}{L_{t-1}} \right]_{i} \right]$$
 [5]

It is from equation [5] that I will draw the different empirical specifications presented next.

### Option I: Islam - Style Regressions

Following Islam (1995), equation [5] can be converted into a dynamic panel data model with  $\ln A_{i,0}$  as the time-invariant country fixed effect ( $D_i$ ):

$$d \ln \left[ \frac{Y_t}{L_t} \right]_i = \beta_0 + \beta_1 \ln s_{i,t} + \beta_2 \ln \left( n_{i,t} + g_{i,t} + \delta_i \right) + \beta_3 D_i + \beta_4 t + \beta_5 \ln \left[ \frac{Y_{t-1}}{L_{t-1}} \right]_i$$
 [6]

Equation [6] captures the basic elements that determine GDP growth. Unreported estimations of equation [6] for all groups in the sample show that all variables are generally statistically significant and have the expected coefficients: positive for the savings rate, negative for the population growth rate and negative for the previous year's GDP.

The way in which I incorporate natural disasters into equation [6] is by including two additional terms to obtain equation [7]. The additional terms are two because I distinguish contemporary disasters from ones that occurred a few years ago: The contemporary disaster measure is the aggregation of the last x years of disasters, while the past disaster measure is the aggregation since the first year in the sample but omitting the last x years. The economics literature on natural disasters has not arrived at any definite conclusion regarding the number of years after which the economic effects of disasters disappear: Albala-Bertrand (1993) studies disaster impact up to two years after disaster occurrence, but Raddatz (2007) finds that climactic disasters can have an effect on GDP even five years after occurrence. Therefore, I use different time frames (Different x's in equation [7]) to see if there are any significant differences in the results. I also include a lagged measure of openness (exports plus imports as a share of GDP) to control for external effects that are not taken into account by the Solow model.

$$d \ln \left[ \frac{Y_t}{L_t} \right]_i = \beta_0 + \beta_1 \ln s_{i,t} + \beta_2 \ln \left( n_{i,t} + g_{i,t} + \delta_i \right) + \beta_3 D_i + \beta_4 t$$

$$+\beta_5 \ln \left[ \frac{Y_{t-1}}{L_{t-1}} \right]_i + \beta_6 \sum_{\tau=t-(x-1)}^t NatDis_{i,\tau} + \beta_7 \sum_{\tau=0}^{t-x} NatDis_{i,\tau} + \beta_8 Open_{i,t-1}$$
 [7]

Table 3 shows estimates of  $\beta_6$  and  $\beta_7$  for each group of countries, using different disaster measures and time frames. Estimates were obtained using the fixed effects panel data estimator with robust standard errors<sup>6</sup>. To facilitate the interpretation of the parameter estimates,

<sup>&</sup>lt;sup>6</sup> There is some literature discussing the biases that arise when a dynamic panel data model is estimated using fixed effects. As an alternative, other authors have employed the Hausman – Taylor

Table 4 shows the estimated effect of a one standard deviation increase in the corresponding disaster measure on yearly GDP growth according to the estimated coefficients.

The main advantage of the fixed effects estimator is that it controls for time invariant country effects. Characteristics such as area, location, geography and any other feature that does not change with time are controlled for by the country fixed effect. For example, the literature has recognized that SIDS have a particular vulnerability to natural disasters. This is taken care of by the country fixed effect. More importantly, like I mentioned in Section III, some countries are predisposed to certain natural disasters and they know about it. Tornadoes are a characteristic of the USA just as typhoons are prevalent in Bangladesh. The country fixed effect included in my estimations controls for this source of endogeneity.

The results in column 1 of Table 3 show that for the group of countries with low disaster incidence the amount of contemporary damages as a percentage of GDP appears to have a positive effect on GDP growth. As the number of years included in the contemporary measure increases, the effect appears to fade away. This may be indicating the presence of a positive investment surge following a natural disaster with a well-defined time span of between two and three years. The same column in Table 4 shows that an increase of one standard deviation in the share of damages in the last two to three years causes an increase of around 0.3 percentage points in the growth rate today. However, when the disaster measure used is DISASTERS, past natural disasters are the ones which appear to have a positive effect.

Table 4 says that this effect of past disasters is slightly more than one percentage point per standard deviation in the number of disasters. This result may be indicating that in the countries which are only seldom affected by natural disasters, these events provide valuable opportunities for technological upgrading and therefore lead to higher growth rates after some years.

For the medium incidence group, column 2 shows that only the cumulative percentage of people killed has a significant effect on GDP growth. The effect is negative and, according to Table 4, corresponds to a decrease of about one percentage point in annual GDP growth following a one standard deviation increase in aggregate share of killed population. This result suggests that these countries are sensitive to human losses, perhaps because their population is highly educated. For some countries in this group, such as Taiwan, Switzerland or the UK this seems plausible, but for others, like Bolivia, Guatemala or Algeria not quite (see Table 6 in Appendix 1 for the complete list of countries in this group). In fact, close examination of the variable CUM\_KILLED for this group of countries reveals that it is Guatemala and Nicaragua, and to a lesser degree Haiti, the countries with significantly higher cumulative shares of population killed. Therefore, it is probably better to interpret the negative disaster effects

estimator (Noy, 2009) or the Arellano – Bond estimator (Loayza, Olaberría, Rigolini, & Christiaensen, 2009). Nevertheless, I use the fixed effects estimator in this paper for two simple reasons: a) Judson & Owen (1999) show that the bias of the LSDV estimator (equivalent to fixed effects) decreases as T increases and that it becomes relatively small when T>30; b) Estimators such as the Hausman – Taylor and Arellano – Bond are both random effects estimators, and are therefore inappropriate for the country-level data being used.

estimated for this group as capturing the negative impact of a long series of deadly disasters on these small Caribbean economies.

In the group of countries with prevalence of climatic disasters, only the contemporary percentage of population killed has a significant and positive effect on growth of between one half and one percentage point per standard deviation increase. The countries that appear to be driving this result are all on the pacific coast of South America: Ecuador, Peru, Chile and Colombia. Why do these countries grow more as the share of population killed increases? One possible explanation is that for this set of countries KILLED is the variable which best captures the magnitude of disasters: a higher share of people killed is more telling about the real impact of a natural disasters than the number of people affected (which is likely to be high under any circumstances) or the amount of damages (which has recording problems and is perhaps generally low). These countries may be growing more in the short run due to an investment surge following a natural disaster. It may also be the case that a high disaster death toll is the only thing capable of triggering exceptional spending on the part of government in a region where floods and capital losses are relatively common.

For the group of countries with high prevalence of geologic disasters, Table 3 and Table 4 suggest that only the cumulative share of damages is significant and that it has a positive effect of about 0.7 additional percentage points of GDP growth per one standard deviation increase in this cumulative share. This result can be interpreted in terms of the opportunities which disasters provide for technological upgrading discussed at the end of Section II.

Moving on to the country classification according to disaster impact, I find that for the group of countries which have had a relatively small share of population affected by natural disasters, column 5 of Table 3 shows a systematically positive effect of both contemporary and past disasters on GDP growth when disaster impact is captured using the variable DISASTERS. When the disaster measure used is DAMAGES, it is the contemporary share of damages that seems to be most important. The large number of countries included in this group makes it harder to interpret these results. However, the fact that these countries are characterized by low disaster impact may be the key towards understanding the positive effects of disasters: low impact natural disasters become an opportunity for new investments and technological progress without most of the negative consequences generally associated with events of this nature (e.g. large human or capital losses).

For the middle impact countries it is the other two disaster measures, AFFECTED and KILLED, which prove to be significant. For these two variables it is the accumulated amount of disaster impact what appears to have an effect on growth. However, while the cumulative share of affected population seems to have a positive effect of a little less than one percentage point on growth, the cumulative share of people killed has a negative effect of about the same magnitude. A possible explanation for this difference in sign is that AFFECTED captures the investment surge following capital losses while KILLED captures the direct negative effect that the disaster has in terms of human losses.

Lastly, for the group of countries which have had a significant share of population affected by natural disasters, column 7 shows that according to population killed or affected

there is no significant impact of natural disasters on GDP growth, either in the short run or some years after disasters have occurred. However, when disasters are measured in terms of frequency or by the amount of damages, then there appears to be significant negative effects in both the short run and the long run. This sensitivity to the disaster measure employed may be a consequence of some of the problems with the data described in Section III, but it could also be telling us which of the mechanisms discussed in Section II is most important: it is the capital losses, rather than the human losses, which affect negatively the GDP of these countries. More specifically, this result may be reflecting that these countries have a low-skill but numerous labor force working with little capital. The results in Table 4 show that a contemporary increase of one standard deviation in the amount of damages as a share of GDP for these countries implies a reduction of between one and two percentage points in GDP growth. In the long run, such an increase can cause a more dramatic decrease of around three percentage points. If we use DISASTERS as disaster measure instead, the short-term effect is of a similar magnitude, but the effect of a one standard deviation increase in the cumulative amount of disasters implies a GDP growth rate seven percentage points smaller than otherwise expected.

Another set of regressions, which are not reported, included an interaction term between the past measure of disaster impact and the contemporary one. The rationale behind this specification is the idea, briefly mentioned at the end of Section II, that previous disasters may affect a country's vulnerability to future ones. For example, a very destructive earthquake may provide incentives for anti-seismic constructions, so that future earthquakes will not have such a drastic impact. If this is the case, the interaction term should capture this incidence of past disasters on contemporary vulnerability. The most important finding of these regressions has to do with the group of countries with a high prevalence of geologic disasters. Table 3 shows that for this group of countries only CUM\_DAMAGES had a statistically significant positive effect. When the interaction term is included, this effect remains fairly constant. However, both DISASTERS and AFFECTED become significant as well. For both of these sets of variables both the contemporary and past disaster measures are significant and positive, while the interaction term has a negative coefficient and is also significant for all time frames considered. This result suggests that, in fact, quite the opposite has happened to what was expected and that previous disasters make current disasters more destructive for the economy. Perhaps in this set of countries reconstruction projects have not been of a very high quality, but this hypothesis needs to be explored further.

In order to make my results comparable to some of the others available in the economic literature on natural disasters, I also ran these Islam-style regressions classifying countries in terms of their stage of development. I used OECD membership as an indicator and classified countries into two groups: Developing countries and Developed countries. The statistically significant results are the following: when AFFECTED is used as disaster measure, past disasters have a positive effect on GDP growth for developing countries, while contemporary disasters have a positive effect for OECD countries. I additionally found that when DISASTERS is used as a disaster measure, past disasters have a positive effect in LDC's and a negative one in more developed countries.

The preliminary conclusion that can be drawn from the estimates in Table 3 is that there is evidence of an effect of natural disasters on economic growth. A more novel finding is that the effect goes beyond the 2-5 years suggested by case studies. As I have mentioned throughout, the aim of this paper is to study the existence and timing of the mentioned effect. A question for future research is through which of the channels discussed in Section II do natural disasters impact economic growth. Among the variables that one would like to include in answering this question are government spending, investment, quality of institutions and depth of financial markets.

Table 3: Estimates of the Effect of Past and Contemporary Natural disasters on GDP Growth Rate ( $m{\beta}_6 ~\&~ m{\beta}_7$ )

COEEEICIENT			Disaster	Incidence		Po	pulation Affe	cted
	EFFICIENT	(1) Low	(2) Medium	(3) Climatic	(4) Geologic	(5) Low	(6) Medium	(7) High
# Years	Disasters				of Population	n Affected		
	Past		0.0166	-0.0179	0.00958	0.0141	0.0281**	0.00822
2	rası	[0.017]	[0.012]	[0.019]	[0.0065]	[0.034]	[0.013]	[0.0091]
_	Contemporary	-0.0111	0.0302	0.0777**	0.0227	0.164**	0.0296	-0.00260
	, ,	[0.024]	[0.039]	[0.038]	[0.030]	[0.084]	[0.030]	[0.021]
	Past		0.0172	-0.0183	0.00839	-0.00280		0.00567
3		[0.017] -0.00701	[0.012] 0.0230	[0.022] 0.0508	[0.0063] 0.0330	[0.036] 0.135**	[0.013] 0.0254	[0.010] 0.00774
	Contemporary	[0.022]	[0.030]	[0.032]	[0.025]	[0.067]	[0.024]	[0.016]
		0.00557	0.0155	-0.0404	0.0128	0.00454	0.0285**	0.0103
_	Past	[0.018]	[0.013]	[0.028]	[0.0080]	[0.039]	[0.014]	[0.013]
5	Cantonnororu	-0.0148	0.0276	0.0405	0.0136	0.0187	0.0283	-0.000139
	Contemporary	[0.020]	[0.023]	[0.031]	[0.017]	[0.062]	[0.020]	[0.012]
# Years	Disasters			Percentag	ge of Populati	on Killed		
	Past	0.654		1.311	0.377	5.590	-6.450**	-10.88**
2	1 431	[2.61]	[3.65]	[3.28]	[2.74]	[20.5]	[2.76]	[5.12]
-	Contemporary	-5.735	1.511	14.29***	-1.163	27.37	1.420	-0.856
	,	[3.99]	[3.61]	[3.32]	[8.22]	[42.0]	[3.73]	[6.10]
	Past	-0.00466 [2.55]	-11.64*** [3.70]	2.098 [3.46]	2.095 [2.65]	-2.378 [20.9]	-6.284** [2.82]	-9.042 [5.58]
3		1.051	3.434	13.94***	-6.668	-7.481	4.178	-5.418
	Contemporary	[7.99]	[3.46]	[3.44]	[7.85]	[33.8]	[3.54]	[6.58]
	Past	-1.217	-12.38***	-0.155	4.459**	8.482		-13.78**
5	rast	[2.66]	[4.14]	[3.70]	[2.25]	[23.2]	[3.16]	[5.70]
	Contemporary	4.392	2.278	15.72***	2.705	-32.57	5.519*	-4.898
								[5.61]
# Years	Disasters	15.07	100.0		as Percentag		47.04	C1F C***
	Past	-15.97 [68.3]	-100.9 [95.6]	655.2** [313]	761.5** [356]	145.7 [116]	-47.94 [80.7]	-615.6*** [195]
2		249.1***	-196.1	-168.1	-45.72	278.8***	-72.93	-481.0**
	Contemporary	[72.8]	[174]	[353]	[666]	[71.5]	[176]	[230]
	5 .	-24.97	-104.2	820.0**	652.8*	189.4	-82.89	-661.4***
3	Past	[69.8]	[98.2]	[325]	[349]	[124]	[83.3]	[202]
3	Contemporary	234.5***	-94.32	-193.6	536.1	235.6***	136.6	-509.2**
	Contemporary	[72.6]	[153]	[322]	[587]	[74.2]	[147]	[217]
	Past	49.93 [74.2]	-120.1 [113]	384.7 [374]	664.7* [386]	313.3*** [112]	-126.3 [94.6]	-713.5*** [242]
5		147.7*	18.85	146.0	315.8	185.6***	128.1	-671.5***
	Contemporary	[82.9]	[124]	[292]	[432]	[71.2]	[132]	[201]
# Years	Disasters	-			ımber of Disa	sters		
		0.0139***	0.00441	0.0113*	-0.00485	0.0149***	-0.00517	-0.0642***
2	Past	[0.0048]	[0.0040]	[0.0063]	[0.0040]	[0.0029]	[0.0055]	[0.021]
4	Contemporary	0.0122	0.00649	-0.00432	0.00688	0.0111**	-0.00145	-0.0801**
	- Jones in portary	[0.0077]	[0.0067]	[0.012]	[0.0066]	[0.0054]	[0.010]	[0.033]
	Past		0.00267	0.00734	-0.00347	0.0133***	-0.00346	-0.0693*** [0.026]
3		[0.0049] 0.0157**	[0.0044] 0.000997	[0.0080] -0.00647	[0.0042] 0.00842	[0.0030] 0.0107**	[0.0055] 0.00127	-0.0685***
	Contemporary	[0.0068]	[0.0054]	[0.015]	[0.0053]	[0.0047]	[0.00127	[0.025]
	D- :		0.00292		0.00236	0.0140***	0.000558	-0.0649**
_	Past	[0.0056]	[0.0053]	[0.0097]	[0.0048]	[0.0034]	[0.0065]	[0.026]
5	Contemporary	0.00908	0.00479	-0.00108	0.00294	0.00819*	0.000948	-0.0672***
<u> </u>		[0.0061]	[0.0054]	[0.013]	[0.0045]	[0.0043]	[0.0085]	[0.021]
Kobust s	standard errors	ın brackets	. *** p<0.01,	"* p<0.05, * μ	0<0.1			

Table 4: Expected change in GDP growth after an Increase of One (1) Standard Deviation in the Disaster Measure

			Disaste	er Incidence		Po	pulation Affe	cted
COEFFICIENT		(1) Low			(4) Geologic			(7) High
# Years	Disasters			Percentage	of Population	Affected		
	Past	-0.01	0.34	-0.39	0.58	0.07	0.70 **	0.64
2	Contemporary	-0.06	0.17	0.44 **	0.26	0.19 **	0.23	-0.06
	Past	-0.03	0.34	-0.39	0.48	-0.01	0.75 **	0.42
3	Contemporary	-0.05	0.16	0.36	0.50	0.20	0.24	0.21
_	Past	0.08	0.28	-0.80	0.66	0.02	0.64 **	0.71
5	Contemporary	-0.13	0.27	0.40	0.31	0.04	0.35	-0.01
# Years	Disasters			Percentage	e of Populatio	n Killed	•	
	Past	0.02	-1.06 ***	0.17	0.07	0.07	-0.87 **	-2.64 **
2	Contemporary	-0.06	0.04	0.51 ***	-0.05	0.05	0.06	-0.05
	Past	0.00	-1.08 ***	0.27	0.39	-0.03	-0.84 **	-2.17
3	Contemporary	0.01	0.12	0.62 ***	-0.33	-0.02	0.20	-0.43
	Past	-0.04	-1.13 ***	-0.02	0.81	0.11	-1.04 **	-3.22 **
5	Contemporary	0.08	0.10	0.92 ***	0.18	-0.11	0.36 *	-0.51
# Years	Disasters			Damages	as Percentage	of GDP	l	ı
	Past	-0.04	-0.29	0.91 **	0.78 **	0.16	-0.17	-2.83 ***
2	Contemporary	0.34	-0.18	-0.09	-0.01	0.31	-0.09	-0.88 **
	Past	-0.05	-0.28	1.11 **	0.63	0.20	-0.28	-2.96 ***
3	Contemporary	0.36	-0.11	-0.12	0.18	0.28	0.20	-1.14 **
_	Past	0.10	-0.30	0.49	0.56 *	0.30 ***	-0.39	-3.01 ***
5	Contemporary	0.26	0.03	0.11	0.16	0.24	0.26	-1.92 ***
# Years	Disasters			log Nu	mber of Disas	ters		
3	Past	1.12 ***	0.49	1.32	-0.71	1.84	-0.72	-7.40 ***
2	Contemporary	0.24	0.15	-0.09	0.16	0.24	-0.03	-1.40 **
	Past	1.04	0.29	0.85	-0.51	1.62	-0.48	-7.91 ***
3	Contemporary	0.38	0.03	-0.18	0.25	0.29	0.04	-1.47 ***
_	Past	1.16	0.31	0.80	0.34	1.67 ***	0.08	-7.26 **
5	Contemporary	0.29	0.19	-0.04	0.12	0.30	0.03	-1.91 ***
*** p<0.0	1, ** p<0.05, * p	<0.1		•	•		•	

### Option II: Structural Model, Steady State Effects

Ultimately, the question that I would like to answer is whether natural disasters can have permanent effects on economic growth. The Islam-style regressions presented in the previous section simply added some variables related to disaster impact to a growth specification based on the Solow model. In this section I propose a way of exploring natural disaster impact that is more articulated with the internal dynamics of the Solow model. The specification derived from this structural model has the valuable characteristic of allowing me to assess if there is any evidence of a permanent effect of natural disasters on GDP growth.

As shown in equation [4], the Solow growth model predicts that economies will grow in the steady state at the rate of technical progress, g. Therefore, a natural way of examining long-run effects of natural disasters on growth is by asking whether natural disasters have an effect on the steady state growth rate. In order to test this hypothesis we can express the steady state growth rate as a constant plus a term which depends on natural disasters:

$$g_{i,t} = \gamma_0 + \beta_1 \sum_{\tau=0}^{t} NatDis$$
 [8]

where  $\sum_{\tau=0}^t NatDis$  is a cumulative measure of natural disasters and  $\beta_1$  is the coefficient that captures whether those natural disasters have an effect on the long-run growth rate. We use a cumulative measure of disaster effects because the structural change in the economy that we are looking for is more naturally associated with the cumulative effect of natural disasters over a long period of time. The hypothesis that we want to test is whether  $\beta_1$  is statistically different from zero.

However, in doing this analysis it is necessary to control for any short-term effects of natural disasters, additional to the long-term effect on the steady state growth rate. According to the Solow model if any such short-term effects exist, they should be due to natural disasters affecting the convergence rate at which the economy approaches its steady state. We can therefore also express the convergence rate as a constant plus a term which depends on contemporary natural disasters:

$$(1 - e^{-\lambda_i}) = \gamma_1 + \beta_2 NatDis$$
 [9]

Following these assumptions, we can express equation [5] as

$$d \ln \left[ \frac{Y_t}{L_t} \right]_i = \gamma_0 + \beta_1 \sum_{\tau=0}^t NatDis + (\gamma_1 + \beta_2 NatDis) \left[ \frac{\alpha}{1-\alpha} \ln s_i - \frac{\alpha}{1-\alpha} \ln s_i \right]$$

$$\ln(n_{i,t} + g_{i,t} + \delta_i) + \ln A_{i,0} + (\gamma_0 + \beta_1 \sum_{\tau=0}^{t} NatDis)t - \ln\left[\frac{Y_{t-1}}{L_{t-1}}\right]_i$$
 [10]

The empirical specification we obtain is:

$$d \ln \left[ \frac{Y_{t}}{L_{t}} \right]_{i} = \gamma_{0} + \gamma_{1} \gamma_{2} D_{i} + \boldsymbol{\beta}_{1} \left( \sum_{\tau=0}^{t} NatDis \right) + \gamma_{1} \left( \frac{\alpha}{1-\alpha} \right) \ln s_{i,t}$$

$$-\gamma_{1} \left( \frac{\alpha}{1-\alpha} \right) \ln \left( n_{i,t} + g_{i,t} + \delta_{i} \right) + \gamma_{0} \gamma_{1} t - \gamma_{1} \ln \left[ \frac{Y_{t-1}}{L_{t-1}} \right]_{i}$$

$$+\beta_{2} \left( \frac{\alpha}{1-\alpha} \right) \ln s_{i,t} * NatDis - \beta_{2} \left( \frac{\alpha}{1-\alpha} \right) \ln \left( n_{i,t} + 0.05 \right) * NatDis$$

$$+\beta_{2} \gamma_{2} D_{i} * NatDis + \gamma_{1} \beta_{1} \left( \sum_{\tau=0}^{t} NatDis \right) * t + \gamma_{0} \beta_{2} t * NatDis \left[ 17 \right]$$

$$+\beta_{1} \beta_{2} \left( \sum_{\tau=0}^{t} NatDis \right) * NatDis * t - \beta_{2} NatDis * \ln \left[ \frac{Y_{t-1}}{L_{t-1}} \right]_{i} + \beta_{3} \operatorname{Open}_{i,t-1}$$
[11]

Despite the cumbersome amount of parameters to be estimated, this specification has the appealing characteristic of allowing us to focus exclusively on the parameter that corresponds to the cumulative disaster measure, since this parameter ( $\beta_1$ ) is the one associated with the impact of natural disasters on the steady state growth rate. Table 5 shows estimates of  $\beta_1$  for each group of countries.

Table 5: Estimates of the effect of Natural Disasters on the Steady State Growth Rate ( $\beta_1$ )

Disaster Measure		Disaster Incidence				Population Affected			
Disaster Measure	(1) Low	(2) Medium	(3) Climatic	(4) Geologic	(5) Low	(6) Medium	(7) High		
Percentage of	-0.0321	-0.0947*	-0.00248	-0.0269	0.129	-0.0844**	-0.0427		
Population Affected	[0.038]	[0.049]	[0.056]	[0.032]	[0.12]	[0.038]	[0.027]		
Percentage of	8.858	-1.373	18.09**	-14.54**	11.87	-1.605	-18.55***		
Population Killed	[9.74]	[11.8]	[7.51]	[6.48]	[35.3]	[6.89]	[5.54]		
Damages as	-123.0	-177.9	594.3	-1715	204.6	-169.4	-1040**		
Percentage of GDP	[273]	[415]	[1083]	[1214]	[343]	[338]	[423]		
log Number of	0.00304	0.00106	0.0199***	0.00673	0.00881**	-0.0100	-0.0643**		
Disasters	[0.0079]	[0.0052]	[0.0072]	[0.0068]	[0.0038]	[0.0088]	[0.025]		
Robust standard errors	Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1								

Table 5 shows that for the group of countries which have been very significantly affected by natural disasters (Column 7), this history of devastating natural phenomena has indeed had a permanent negative effect on their growth rate. Rasmussen (2004) discusses some of the ways in which small Caribbean islands belonging to this group have been affected by natural disasters. In the case of the cumulative share of population killed, an increase of one standard deviation in this disaster measure implies a permanent decrease in the GDP growth rate of about 4.5 percentage points. In the case of DAMAGES, a similar increase in the disaster measure would cause a permanent decrease in the GDP growth rate of around five percentage points. When the disaster measure is the log of the number of disasters, the associated permanent decrease in the GDP growth rate is of about seven percentage points.

How do these results compare to the ones obtained with the Islam-style regressions? For the low incidence group we find that the positive effects identified before can be classified as temporary. For the medium incidence group, no longer does the share of population killed appear to have any effect, which suggests that the impact reported in Table 3 was only temporary. In the case of countries which are mainly affected by climatic disasters, the fraction of population killed, which had a positive contemporary effect in the Islam-style regressions, may actually have a more profound and long-lasting effect on economic performance. The positive effect of DAMAGES for the 'geologic' family appears to be temporary and is probably due to a finite investment surge. For the set of low-impact countries, there is also some evidence of the number of natural disasters being related with higher long-run growth, something which was also found in the Islam-style regressions. Lastly, for the group of countries which were termed as 'medium' in terms of disaster impact, the percentage of population affected seemed to have a positive effect on growth, but the structural model tells a different story and the long-run effect appears to be negative.

### V. Concluding Remarks

Do natural disasters have long-term effects on GDP growth rates? Case studies suggest that the economic effects of natural disasters usually vanish after a few years, while the economic literature using panel datasets with the EM-DAT database is inconclusive on the matter.

The results in this paper show that for certain groups of countries that share important characteristics related to disaster prevalence and vulnerability there is indeed evidence of disaster impact beyond the 2-5 years in which reconstruction and adaptation are expected to have an effect on the economy. However, once a structural model is employed to determine whether these effects can be classified as permanent structural changes, I find that only for a very small number of countries which share a history of highly devastating natural disasters is such a conclusion warranted.

In any case, the growth effects beyond the five years following a disaster are economically significant as a practical policy matter. The very-long-term impacts may require

deliberate public strategies to mitigate their effect on the countries' development. That they appear in some groups of countries and not in others hints at the variety of microeconomic and institutional issues that are involved. I have not examined specific channels through which these effects come to be or specific economic sectors affected, nor have I explored the effectiveness of state or private sector reactions to the catastrophes. This is an active field of research, as the extensive literature shows; less work has been done on the long-term impact of these disasters on poverty. These are all avenues open for future research.

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# VII. Appendix 1: Countries in the sample, their classification and some summary statistics

Table 6: Groups of Countries in the Sample According to Disaster Impact

Country			T-4-1 N	T-4-1 N	T-4-1 N	T-1-1 4	Classifi	
1960-1996	Country	_				Total Amount of		
Algeria         1.6.1         30         1.025,344         3,345         3,071         Medium         Low	Country			•				
Angela   -0.86   1   100.000   0   3   Low   Low   High Argentina   1.22   47   16.800.000   822   5.995   Medium   Medium   Low   High Argentina   1.22   47   16.800.000   823   5.995   Medium   Medium   Low   High Argentina   1.23   47   16.800.000   828   1.010   Medium   Low	Algoria							- ·
Antigua and Barbuda					,	,		
Argentina 1.23 47 16,800,000 820 5,995 Medium Medium Australia 2.25 109 8,708,772 734 9,5825 6,000 Medium Australia 2.26 109 0 88 1,000 Medium Legal Australia 2.26 2.26 4 5,302 0 8 1,000 Medium Legal Australia 2.26 4 5,312 3 2 1,000 Low Legalum 2.274 20 2,600 8 79 Medium Legal	•							
Australia		1						Ŭ
Austria								
Bangladesh		1						
Barbados								
Selgium					,			
Bentin		1						
Solivian								
Sotswana			22					
Brazil								
Burkina Faso	Brazil					5,293		Low
Barundi	Burkina Faso	0.80	4		16		Low	Low
Cameron		0.81	1	3,600	12	0	Low	Low
Cape Verde         3.43         4         126,080         64         3         Low Medium Central African Republic         -2.26         4         36,288         7         0         Low Low Low Common			5					
Central African Republic         -2.26         4         36,288         7         0         Low         Low           Chad         0.02         6         90,112         108         0         Low         Low           Chile         2.59         44         7164,736         9330         2,96         Climatic         Medium           Colombia         2.34         80         6,715,416         27,754         2,215         Climatic         Medium           Comporos         -0.41         6         140,288         60         37         Low	Canada	2.28	53	562,304	225	4,301	Geologic	Low
Chaid         0.02         6         90.112         108         0         Low         Low           Chile         2.59         44         7,164,756         9,330         2,926         Climatic Medium           Colombia         2.34         80         6,716,416         27,754         2,215         Climatic Medium           Compo         1.71         1         60         140,288         60         37         Low         Low           Congo         1.71         1         640         154         0         Low         Low           Cost Gilvoire         0.44         2         7,040         28         0         Low         Low           Cote d'Ivoire         0.44         2         7,040         28         0         Low         Low           Copyrus         5.04         4         6,272         7         4         Low         Low           Denmark         2.46         9         0         11         250         Low         Low           Dominican Republic         2.81         20         2,992,064         2,032         293         Low         Medium           Equatoria Guinea         1.65         52		3.43			64		_	Medium
Chile	Central African Republic	-2.26	4	36,288	7	0	Low	Low
Colombia         2.34         80         6,716,416         27,754         2,215         Climatic Medium Comoros         -0.41         6         140,288         60         37         Low Low Comoros         -0.41         6         140,288         60         37         Low Low Low Cost alica           Corgo         1.71         1         640         154         0         Low Low Cost alica         1.12         31         1,514,368         387         887         Medium Medium Cost divore           Cote d'Ivoire         0.44         2         7,040         28         0         Low Low Low Low Low Denmark           Denmark         2.46         9         0         11         250         Low Low Low Denmark           Dominican Republic         2.81         20         2,952,064         2,032         293         Low Medium Low Ecuador           Ecuador         1.65         52         1,858,816         6,682         1,492         Climatic Low Company           Egypt         2.53         15         296,832         1,365         305         Medium Low God Medium Low Company           Egypt         2.53         15         296,832         1,365         305         Medium Medium Low Company           Esylate Condoct	Chad	0.02	6	90,112	108	0	Low	Low
Comoros         -0.41         6         140,288         60         37         Low         Low           Congo         1.71         1         640         154         0         Low         Low           Costa Rica         1.12         31         1,514,368         387         887         Medium         Medium           Cote d'Ivoire         0.44         2         7,040         28         0         Low         Low           Cyprus         5.04         4         6,272         7         4         Low         Low           Deminica         3.39         8         8,85,88         43         73         Low         High           Dominica Republic         2.81         20         2,952,064         2,032         293         Low         Medium           Egypt         2.53         15         296,832         1,365         305         Medium         Low           Elyst         2.53         15         296,832         1,365         305         Medium         Low           Elyst         2.53         15         296,832         1,365         305         Medium         Medium         Low         Low         Low         Low	Chile	2.59	44	7,164,736	9,330	2,926	Climatic	Medium
Congo         1.71         1         640         154         0         Low         Low           Costa Rica         1.12         31         1,514,368         387         887         Medium         Medium         Medium         Medium         Medium         Medium         Medium         Medium         Low         High         Medium         Low         High         Medium	Colombia	2.34	80	6,716,416	27,754	2,215	Climatic	Medium
Costa Rica	Comoros	-0.41	6	140,288	60	37	Low	Low
Cote d'Ivoire         0.44         2         7,040         28         0         Low         Demonina         2.92         293         Low         Medium         Low         High         Medium         Low         Low<	Congo	1.71	1	640	154	0	Low	Low
Cyprus         5.04         4         6,272         7         4         Low         Low           Denmark         2.46         9         0         11         250         Low         High         Dominican         3.39         8         85,888         43         73         Low         High         Modison         High         Dominican Republic         2.81         20         2,952,064         2,032         293         Low         Medium         Medium         Medium         Low         Medium         Medium         Low         Medium         Low         Medium         Low	Costa Rica	1.12	31	1,514,368	387	887	Medium	Medium
Denmark   2.46   9	Cote d'Ivoire	0.44	2	7,040	28	0	Low	Low
Dominica   3.39	Cyprus	5.04	4	6,272	7	4	Low	Low
Dominican Republic         2.81         20         2,952,064         2,032         293         Low Medium           Ecuador         1.65         52         1,858,816         6,682         1,492         Climatic Low           Egypt         2.53         15         296,832         1,365         305         Medium         Low           Efyalvador         0.92         12         1,065,984         2,748         1,822         Medium         Medium           Equatorial Guinea         -0.38         0         0         0         0         Low         Low           Fiji         2.05         30         984,320         228         605         Medium         Medium           Finland         2.82         1         0         0         0         Low         Low           France         2.69         66         955,904         610         6,896         Geologic         Low           Gabon         3.25         1         10,496         0         0         Low         Low           Gambia         -0.12         2         8,960         0         0         Low         Low           Gambia         -0.12         2         8,960	Denmark	2.46			11	250	Low	Low
Ecuador         1.65         52         1,858,816         6,682         1,492         Climatic Low Egypt         Low Egypt         2.53         15         296,832         1,365         305         Medium Low Medium Elow Indian           El Salvador         0.92         12         1,065,984         2,748         1,822         Medium Medium Medium Equatorial Guinea           Fiji         2.05         30         984,320         228         605         Medium Medium Medium Medium Medium Medium Medium Indian           Finance         2.69         66         955,904         610         6,896         Geologic Low Gabon           Gabon         3.25         1         10,496         0         0         0         Low Low Gambia           Gambia         -0.12         2         8,960         0         0         0         Low Low Gambia           Greece         3.55         44         835,328         1,688         3,377         Medium Low Greece           Grenada         3.45         4         1,024         6         10         Low Low Guinea History           Guinea         -0.05         3         34,560         274         8         Low Low Guinea History           Guinea Bissau         1.36         <	Dominica			85,888	43		Low	High
Egypt         2.53         15         296,832         1,365         305         Medium         Low           El Salvador         0.92         12         1,065,984         2,748         1,822         Medium         Medium           Equatorial Guinea         -0.38         0         0         0         0         0         Low         Low           Fiji         2.05         30         984,320         228         605         Medium         Medium           Finland         2.82         1         0         0         0         0         Low         Low           France         2.69         66         955,904         610         6,896         Geologic         Low           Gabon         3.25         1         10,496         0         0         Low         Low           Gambia         -0.12         2         8,960         0         0         Low         Low           Greece         3.55         44         835,328         1,688         3,377         Medium         Low           Greated         3.45         4         1,024         6         10         Low         Low           Greated         3.45 <td>Dominican Republic</td> <td>1</td> <td></td> <td></td> <td>2,032</td> <td></td> <td>Low</td> <td>Medium</td>	Dominican Republic	1			2,032		Low	Medium
El Salvador   0.92	Ecuador					,		
Equatorial Guinea         -0.38         0         0         0         0         Low Low Low Fiji           Fiji         2.05         30         984,320         228         605         Medium Medium Medium Finland           Finland         2.82         1         0         0         0         Low Low Low Gow Low Gow Gow Gow Gow Gow Gow Gow Gow Gow G								
Fiji         2.05         30         984,320         228         605         Medium Medium Medium Finland           Finland         2.82         1         0         0         0         Low Low Low Good           France         2.69         66         955,904         610         6,896         Geologic Low Good           Gabon         3.25         1         10,496         0         0         Low Low Good           Gambia         -0.12         2         8,960         0         0         Low Low Good           Ghana         -0.27         5         730,368         156         87         Low Low Good           Greece         3.55         44         835,328         1,688         3,377         Medium Low Good           Guatemala         3.45         4         1,024         6         10         Low Low Good           Guinea         -0.05         3         34,560         274         8         Low Low Good           Guinea-Bissau         1.35         2         5,632         2         0         Low Low Good           Guyana         1.30         3         58,880         0         0         0         Low Low Good           Haiti </td <td></td> <td>+</td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td>		+						
Finland         2.82         1         0         0         0         Low         Low           France         2.69         66         955,904         610         6,896         Geologic         Low           Gabon         3.25         1         10,496         0         0         0         Low         Low           Gambia         -0.12         2         8,960         0         0         0         Low         Low           Ghana         -0.27         5         730,368         156         87         Low         Low           Greece         3.55         44         835,328         1,688         3,377         Medium         Low           Grenada         3.45         4         1,024         6         10         Low         Low           Guiaemala         1.26         20         5,100,032         24,052         1,128         Medium         High           Guinea         -0.05         3         34,560         274         8         Low         Low           Guinea-Bissau         1.35         2         5,632         2         0         Low         Low           Haiti         2.99         28 <td>· ·</td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td>	· ·							
France         2.69         66         955,904         610         6,896         Geologic God         Low Low Gabon           Gabon         3.25         1         10,496         0         0         0         Low Low Gabon           Gambia         -0.12         2         8,960         0         0         0         Low Low Gabon           Ghana         -0.27         5         730,368         156         87         Low Low Low Gabon           Greece         3.55         44         835,328         1,688         3,377         Medium Low Low Gabon           Grenada         3.45         4         1,024         6         10         Low Low Low Gabon           Guatemala         1.26         20         5,100,032         24,052         1,128         Medium High Guinea           Guinea Guinea Bissau         1.35         2         5,632         2         0         Low Low Low Guinea-Bissau           Guinea-Bissau         1.30         3         58,880         0         0         0         Low Low Low Low Guinea-Bissau           Haiti         2.99         28         3,364,352         7,936         342         Medium Medium Low Low Guinea-Bissau         1,152         444         Geol		1		,				
Gabon         3.25         1         10,496         0         0         Low         Low           Gambia         -0.12         2         8,960         0         0         Low         Low           Ghana         -0.27         5         730,368         156         87         Low         Low           Greece         3.55         44         835,328         1,688         3,377         Medium         Low           Guatemada         1.26         20         5,100,032         24,052         1,128         Medium         High           Guinea         -0.05         3         34,560         274         8         Low         Low           Guinea-Bissau         1.35         2         5,632         2         0         Low         Low           Guyana         1.30         3         58,880         0         0         Low         Low           Haiti         2.99         28         3,364,352         7,936         342         Medium         Medium           Honduras         0.78         25         1,285,120         11,924         873         Low         Medium           Hong Kong         6.21         184         <								
Gambia         -0.12         2         8,960         0         0         Low         Low           Ghana         -0.27         5         730,368         156         87         Low         Low           Greece         3.55         44         835,328         1,688         3,377         Medium         Low           Grenada         3.45         4         1,024         6         10         Low         Low           Guinea         1.26         20         5,100,032         24,052         1,128         Medium         High           Guinea         -0.05         3         34,560         274         8         Low         Low           Guinea-Bissau         1.35         2         5,632         2         0         Low         Low           Guyana         1.30         3         58,880         0         0         0         Low         Low           Haiti         2.99         28         3,364,352         7,936         342         Medium         Medium           Hong Kong         6.21         184         2,187,264         1,152         444         Geologic         Medium           Ireland         2.80		1		,		,	_	
Ghana         -0.27         5         730,368         156         87         Low         Low           Greece         3.55         44         835,328         1,688         3,377         Medium         Low           Grenada         3.45         4         1,024         6         10         Low         Low           Guinea         1.26         20         5,100,032         24,052         1,128         Medium         High           Guinea         -0.05         3         34,560         274         8         Low         Low           Guinea-Bissau         1.35         2         5,632         2         0         Low         Low           Guyana         1.30         3         58,880         0         0         0         Low         Low           Haiti         2.99         28         3,364,352         7,936         342         Medium         Medium           Honduras         0.78         25         1,285,120         11,924         873         Low         Medium           Hong Kong         6.21         184         2,187,264         1,152         444         Geologic         Medium           Iceland         2.				,				
Greece         3.55         44         885,328         1,688         3,377         Medium         Low           Grenada         3.45         4         1,024         6         10         Low         Low           Guatemala         1.26         20         5,100,032         24,052         1,128         Medium         High           Guinea         -0.05         3         34,560         274         8         Low         Low           Guinea-Bissau         1.35         2         5,632         2         0         Low         Low           Guyana         1.30         3         58,880         0         0         0         Low         Low           Haiti         2.99         28         3,364,352         7,936         342         Medium         Medium         Medium         Medium         Medium         Medium         Medium         Hong         Medium         Hong         Medium         Low         Low         Low         Low         Medium         Low         Low         Low								
Grenada         3.45         4         1,024         6         10         Low         Low           Guatemala         1.26         20         5,100,032         24,052         1,128         Medium         High           Guinea         -0.05         3         34,560         274         8         Low         Low           Guinea-Bissau         1.35         2         5,632         2         0         Low         Low           Guyana         1.30         3         58,880         0         0         0         Low         Low           Haiti         2.99         28         3,364,352         7,936         342         Medium         Medium           Honduras         0.78         25         1,285,120         11,924         873         Low         Medium           Hong Kong         6.21         184         2,187,264         1,152         444         Geologic         Medium           Iceland         2.80         10         5,120         52         247         Medium         Low           India         2.55         236         574,000,000         101,426         25,400         Geologic         Medium           Ireland </td <td></td> <td>1</td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td>		1						
Guatemala         1.26         20         5,100,032         24,052         1,128         Medium         High           Guinea         -0.05         3         34,560         274         8         Low         Low           Guinea-Bissau         1.35         2         5,632         2         0         Low         Low           Guyana         1.30         3         58,880         0         0         0         Low         Low           Haiti         2.99         28         3,364,352         7,936         342         Medium         Medium           Honduras         0.78         25         1,285,120         11,924         873         Low         Medium           Hong Kong         6.21         184         2,187,264         1,152         444         Geologic         Medium           Iceland         2.80         10         5,120         52         247         Medium         Low           India         2.55         236         574,000,000         101,426         25,400         Geologic         Medium           Ireland         3.84         6         3,584         36         38         Low         Low           Israel </td <td></td> <td>1</td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td>		1						
Guinea         -0.05         3         34,560         274         8         Low Low Low Low Guinea-Bissau           Guinea-Bissau         1.35         2         5,632         2         0         Low Low Low Low Low Guyana           Haiti         2.99         28         3,364,352         7,936         342         Medium Medium Medium Medium Medium Medium Medium Medium Guinea           Hong Kong         6.21         184         2,187,264         1,152         444         Geologic Medium Low Guinea           India         2.80         10         5,120         52         247         Medium Low Geologic Medium Guinea           India         2.55         236         574,000,000         101,426         25,400         Geologic Medium Geologic Medium Guinea           Indonesia         4.63         153         8,991,488         14,728         14,400         Climatic Low Guinea           Ireland         3.84         6         3,584         36         38         Low Low Low Guinea           Israel         3.17         7         512         24         595         Low Low Guinea           Italy         3.06         65         2,179,072         5,760         34,400         Climatic Low Guinea           Jamaica								
Guinea-Bissau         1.35         2         5,632         2         0         Low         Low           Guyana         1.30         3         58,880         0         0         Low         Low           Haiti         2.99         28         3,364,352         7,936         342         Medium         Medium           Honduras         0.78         25         1,285,120         11,924         873         Low         Medium           Hong Kong         6.21         184         2,187,264         1,152         444         Geologic         Medium           Iceland         2.80         10         5,120         52         247         Medium         Low           India         2.55         236         574,000,000         101,426         25,400         Geologic         Medium           Indonesia         4.63         153         8,991,488         14,728         14,400         Climatic         Low           Ireland         3.84         6         3,584         36         38         Low         Low           Israel         3.17         7         512         24         595         Low         Low           Italy         3.06		1			,	,		
Guyana         1.30         3         58,880         0         0         Low         Low           Haiti         2.99         28         3,364,352         7,936         342         Medium         Medium           Honduras         0.78         25         1,285,120         11,924         873         Low         Medium           Hong Kong         6.21         184         2,187,264         1,152         444         Geologic         Medium           Iceland         2.80         10         5,120         52         247         Medium         Low           India         2.55         236         574,000,000         101,426         25,400         Geologic         Medium           Indonesia         4.63         153         8,991,488         14,728         114,400         Climatic         Low           Ireland         3.84         6         3,584         36         38         Low         Low           Israel         3.17         7         512         24         595         Low         Low           Italy         3.06         65         2,179,072         5,760         34,400         Climatic         Low           Jamaica				,				
Haiti         2.99         28         3,364,352         7,936         342         Medium         Medium           Honduras         0.78         25         1,285,120         11,924         873         Low         Medium           Hong Kong         6.21         184         2,187,264         1,152         444         Geologic         Medium           Iceland         2.80         10         5,120         52         247         Medium         Low           India         2.55         236         574,000,000         101,426         25,400         Geologic         Medium           Indonesia         4.63         153         8,991,488         14,728         11,400         Climatic         Low           Ireland         3.84         6         3,584         36         38         Low         Low           Israel         3.17         7         512         24         595         Low         Low           Italy         3.06         65         2,179,072         5,760         34,400         Climatic         Low           Jamaica         1.27         17         1,413,376         280         1,451         Low         Medium           Ja								
Honduras         0.78         25         1,285,120         11,924         873         Low Medium           Hong Kong         6.21         184         2,187,264         1,152         444         Geologic Medium           Iceland         2.80         10         5,120         52         247         Medium         Low           India         2.55         236         574,000,000         101,426         25,400         Geologic Medium           Indonesia         4.63         153         8,991,488         14,728         14,400         Climatic         Low           Israel         3.84         6         3,584         36         38         Low         Low           Israel         3.17         7         512         24         595         Low         Low           Italy         3.06         65         2,179,072         5,760         34,400         Climatic         Low           Japan         4.85         132         9,846,528         12,350         164,000         Climatic         Low		1		,				
Hong Kong         6.21         184         2,187,264         1,152         444         Geologic Medium Low Iceland         Medium Low Iceland         2.80         10         5,120         52         247         Medium Medium Low Iceland         Low Iceland         2.55         236         574,000,000         101,426         25,400         Geologic Medium Iceland         Medium Iceland         1,400         Climatic Iceland         Low Iceland         3.84         6         3,584         36         38         Low Iceland         Iceland         Low Iceland         Low Iceland         Low Iceland         Low Iceland         Iceland         Low Iceland         Iceland         Low								
Iceland         2.80         10         5,120         52         247         Medium         Low           India         2.55         236         574,000,000         101,426         25,400         Geologic         Medium           Indonesia         4.63         153         8,991,488         14,728         14,400         Climatic         Low           Ireland         3.84         6         3,584         36         38         Low         Low           Israel         3.17         7         512         24         595         Low         Low           Italy         3.06         65         2,179,072         5,760         34,400         Climatic         Low           Jamaica         1.27         17         1,413,376         280         1,451         Low         Medium           Japan         4.85         132         9,846,528         12,350         164,000         Climatic         Low								
India         2.55         236         574,000,000         101,426         25,400         Geologic Medium           Indonesia         4.63         153         8,991,488         14,728         14,400         Climatic Low           Ireland         3.84         6         3,584         36         38         Low Low           Israel         3.17         7         512         24         595         Low Low           Italy         3.06         65         2,179,072         5,760         34,400         Climatic Low           Jamaica         1.27         17         1,413,376         280         1,451         Low         Medium           Japan         4.85         132         9,846,528         12,350         164,000         Climatic Low								
Indonesia         4.63         153         8,991,488         14,728         14,400         Climatic         Low           Ireland         3.84         6         3,584         36         38         Low         Low           Israel         3.17         7         512         24         595         Low         Low           Italy         3.06         65         2,179,072         5,760         34,400         Climatic         Low           Jamaica         1.27         17         1,413,376         280         1,451         Low         Medium           Japan         4.85         132         9,846,528         12,350         164,000         Climatic         Low								
Ireland         3.84         6         3,584         36         38         Low         Low           Israel         3.17         7         512         24         595         Low         Low           Italy         3.06         65         2,179,072         5,760         34,400         Climatic         Low           Jamaica         1.27         17         1,413,376         280         1,451         Low         Medium           Japan         4.85         132         9,846,528         12,350         164,000         Climatic         Low				, ,	,			
Israel         3.17         7         512         24         595         Low         Low           Italy         3.06         65         2,179,072         5,760         34,400         Climatic         Low           Jamaica         1.27         17         1,413,376         280         1,451         Low         Medium           Japan         4.85         132         9,846,528         12,350         164,000         Climatic         Low								
Italy         3.06         65         2,179,072         5,760         34,400         Climatic         Low           Jamaica         1.27         17         1,413,376         280         1,451         Low         Medium           Japan         4.85         132         9,846,528         12,350         164,000         Climatic         Low								
Jamaica         1.27         17         1,413,376         280         1,451         Low Medium           Japan         4.85         132         9,846,528         12,350         164,000         Climatic         Low								
Japan 4.85 132 9,846,528 12,350 164,000 Climatic Low								
	Jordan	1.72			324	,	Low	

	Average GDP	Total Number of	Total Number of	Total Number of	Total Amount of	Classifi	cation
Country	Growth Rate	Natural Disasters	People Affected	Casualties	Damages (US\$ Million)	Disaster	Disaster
•	1960-1996	1960-1996	1960-1996	1960-1996	1960-1996	Incidence	Impact
Kenya	1.26	7	37,888	272	10	Low	Low
Korea, Republic of	6.64	44	3,524,608	5,332	3,201	Medium	Low
Lesotho	2.87	6	180,224	40	0	Low	Low
Luxembourg	3.18	3	0	0	0	Low	Low
Madagascar	-1.54	21	4,935,168	1,402	1,113	Low	Medium
Malawi	1.21	8	740,096	1,194	29	Low	Low
Malaysia	4.22	16		634	75	Medium	Low
Mali	-0.22	2		16	0		Low
Mauritania	1.10	3		0	0	Low	Low
Mauritius	3.49	18	1,027,328	64	566	Low	High
Mexico	1.86	92	2,754,560	13,454	8,909	Climatic	Low
Morocco	3.34	18	497,152	13,268	219	Medium	Low
Mozambique	-1.74	15	6,273,280	1,306	374	Low	
Namibia	0.82	0	, ,	1,500	0	Low	Low
Nepal	1.64	41	2,624,256	7.680	1.254	Medium	Low
Netherlands	2.45	11	262,144	7,080	1,841	Low	Low
New zealand	1.14	66	38,912	36	312	Medium	Low
	-0.74	20		10,932			Medium
Nicaragua	-0.74	3	, ,	10,932	1,723 11	Low	
Niger		6					Low
Nigeria	0.25	5		272	67	Low	Low
Norway	3.25		,	-	437	Low	Low
Pakistan	2.50	58	39,200,000	22,832	2,615	Climatic	
Panama	2.59	13	67,072	172	97	Low	Low
Papua New Guinea	0.93	33	409,856	592	453	Climatic	Low
Paraguay	2.78	11	894,976	80	85	Low	Low
Peru	1.21	68	7,159,040	73,860	1,911	Climatic	
Philippines	1.37	215	102,000,000	44,104	8,284	Climatic	
Saint Kitts and Nevis	6.30	5		0		Low	Low
Saint Vincent and the Grenadines	3.49	9	,	8	31		Medium
Sao Tome and Principe	1.53	0					Low
Senegal	-0.60	7	,	0		Low	Low
Seychelles	3.51	0		0			Low
Sierra Leone	0.14	3	,	68	4	Low	Low
Singapore	7.54	0		0			Low
South Africa	1.28	29	588,288	1,340	1,369	Medium	Low
Spain	3.66	40	817,408	1,863	9,381	Geologic	Low
Sri Lanka	2.37	32	9,459,712	1,944	475	Medium	Low
Sweden	2.18	7	0	12	187	Low	Low
Switzerland	1.47	25	192	265	1,162	Medium	Low
Syrian Arab Republic	3.67	3	245,248	0	44	Low	Low
Taiwan, Province of China	6.84	31	168,448	1,428	1,405	Medium	Low
Tanzania, United Republic of	0.81	16	880,640	360	7	Low	Low
Thailand	5.35	36	21,800,000	2,996	4,274	Low	Low
Togo	0.27	3	136,192	4	0	Low	Low
Trinidad and Tobago	2.41	9	51,200	100	35	Low	Low
Tunisia	2.88	11	452,608	1,036	414	Low	Low
Turkey	2.68	50	1,460,736	13,748	482	Climatic	Low
Uganda	1.70	5		156	71	Low	Low
United Kingdom	2.07	31	3,733,760	406	3,142	Medium	Low
United States	2.32	272	2,030,080	13,060	163,000	Geologic	Low
Uruguay	1.36	4		0	,	_	Low
Venezuela	0.43	13	194,048	612	58	Medium	Low
Zaire	-2.78	0	,				Low
Zambia	-1.66	2		12	200	Low	Low
Zimbabwe	1.15	2	,-		0		Low
	1.13	_			ı		