Macroeconomic Cost Estimation of Natural Disaster

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Abstract

As natural disasters have been occurring more frequently than ever before, determining its economic impact is crucial for different parties for asset and live loss compensation, reconstruction, and international aid. However, literature disagrees largely on its direction, magnitude, and duration. One critical reason of this disagreement is the method of estimating the counterfactual growth of the affected economy. This study uses a synthetic cohort of countries to predict the counterfactual growth for five case studies of extremely large disasters. We find that all five cases experienced no immediate short-run loss. For the medium- and long-run, one case (2003 Luxembourg extreme heatwave) has experienced permanent loss of growth; one case (2005 Pakistan earthquake) experiences medium-run economic boom but not in the long-run; and two other cases (2004 Indonesia earthquake and tsunami and 2003 Spain heatwave) have permanent economic gain; one case (2003 Sri Lanka earthquake) experience no significant effect. The results suggest that the initial phase of economic development and the type of a disaster have no unifying effect on the impact of the disasters. Instead, pre-disaster idle production capacity and the composition of aids might have effects on the impact.

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Introduction

Natural disasters have been occurring at an alarming magnitude and colossal costs as never before. According to Benson and Clay (2004), the reported global costs of natural disasters increased 15 times from 1950 to 1990. For the past thirty years, directly lost reported around the world for extreme weather alone is substantial: an average of $28 billion for tropical cyclones, $10 billion from inland floods, $7 billion from small-scale storm-related events (Ranson et al., 2016). Therefore, estimation of the impact of large disasters is especially crucial for different parties for asset loss and live loss compensation, recovery and reconstruction, and international aid.

However, the direction and the actual cost of natural disasters remain the center of the debate. While the mainstream academics regard the impact of the disaster negative over the long term despite the difference in the countries and the type of disasters analyzed in the studies (Hallegatte, 2008; Berlemann and Wenzel, 2015; Charvériat, 2000; Cochrane, 1994; McDonald et al.,2018; Vu and Hammes, 2010; Felbermayr and Gröschl, 2014; Bluedorn, 2005), some other regard it to be only transitory and thus the economy would recover after a period (Ghimire and Ferreira,2013; Hochrainer, 2009).

On the contrary, some regard natural disasters as an economic stimulus through the process of "creative destruction" suggested by Albala-Betrand (1993) (Hornbeck & Keniston, 2014; Skidmore & Toya, 2013; Cuaresma, Hlouskova, & Obersteiner, 2007; Okazaki, Okubo & Strobl, 2019; Fomby et al., 2011; Loayza et al, 2012). Lastly, some scholars find some disasters have no significant impact on the economy (Baker & Bloom, 2013; Cavallo et al.,2013; Dahlen & Peter, 2012). Therefore, the contradicting theories motivate this paper to seek the direction of the impact of natural disasters.

One critical but seemingly impossible step that has caused many disagreements on the effects of a disaster is predicting the counterfactual growth path for the affected country. In other words, one has to forecast the economic performance for the scenario where the disaster had not happened. While some researchers use autoregressive methods, some others use synthetic cohort to predict the counterfactual growth trends.

Hence, this ongoing debate over the impact of disasters motivated this paper to answer the following question: what is the direction of the impact in the short- and long-run? If it is negative, what is the cost in the short term and long term? How long does it take for the economy to recover from the disaster? If not, what is the theoretical approach that could best explain the phenomena?

To tackle these questions, this paper is organized into two parts: conceptual framework and regression analysis. First, we need to understand what the consequences of a natural disaster could be and how they affect the economic performance of a country. This paper then surveyed the literature to pinpoint the disagreements on the various economic consequences. To explain the disagreements among scholars, this paper looks into different theoretical approaches and more technical implementation methods. This paper then chooses the most appropriate methodology from Cavallo et al. (2013) and modifies it to fit the scope of the paper due to time constraints. Instead of aggregating all the cases and averaging an effect, this study chooses five disasters and formulates the counterfactual growth of the country by regressing on a synthetic cohort of countries with the same secular trends as the disaster country. The divergence of the actual GDP and the counterfactual for the country is, therefore, the impact of the natural disaster.

The results of this paper show that the five cases show three different impacts of natural disasters for both direct and indirect costs in the long run. While the case of Luxemburg illustrates a negative impact and Sri Lanka an insignificant impact, the rest of the cases indicate an economic stimulus caused by the disaster. This country- and disaster-based case study might not be as representative as the method of Cavallo et al. where all the impact by disasters during the period were aggregated and averaged. Nevertheless, these individual cases still can shed light on how the different disaster responses and different initial conditions of the affected country could affect or mediate the impact of disasters.

Conceptual Framework

Types of Costs

To understand the loss of a natural disaster, different categories of loss needs to be addressed. The most popular categorization is direct versus indirect loss. Under each category, it is further divided into market and non-market loss. Direct loss, as its name suggests, is immediate results of physical damage of the disaster. It is usually more tangible and more likely to be observed and reported. The most common example is the loss of agricultural products or houses destroyed after a natural disaster. Since these goods are marketable, their value easily obtained through self-reporting or reconstruction costs, especially for asset loss. Such data are usually collected by the insurance company and natural disaster databases such as EM-DAT as the number of death and the number of people affected (Hallegattte and Przyluski, 2010). Nevertheless, there are other non-marketable direct loss, such as environment and loss of life, which are harder to determine.

On the other hand, an indirect loss is the secondary effect of the disaster on the economy, usually through the loss of capital or labor and the interruption of business. Therefore, an indirect loss is usually accounted for as output loss. Due to the multiplication effect of the direct loss, an indirect loss is captured by the overall economic performance through macroeconomic variables. Although there is a fine line between direct and indirect loss, one major distinction is the time period of effects. Direct loss is usually more instant when the disaster occurs, whereas indirect loss can last for a long period of time (Murlidharan and Shah, 2010). As compared to direct loss, an indirect loss is more extensively studied by economists and concerned by local government or international aids to determine the scale of the disaster and future reconstruction and recovery. Thus, this paper will also focus on indirect loss through macroeconomic indicators.

Disagreements on the Direction and Magnitude of Loss

Different approaches are used to assess and aggregate the costs and the most common two methods involve using insurance reporting and panel macroeconomic data (Ranson et al., 2016). The former usually relies heavily on the accuracy and completeness of the reporting and sometimes is constrained to certain types of damage (e.g. infrastructure damage) (Ranson, Tarquinio, & Lew, 2016). On the other hand, estimation based on observable macroeconomic indicators has greater flexibility to check both long-term and short-term impact (Cavallo et al., 2013) as well as both regional and national impact. These indicators usually have data readily available. Therefore, economic growth data will be discussed in this paper instead of insurance reporting.

However, the literature on the macroeconomic estimation of disaster loss significantly disagrees with the direction of the economic impacts over both short terms and over long terms. Some posit that there is an overall negative impact on the economy, while others find it a stimulus to the economy. A few scholars find it generally has no impact on the economy. The conclusion depends on the type of disaster, time period, level of economic development of the affected country as summarized in the following table (Fig.1).

Direction of impact	study	type of disaster	average disaster impact
positive	Hornbeck & Keniston, 2014	Fire	Substantial economic gains from the created opportunity for widespread reconstruction. Land value increased to be equal to the value of building burned.
	Albala-Bertrand, 1993	all	Capital loss is compensated by response expenditure; thus, growth rate is unlikely to fall and slightly increases.
	Skidmore & Toya, 2013	all	Disaster increases expected return to physical capital, and increase technological advancement, thus increase growth.

	Cuaresma, Hlouskova, & Obersteiner, 2007	all	Disaster has a robust positive correlation between frequency and long-run economic growth. Only developed countries enjoy capital upgrading through trade.
	Okazaki, Okubo & Strobl, 2019	earthquake	Disaster caused an upgrade of machine technology and/or survival of efficient firms in 1923 Great Kanto Earthquake.
	Fomby et al., 2011	all	Some disasters induce positive effect on growth.
	Loayza et al, 2012	all	Moderate disasters (like moderate flood) can have a positive growth effect in some sectors, while severe disaster has a negative effect
negative	Hallegatte, 2008	Hurricane	Total lost is estimated at $149 billion with $107 billions of direct losses. Total loss increases nonlinearly with direct loss.
	Berlemann & Wenzel, 2015	drought	Drought has significantly negative long-term growth in both developed and developing countries.
	Charvériat, 2000	all	In a short run, real growth rate falls. Smaller countries are particularly more vulnerable to the impact than larger countries, where disasters are more limited to an area.
	Cochrane, 1994	all	Disaster shock lowers credit rating and causes indebtedness, thus reducing investment and long-term growth.
	McDonald et al.,2018	earthquake	One year after the earthquake, there is a NZ$156-686 millions of losses.
	Hochrainer, 2009	all	In a medium term (up to 5 years), disasters cause a small negative effect on GDP. Aid and inflow of remittances reduce the adverse impact
	Vu and Hammes, 2010	all	Deaths caused by natural disaster reduces GDP and GDP growth. Regional difference in the impact is observed.
	Felbermayr & Gröschl, 2014	all	Disaster has a strong negative impact on growth, mainly by earthquake and some meteorological disaster. Poor countries suffer more from geophysical disasters while rich more by meteorological.
	Bluedorn, 2005	hurricane	Hurricane destroys capital and reduces GDP by 5% initially and 3-8 years by 2.7%.
	Ghimire and Ferreira,2013	flood	Flood increase the probability of conflict incidence by having a negative effect on short-run GDP.

mixed	Cavallo *et al.*,2013	all	Only extremely large disasters have a negative effect on output for both long term and short term. For countries having political revolution after the disasters, if control for political changes, extremely large disasters show no effect on economic growth.
	Baker & Bloom, 2013	all	Natural disasters have no significant impact on stock market volatility.
	len & Peter, 2012	all	Negative effect on growth in general for uninsured disasters after 10 years. Insured disaster has no significant effect on GDP.

Fig.1 Disaster literature review, by author

From the Fig.1, we can see there is a general debate over the direction of the impact. The mainstream academic view regard the impact of the disaster negative over short- or long-term despite the difference in the countries and the type of disasters analyzed in the studies (Hallegatte, 2008; Berlemann and Wenzel, 2015; Charvériat, 2000; Cochrane, 1994; McDonald et al.,2018; Vu and Hammes, 2010; Felbermayr and Gröschl, 2014; Bluedorn, 2005; Ghimire and Ferreira,2013; Hochrainer, 2009). Another school of thought is that the natural disasters provide an economic stimuli through the process of "creative destruction" suggested by Albala-Betrand (1993) (Hornbeck & Keniston, 2014; Skidmore & Toya, 2013; Cuaresma, Hlouskova, & Obersteiner, 2007; Okazaki, Okubo & Strobl, 2019; Fomby et al., 2011; Loayza et al, 2012). Lastly, some scholars find some disasters have no significant impact on the economy (Baker & Bloom, 2013; Cavallo et al.,2013; Dahlen & Peter, 2012).

Moreover, among the scholars who agree with the direction of the impact, there are also disagreements over the period of impact. Some consider the impact to be long-term or permanent ((Hallegatte, 2008; Berlemann and Wenzel, 2015; Charvériat, 2000; Cochrane, 1994; McDonald et al.,2018; Vu and Hammes, 2010; Felbermayr and Gröschl, 2014; Bluedorn, 2005), whereas others consider it to be transitory (Ghimire and Ferreira,2013; Hochrainer, 2009).

The type and the intensity of the disaster and the difference in affected country also raise conflicting views among the scholars. For example, Felbermayr and Gröschl (2014) suggest that mainly earthquake and some meteorological disasters have a strong negative impact on growth. Regarding the different intensity of disasters, Loayza et al. (2012) point out the distinctions between moderate and severe disasters - moderate disasters (like moderate flood) can have a positive growth effect in some sectors, while severe disaster has a negative effect. The phase of development of the countries also marks a difference where poor and rich countries suffer differently from different types of disasters (Felbermayr and Gröschl, 2014; Berlemann and Wenzel, 2015; Vu and Hammes, 2010).

Therefore, the critical question arise among the debate is: what has caused these disagreements over the costs of the disasters? The next sections seek to explore the difficulties that are inherent to the nature of the disaster and the different implementing methodologies in determining the impact of the disaster.

Challenges of measuring the Impact of Disaster

The inherent complexity of natural disasters has made estimation of cost difficult, due to the multiplicity of dimension of harm caused and the indefinite geographic area and time period of impact. Beyond the disasters itself, the distinctive published databases and counterfactual growth projections further complicate this already challenging estimation.

The multiplicity of dimension of harm from disaster makes loss estimation remains a great challenge. The costs associated are accounted from different perspectives, different key players, like media, insurance companies, and international organizations, have different definitions regarding the cost of disasters concerning their agendas, which further translate into different methodologies of assessment.

Published estimates are hard to compare as they incorporate or emphasize different subsets of the different dimensions of the costs. While disaster database like EM-DAT or others by the insurance companies only account for direct loss and asset loss for the reparation of damage (Ranson et al., 2016), there are other more indirect costs: output losses, intangible losses, non-market loss, welfare losses and a combination of the aforementioned (Hallegatte & Przyluski, 2010). It is, therefore, hard to compare across disasters or countries.

Another difficulty of the estimation is the determination of the geographical area and the timeline of the impact. It is hard to determine the boundary the disaster has an impact until and the time the disaster stops to have an impact. The economic ripple effect is not only amplified by the disruption of business of the country or region that directly receives the disaster, but also its neighboring regions that conduct economic activities. For example, globally hurricane Katrina caused world oil prices to soar. Therefore, the geographic perimeter of cost analysis is decided by the purpose of the decision-makers, whether it is the local government or international organizations (Hallegattte and Przyluski, 2010).

Projecting a counterfactual baseline growth model also remains a problem. To determine the loss, the post-event GDP is compared with the prediction of counterfactual GDP, which is the growth trajectory if the disaster did not occur. In some cases, not one but many baselines are estimated according to different scenarios (Hallegattte and Przyluski, 2010). While some researchers use autoregressive methods, some others use synthetic cohort to predict the counterfactual growth trends.

Therefore, the complexity of the disaster itself has caused the impact to be hard to account for. This multifaceted loss of disaster has further caused the different recording methods by databases and caused the disagreements among scholars. Most importantly, it is impossible to know the growth of this economy if the disaster had not happened, thus making the estimation less definite. However, such inherent difficulties are tackled by the scholars with different theoretical approaches and thus distinct implementation methods, further amplifying the variations in their conclusions.

Theoretical Approaches

To explain the different direction and magnitude of findings arise in the debate, scholars came up with distinct theoretical approaches within academic studies using macroeconomic indicators. Three most popular theoretical models are summarized by Ranson et al. (2016) as "Transitory loss", "permanent loss", and "creative destruction". Within each mechanism, there are also various disagreements among scholars due to the assumptions of the economy.

Both "transitory loss" and "permanent loss" indicate an adverse impact on the economy and they differ only by the time span of the impact. Both theories agree that the loss of capital due to the disaster will cause the economy to be below equilibrium. However, for the former, the economy is assumed to have a declining return to scale. Any loss of capital will increase the marginal product of capital and thus over time, the economy will grow back to its former path (Fig.2 scenario A). For the later, the underlying assumption changes to constant returns to scale. Therefore, the loss of capital will shift the growth path down (Fig.2 scenario C). Over time the economy, with no incentive to compensate investments with short-term consumption will continue along with the new growth path (Ranson et al., 2016).

There is also extension and variation to the two theories where capital flexibility and trade-offs of "investment-consumption" are accounted for. When there is no flexibility in the production process, the loss of capital will result in a reduction in output and unaffected capital will not be able to increase its own production to compensate for this reduction. However, when there is limited flexibility, the unaffected capital, such as workers at factories that are not destroyed by the hurricane, will be able to work more hours to boost business (Hallegatte & Przyluski, 2010). Nevertheless, Murlidharan and Shah (2003) explain that this delay of recovery is due to the difference between maturing capital and productive capital which serve different functions in the process of production. The former is used in the ongoing construction process while only the latter is used for producing goods and services. Moreover, due to capital inflexibility, reconstruction cannot be accomplished by increasing production of unaffected capital, and the forced investment into reconstruction and replacement will result in further loss in welfare due to trade-off other activities. Therefore, in both senses, the loss will be smaller and more temporary when capital is more flexible in post-event production. Murlidharan and Shah (2003) suggested another extension to Ramsey's growth model for the transitory loss. Interactions between affected and unaffected regions are considered and such spatial propagation of the loss is simulated.

The third view held by various scholars is that such a disastrous event will act as a stimulus to the economy when the marginal product of factor is the limiting factor to a higher growth path. Studies that use endogenous Schumpeterian model of growth through a process of creative destruction posit that a random sequence of technology and innovations induced by the disaster cause growth to be higher (Benson & Clay, 2004; Skidmore & Toya, 2013) (Fig.2 scenario D). Disasters provide an opportunity for industrial firms to relocate and agglomerate and thus improving productivity; change in residential and commercial land use and thus changing building quality; the grouping of small plots and reduction of transaction cost, etc (Hornbeck & Keniston, 2014). In Hallegatte and Przyluski's model (2010), the transitory loss will be compensated by both productions due to capital flexibility and economic stimuli generated by the disaster. Eventually, the economy will be on the same path, but the economy might be above the equilibrium due to this boost (Fig.2, scenario B).

Therefore, the three most popular theoretical approaches, “Transitory loss”, “permanent loss”, and “creative destruction”, illustrate the different empirical findings in the academic debate over the direction and duration of the impact of natural disasters. However, the disagreements among scholars not only arise from their intrinsically different beliefs but also their different implementation methods.

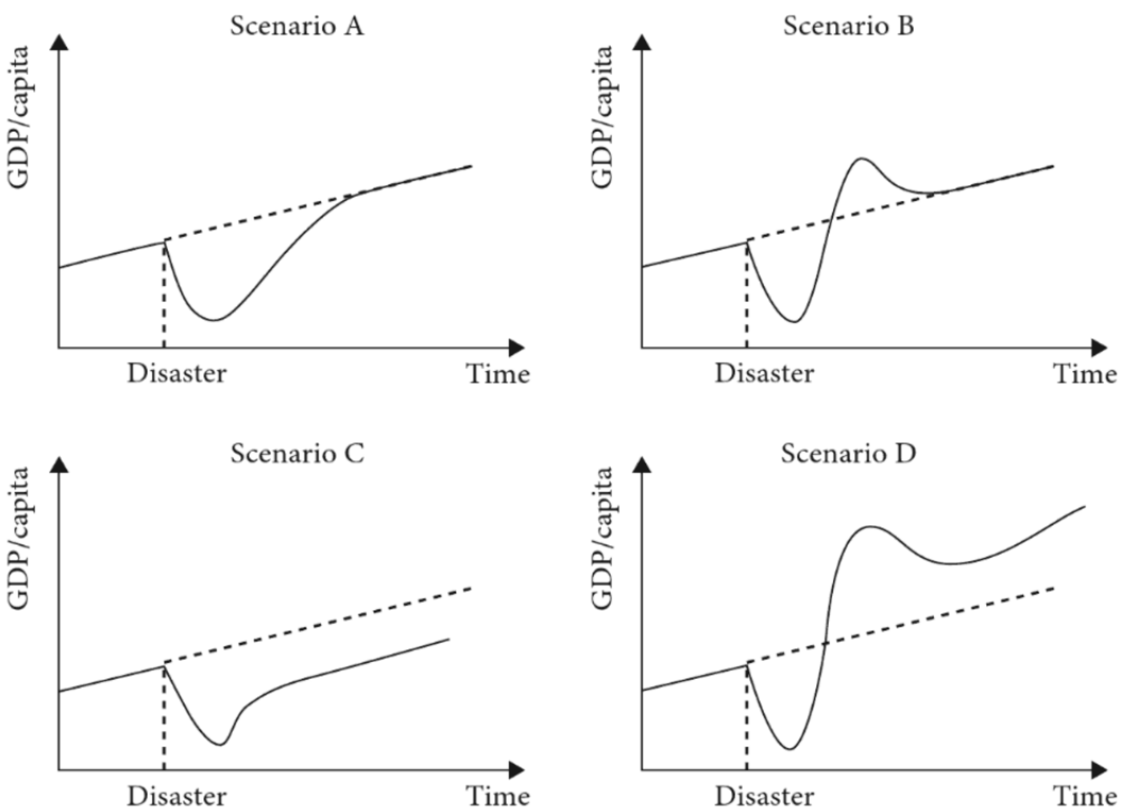


Fig.2 Possible long-term impact of disaster on economic growth (Guha-Sapir et al., 2013)

Implementation Strategies

Even among the scholars who share the same theoretical approaches and use macroeconomic indicators to estimate the loss, there are variations in testing the theories. One fundamental distinction is the macroeconomic indicator used to assess the output loss. (Fomby et al., 2011). While most use GDP to proxy the economic growth, some also focused on land value through property tax (Hornbeck & Keniston, 2014), indebtedness (Cochrane, 1994), or financial market volatility (Baker & Bloom, 2013). Whether macroeconomic data should be aggregated for both agricultural sectors and other sectors would also affect the result significantly, as well as the other macroeconomic data other than GDP growth (Raddatz, 2009). One study concerns how deaths inflicted by natural disasters affect both GDP and GDP growth (Vu and Hammes, 2010).

Studies also include various other variables as controls to assess the vulnerability of the impacted communities, especially for cross-sectional panel analysis. According to Murlidharan and Shah (2003), to achieve a percentage point in economic growth, needs, separately, an increase in 1.2 years of schooling, 40 percentage point of secondary school enrollment, a decrease in 28 percentage points in the share of the central bank in total credit, an increase of 1.7% of GDP in public investment of transport and communication, an increase in trade openness of 40 percentage points, a fall in government consumption of 8 percentage points, etc.

Even though most studies include some forms of the determinant of GDP, the difference between most methods, however, lies in the calculation of counterfactual growth path. A large number of studies use the similar structure of what is proposed by Hochrainer (2009) as “Disaster Risk Management Framework” (Fig.3) to predict the consequences of GDP, using indicators mentioned above. “Exposure” analyzes population and assets exposing to the disaster in a geographically limited impacted area. “Vulnerability” is further divided into physical, economic, social and environmental factors like financial capacity, institutional ability, etc. Lastly, “hazard” focuses on the disaster itself, including the type, intensity, and recurrence. From this framework, literature either uses static economic model which uses a large number of countries to calibrate to a target country (Cavallo et al., 2013) or time series model (Fomby, 2013; Raddtz, 2006; Hochrainer, 2009).which is more dynamic (e.g autoregressive integrated moving average) (Ranson et al., 2016).

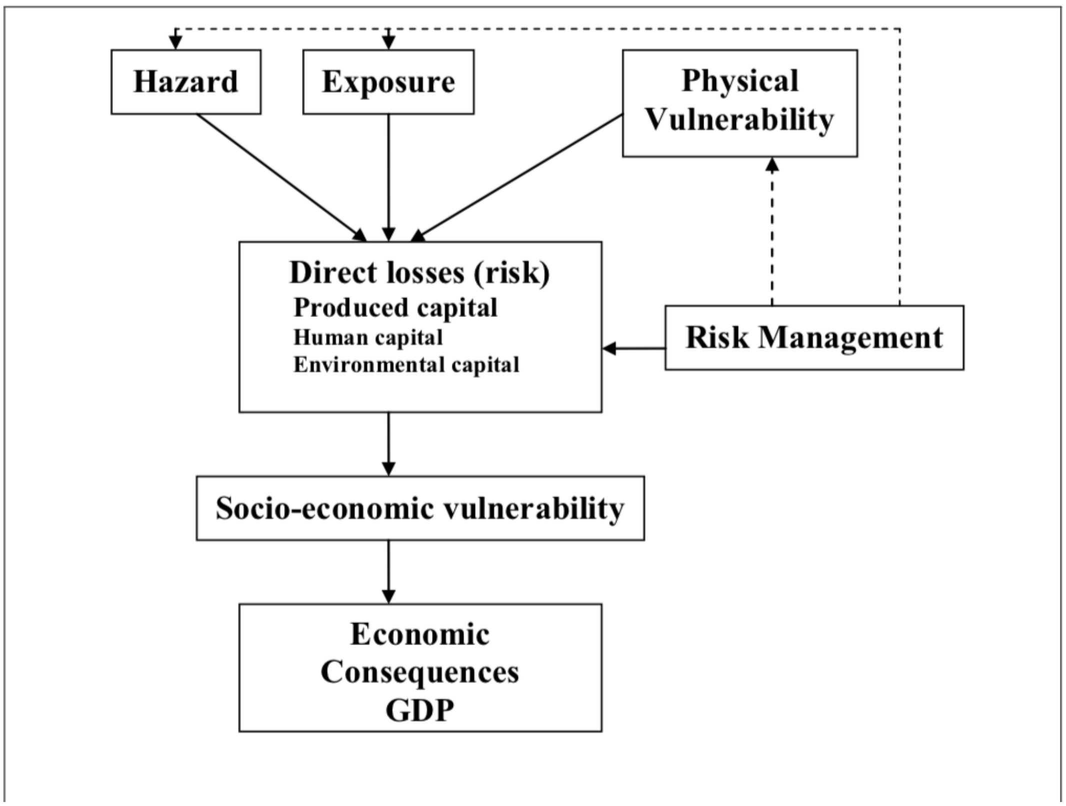


Fig. 3 Conceptual framework used in this study for explaining economic risk due to natural disasters (Hochrainer, 2009)

Another decision to make on aggregation is the type of disaster, as the impact of each type of disaster would be different. A few studies focus on a historical event with an extremely large impact on a particular disaster type. For example, Hornbeck and Keniston (2014) focused only on the Great Chicago fire, while Okazaki, Okubo, and Strobl (2019) only analyzed the 1923 Great Kanto Earthquake. However, most studies either focus on one type of disaster (Berlemann

& Wenzel, 2015; Hallegatte, 2008; Bluedorn, 2005; Ghimire and Ferreira, 2013) or aggregated the same type of disaster and concluded different effects for each category (Felbermayr & Gröschl, 2014; Murlidharan & Shah, 2003). The rest of literature tend to aggregate across different types of disasters (Albala-Bertrand, 1993; Skidmore & Toya, 2013; Cuaresma, Hlouskova, & Obersteiner, 2007; Fomby et al., 2011; Loayza et al, 2012; Charvériat, 2000; Cochrane, 1994; Hochrainer, 2009; Vu and Hammes, 2010; Felbermayr & Gröschl, 2014; Cavallo et al.,2013; Baker & Bloom, 2013; Dahlen & Peter, 2012). Nevertheless, some scholars like Raddatz (2009) argue that such aggregation would mask the contrasting effects (Fomby et al., 2011).

Another concern is how to account for the intensity of the event. While some simply use the frequency (Skidmore & Toya, 2013) and binary variables to indicate the occurrence, some used the reported damage and two-stage least squares on hurricane category dummy variables to gauge the intensity (Ranson, Tarquinio, & Lew, 2016). Some scholars focus on a single abnormally large disaster (Hornbeck & Keniston, 2014; Okazaki, Okubo & Strobl, 2019; McDonald et al.,2018). Other scholars categorize disasters by percentiles to rank different intensities by calculating either death rate (over total population) or physical asset damage reported through the database (Cavallo et al., 2013; Loayza et al, 2012).

Noticeable distinctions also lie in the choice of time period after the disasters. While most conclusions are on the long-run impact and explain through the model of technological advancements, some also focused on short- or medium-run (under five years). Nevertheless, the choice also depends on data availability as a more recent disaster might not have enough macro-economic data for long term comparison after the disaster, whereas earlier or historical disaster lack significant availability on indicators.

Moreover, studies are divided into two groups – cross-country panel analysis and country or disaster specific analysis. However, critics noted a few problems regarding the cross-sectional panel analysis for multiple countries over different disasters. Firstly, endogeneity exists as the empirical studies suggest that richer countries would have less loss than developing countries (Charvériat, 2000; Felbermayr & Gröschl, 2014). Therefore, the loss in economic growth can be affected by itself. Moreover, there might be some omitted variable like latitude that could affect both economic growth and the frequency of disaster (Ranson, Tarquinio, & Lew, 2016), if one simply uses cross-sectional data over a long period of time as did Skidmore and Toya (2013). One solution to this is to separate the rich and the poor country (Fomby et al., 2011) and another is to do a difference-in-difference regression that focuses only on the change of economic growth of the country itself before and after the disaster (Murlidharan & Shah, 2003).

With various distinctive growth theories and empirical models in place, the methodology of Cavallo et al. (2013) is chosen to accomplish the goals of this study. As this thesis strives to identify the direction of the impact of large disasters in both the short- and long-term, Cavallo's method would allow us to generate a counterfactual growth path through a synthetic cohort to show the direction of the impacts.

Cavallo's methods uses a set of countries Js that have not been affected by any natural disasters and have the same secular trend with the disaster-affected country I to simulate the its counterfactual growth. By regressing real GDP per capita of I, one of the most used indicators, on those of Js, a set of weights of each country J for a specific I is obtained. Similar to the "Disaster Risk Management Framework" by Hochrainer (2009) and factors concluded by Murlidharan and Shah (2013), six categories of "GDP predictors" such as trade openness, education level, etc, are used as controls in generating weights for each country in the synthetic cohort. Since it is a country-specific comparison of a growth path before and after the disaster, the shortcoming of endogeneity is avoided.

The intensity of disasters is also accounted in Cavallo's study as death as a share of population, again a very common method of determining the intensity across different type of disasters, is used to generate a batch of extremely large disasters (99th, 90th and 75th percentile). By sorting out these countries as I countries, Cavallo et al. prevent the unfair aggregation of disasters of different intensity.

However, after running individual regression on each I country, Cavallo et al. aggregate the differences between counterfactual and actual GDP over the post-disaster periods with other I countries to see the general effect across G large disasters for the 99th, 90th and 75th percentile. As this aggregation only focuses on the intensity, it ignores the effect of different type of the disasters. Moreover, due to the time constraint and the availability of data, this part of aggregation is not applicable to this study. Thus, only selected countries with extremely large disasters in the 2000s will be analyzed using cross-country comparative studies.

Methodology

As mentioned in the previous section, to find the general direction of the effect of natural disasters on economic growth, this study performed a cross-country comparative study using a synthetic cohort following a modified version of the methodology by Cavallo et al. (2013). The study is done by three steps:1. Identify the disaster case study by ranking the intensity; 2. Generate a synthetic cohort of countries that had not experienced disasters that have the same trends 3. Use the weights of each country in the cohort to predict a counterfactual path of the disaster-affected country using GDP predictors. The three steps generally follow those of Cavallo et al. The difference between this modified version and Cavallo's is that instead of aggregating the effects of disasters across different countries within the 99th, 90th and 75th percentile, only selected countries are analyzed in this study.

Identification of Large Disasters, Disaster Countries and Synthetic Cohort

The definition of the intensity of a disaster is often based on the type of disaster, such as an 8.0 magnitude scale for earthquake and Saffir-Simpson wind speed scale for a hurricane. However, to compare across disasters of different kinds and across the world, two measures are commonly used. One is based on the physical asset loss reported by each country, often based on insurance reporting or evaluation during reconstruction. The other one is the human impact of the number of deaths and people affected. The latter is used in this case as the aim of this study is to re-estimate the economic impact of the disaster and the reported economic impact is usually incomplete as it is based on reporting of government agencies, press, research institutes, non-governmental organizations, international organizations and insurance companies (Ranson et al., 2016).

Following Cavallo et al., this study uses the International Disaster Database (EM-DAT) by Centre for Research on Epidemiology of Disaster (CRED), a typical data source used by most studies (Ranson et al., 2016). The reporting criteria for a disaster to be included in the database are mostly human-based: 10 or more people dead; 100 or more people affected; the declaration of a state of emergency; a call for international assistance (EM-DAT, n.d.). Moreover, the economic estimation of damage is only the value of the year of occurrence, thus largely excluded the long-run indirect loss. Therefore, in this study, I use the percentile-based definition of "extremely large disasters" that focuses on the human-related damage as adopted by Cavallo et al. (2013).

Firstly, from the EM-DAT database, the number of deaths for each disaster is used to divide by the population data from the World Bank Indicator database of that country of the year of the disaster. The disasters are then ranked based on the number of death as a share of the population. Top 99 percentile of the disasters is then selected with a cut off of .0003277 (i.e. ~328 people killed per million population). Thus, 17 countries are selected for disasters that happened from 2000 to 2010 (Fig.3 &4).

To distinguish the effect of this single occurrence of the disaster, countries with repeated disaster occurrence such as Haiti are eliminated from the list. Data availability is also checked for all the GDP predictors listed by Cavallo et al. (2013) as mentioned in the previous section. For this study, GDP predictor data from 1980-2000 is used to proximate the weights for each country, less developed countries often have data missing from earlier years and for some indicators such as secondary school enrollment. Thus, after screening data availability and single occurrence of the disaster, the final countries of choice are Indonesia for the 2004 earthquake. This group of disaster countries is called i countries.

The same procedure is applied to other countries to generate a synthetic cohort (listed as j countries) (Appendix.1). The only difference is that for those countries to be as a comparison, they must have not experienced any disasters in the period of 2000 to 2010. To give a more general context, these countries of interests are selected for different types of disasters across different phases of development. Moreover, only countries with a single occurrence are selected, the impact of this particular disaster is isolated, thus avoiding the problem of aggregation of the type of disaster. For example, Haiti had multiple earthquakes and hurricanes in the 2000s, and it is excluded due to the overlapping indirect impact of the disasters. Therefore, by limiting the scope to country-specific and disaster-specific analysis, this study looks at the general direction, instead of an average magnitude of the indirect impact in both short- and long-run.

Counterfactual Growth Prediction: Computational Details

To synthesize the predicted growth path using the synthetic cohort, each country in the j country group is given a weight based on the period before the disaster. To calculate this weight for each country, different GDP predictors X_{vt} are stacked for each year for the period of time for different countries and the predictor X_{vit} for the i country is regressed with OLS model on the j countries' predictors X_{vjt}. A few assumptions are made for the weights obtained for each j country to be applicable. First of all, it is assumed that all the predictors X_{vt}, regardless if it is education or democratic capacity, have the same weights for the same country. Secondly, by stacking the predictors for each year together, it is also assumed that the weights for each country does not vary over time. Therefore, the two assumptions allow us to obtain a w_{ij} that is the same for each country for different predictors and different years.

Weights are obtained through the regression equation as shown for the period before disaster T_{i0}.

$$X_{vit} = w_{i0} + \sum_{j=1}^{J} w_{ij} X_{vjt} \;\; + e_{vit}$$

Where i=1,…I countries that experience a disaster; j=1,…J is comparison group of countries for synthetic cohort. t=year; T_s = end year for synthetic cohort; T_{i0} = date of disaster for country i v = a,…h variable type.

For the GDP predictors X_v, a set of seven variables are adopted from Cavallo et al.(2003). They are trade openness, capital stock, land area, secondary school attainment, latitude, polity 2, gdp/capita (PPP) (see appendix.2 for sources and definition). Each time-variant variable is indexed using 2000 as base year for each country so as to avoid the extremely large number (like trade) skewing the aggregation. For non-time variant variables such as land area and latitude, they are indexed with regards to the i country.

Using the weights obtained for each j country for a particular i country and the GDP for each j country at year t, we can thus compute the GDP for year t for the target i country:

$$Y_{it}^{N} = \; w_{i0} + \sum_{j=1}^{J} w_{ij} Y_{jt}$$

Thus, we can estimate the counterfactual GDP for the i country from the disaster year T_{i0}:

$ln\ Y_{it} = a + b_1 ln Y_{it}^{N} + b_2 D_{it}$ + e_{it} where D_{it} = 1 for t > T_{i0}

After obtaining the estimated $ln\ Y_{it}$, we can plot Y_{it} against Y_{it}^{N}.

Empirical Testing

Disaster Analysis

This study uses panel data for all the disasters occurred from 2000 to 2010 from EM-DAT. For this period, 2706 disasters are recorded, and they are reported as country-year entries, i.e. for the earthquakes in China in 2009 are aggregated in the same entry but shown as 2 occurrences. The dataset includes both human and physical asset damage reporting. As mentioned in the previous section, only human-based loss is used in determining the severity of the disaster. With population by year data obtained from World Bank Indicator, deaths per million population is used to rank the disasters.

Over time, there is an increasing trend of the frequency of occurrence. Though there were fluctuations from year to year, the frequency of occurrence follows a steady growth over the four decades (Fig.4). From 1995 to 2010, there was a spike of occurrence and the number of occurrences peaked from 2000 to 2005, which is the focus of this study. To further break down the composition of the increasing occurrences, different categories of natural disasters are stacked in (Fig.5). The three major types of disaster whose occurrences are highly correlated – flood, storm, and landslides –and experience a visible increase in occurrence respectively, especially during 2000s. Similarly, the occurrence of extreme temperature events, drought and wildfire, whose occurrences are also highly interlinked, increased drastically from 1997 to 2005. Nevertheless, critics suggested that there might be an increase in the frequency of reporting due to the improvement in the ease of reporting and the higher media coverage. However, the drop of occurrence from 2000 to 2020 might suggest that even as the reporting system keeps advancing, there was no increase in the occurrence. This suggests that the improvement in the reporting system, if it had increased the disaster registered in the database, has exhausted its initial effects and the reporting reflects more accurately after 2000. Overall, there is an increasing in the frequency of occurrence of disaster globally with a period of sudden spike from 1995 to 2005.

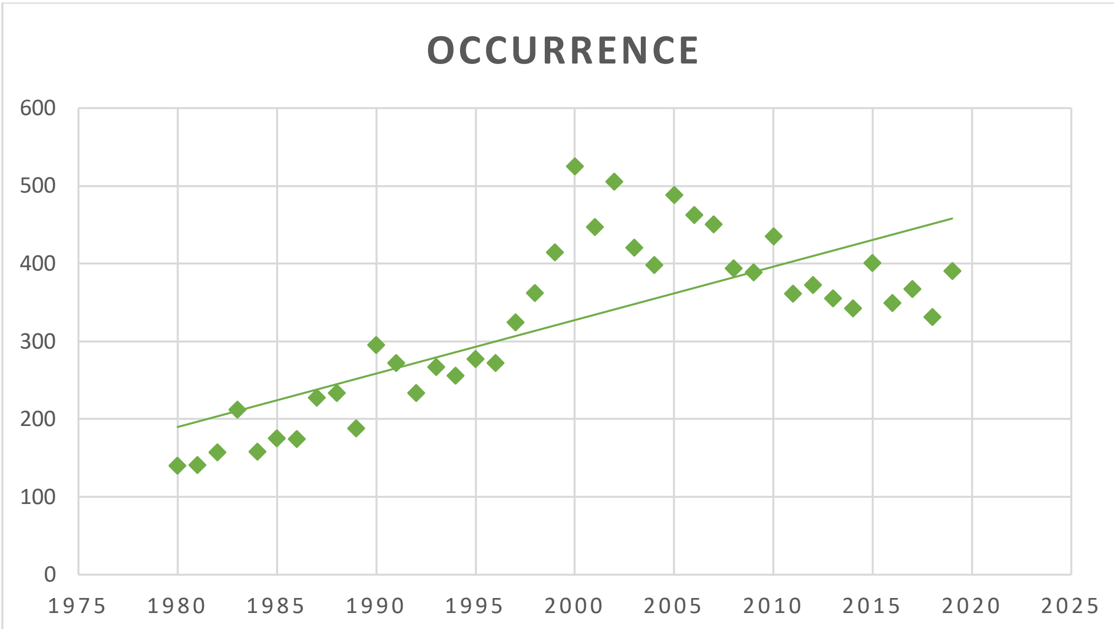


Fig.4 frequency of occurrence sort by year based on EM-DAT data, by author

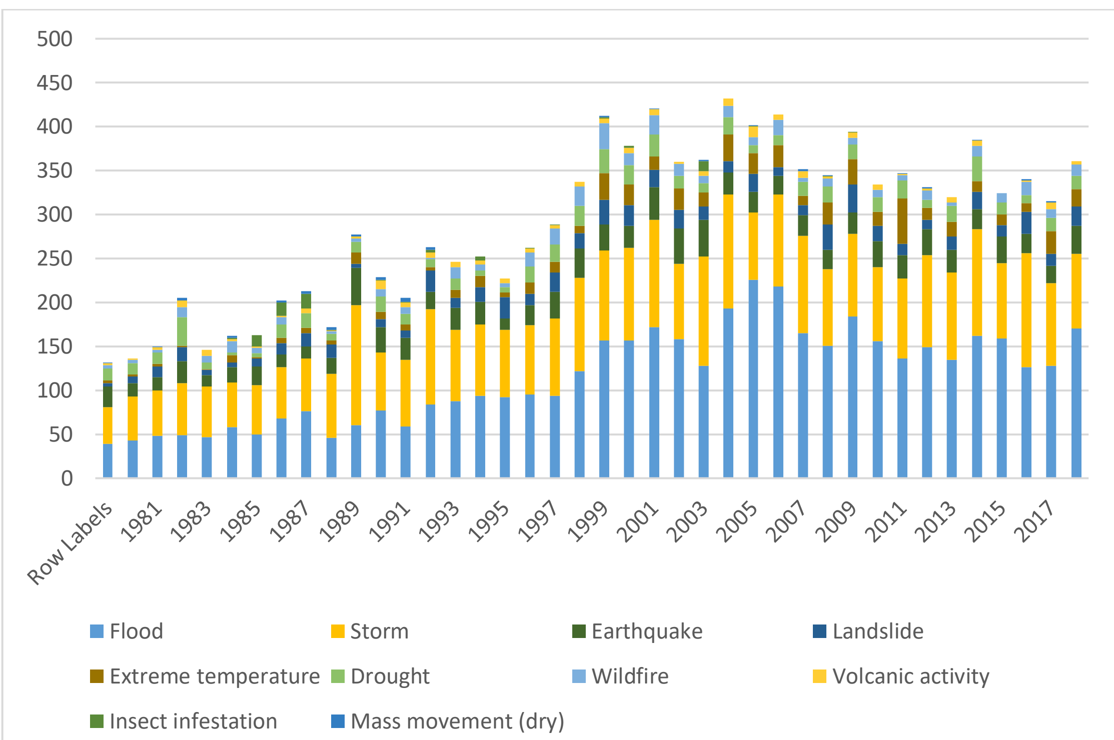


Fig.5 frequency of occurrence sort by year and disaster type based on EM-DAT data, by author

As summarized inFig.5 and mostly in Fig.6, flood consisted 45% of the total occurrence of disasters, followed by storm (26%) and earthquake (7%). However, despite the frequent occurrence of storm and flood, their average human costs are not as high. Instead, earthquake and drought are the most damaging as they caused an average of 230 and 123.90 deaths per million. In Fig.7, we can also see that earthquake is responsible for 68% of human damage during the period, followed by storm (13%) and extreme temperature (9%). This observation is consistent with literature that different types of natural disaster have different costs.

Disaster type	occurrence	Death per million (mean)
Drought	190	123.90
Earthquake	307	230.19
Extreme temperature	249	22.51
Flood	1899	2.82
Landslide	223	1.64
Mass movement (dry)	8	1.44
Storm	1098	15.60
Volcanic activity	65	0.93
Wildfire	147	0.84

Fig.6 Summary of mean deaths as a share of population by disaster type occurred during 2000-2010, by author based on EM-DAT

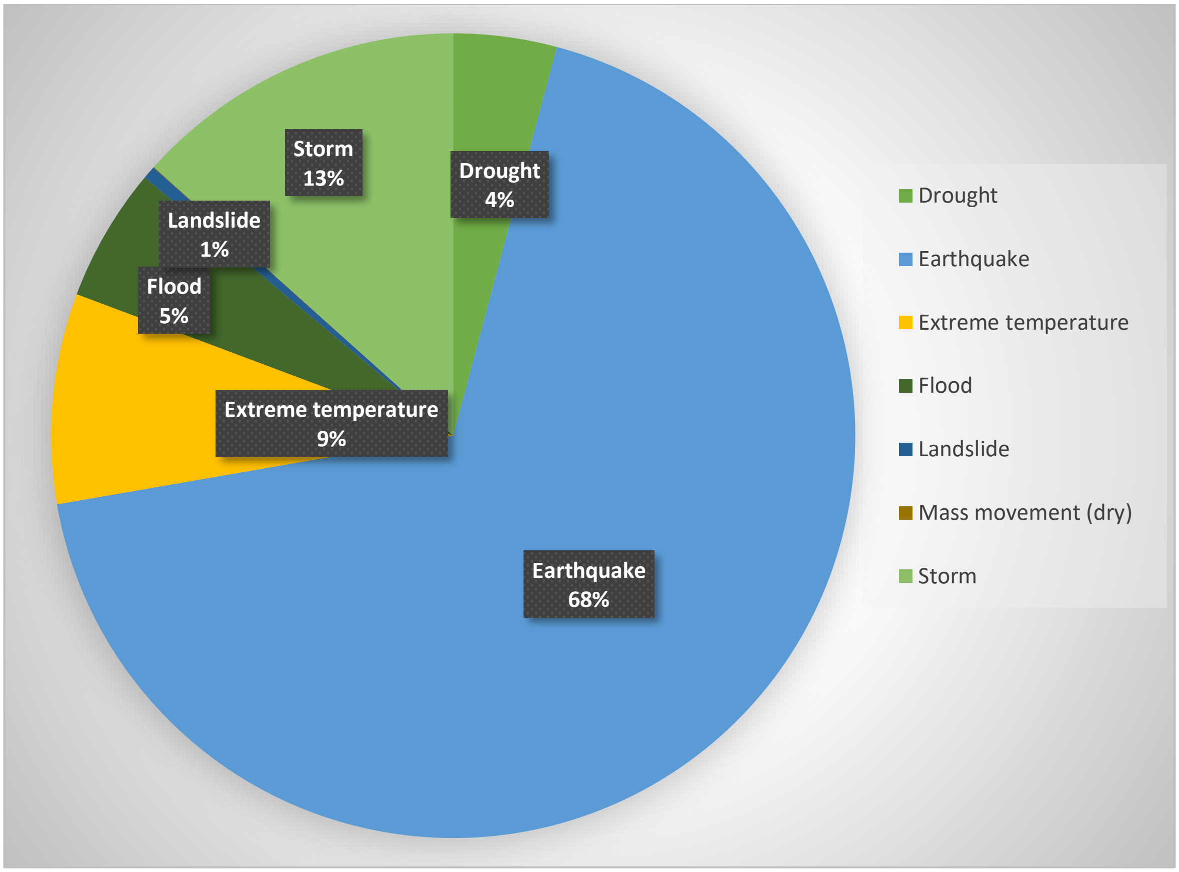


Fig.7 aggregated deaths per million population per disaster type, by author based on EM-DAT

Another type of data is the GDP predictors needed to predict the weights for each country and the estimation of counterfactual growth path. Like Cavallo *et al.*, the data on GDP per capita at purchasing power parity in constant US dollar (PPP) is obtained from WDI. Others GDP predictors (X_v) such as trade openness (import plus export divided by GDP) and secondary school enrollment (share of population officially registered in a given educational program) are also from WDI. Government stability variable is obtained from the International Country Risk Guide dataset by the PRS group. It is an assessment "both of the ability to carry out its declared programs and stay in office", including three subcomponents of government unity, legislative strength and popular support (PRS Group, 2020). Capital stock at current PPPs (in mil. 2011 US$) is obtained from Penn World Table. Geographical indicators such as land area and latitude are from Cavallo et. al (2013). The selection of dataset is largely the same of that of Cavallo *et al*. except the secondary education attainment, which they obtained from Lutz at al. (2007) and I obtained from WDI for the more recent data.

country	Death per million	Year	Disaster type
MDV	327.695	2004	Earthquake
ZWE	345.4084	2008	Epidemic
ITA	350.5126	2003	Extreme temperature
ESP	357.6877	2003	Extreme temperature
GRD	373.753	2004	Storm
LUX	376.4143	2003	Extreme temperature
RUS	390.341	2010	Extreme temperature
IRN	393.3624	2003	Earthquake
FSM	439.1292	2002	Storm
PAK	457.4933	2005	Earthquake
ASM	599.8271	2009	Earthquake
HTI	694.3187	2010	Epidemic
IDN	742.6182	2004	Earthquake
WSM	801.9246	2009	Earthquake
SOM	1660.594	2010	Drought
LKA	1825.9	2004	Earthquake
MMR	2771.22	2008	Storm
HTI	22370.37	2010	Earthquake

Fig.8 I countries with from 99 percentile group for deaths as a share of population, by author based on EM-DAT

Due to the constraints of time and data availability, five countries are selected from the list of countries under the top 99th percentile extremely large disasters in the period of 2000 to 2005 (Fig.8). The countries and disasters are naturally aligned into developed vs less developed countries and the two major types of disasters – earthquake (Pakistan, Sri Lanka, Indonesia) and extreme temperature (Spain, Luxemburg). Though each country has its unique growth path, the general direction is that there is a general small positive effect for most cases in the medium- and long-run. However, the results are varied largely among different countries due to the phase of development of the country or the type of disaster.

Finding

The five countries naturally align into two phases of development and two major disasters. Both Spain and Luxemburg have relatively high incomes and general living standards than Pakistan, Sri Lanka, and Indonesia. During the period of the disasters, Luxemburg's GDP per capita based on Purchasing Power Parity is 25 times of that of Pakistan, 16 times of Indonesia and Sri Lanka, and 2.5 times of Spain (Fig.9). This disparity made Luxemburg an outlier even for developed countries. The unemployment rate for Luxemburg in 2003 was 3.86 % (WDI, n.d.), which was very close to natural unemployment. The rapid growth of GDP and low unemployment rate suggest that the economy might be running on full capacity. On the other hand, Spain has a relatively high income and steady but slow growth rate of around 3% before the year of disaster (WDI, n.d.). However, on a closer glance, Spain has a relatively high unemployment rate of 11.5% (WDI, n.d.), suggesting potential idle capital and the country operating under full production capacity.

Both Spain and Luxemburg were affected severely for the 2003 European Heatwave which was 20-30% higher than the historical seasonal average. It was considered "one of the ten deadliest natural disasters in Europe for the last 100 years and the worst in the last 50 years" (UNEP, n.d.:2). The heatwave was accompanied by low precipitation and thus harming agriculture and forestry severely (UNEP, n.d).

For the less developed countries, Indonesia and Sri Lanka, both being island economies in South East Asia, have very similar growth path and level of income. They both share a rather slow but steady growth of 5.0% and 5.4% respectively (WDI, n.d.). Geographically, both countries suffered the same 2004 Indian Ocean Earthquake (magnitude 9) and the following Tsunami. However, Sri Lanka is in an aseismic region and had minimal destruction due to earthquakes (Gamage and Venkatesan, 2019). On the contrary, Indonesia is "one of the world's most earthquake-prone countries, with an earthquake of magnitude 5 once a week on average" due to its unique position on the "Pacific Ring of Fire" where tectonic plates collide often (Mayberry, 2018). Pakistan's 2005 earthquake happened in Kashmir in the Himalaya Mountains, sitting on top of a web of active geological faults (NASA, 2008). The earthquake of magnitude 7.6, though not as strong as that of the aforementioned 2004 Indian Ocean, still caused severe damage to the area economically.

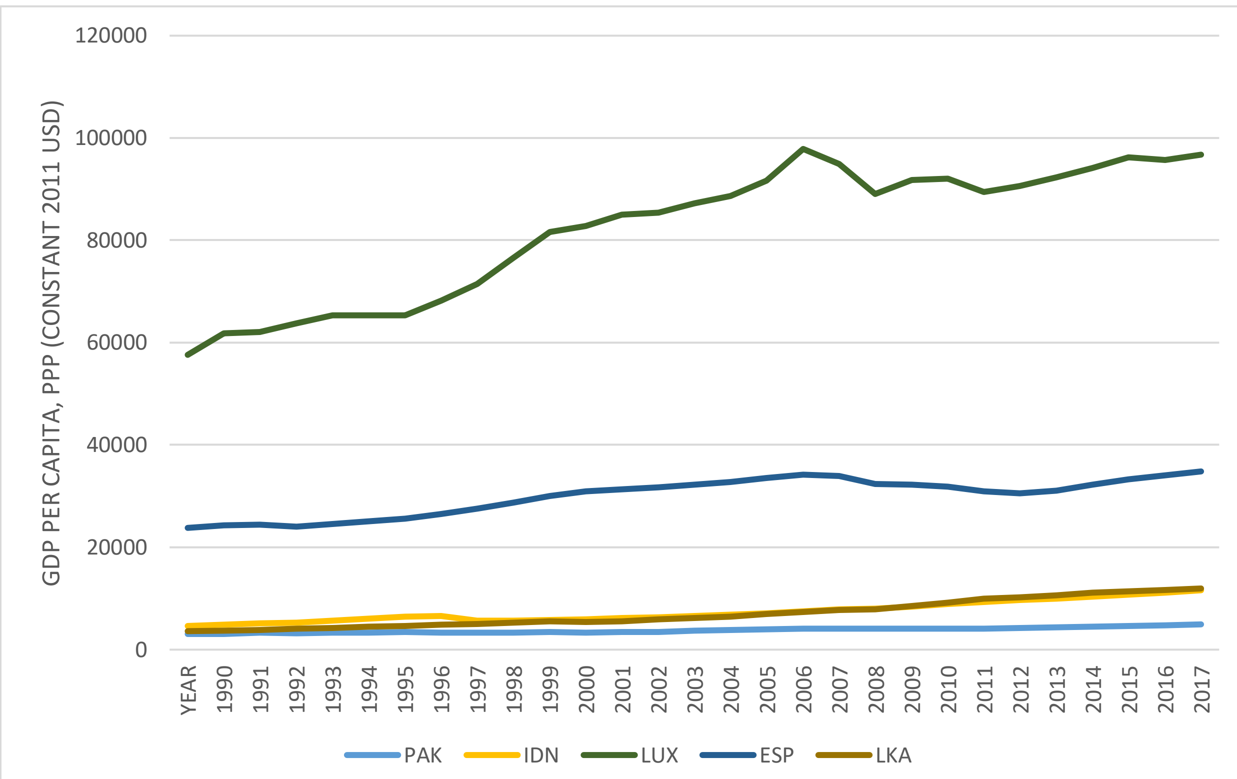


Fig.9 GDP per capita, ppp (constant 2011 USD) for the five case studies

Descriptive Statistics

As shown in the Appendix.2, there are 10 variables used in this analysis and their corresponding descriptive statistics are in Appendix.3 to 9. The first five variables, GDP, secondary school attainment, trade, government stability, and capital stock, are used directly in the regression and they are arranged as time series panel data for each country in the synthetic cohort. Therefore, each country has its own mean, standard deviation, and min, and max values calculated, and it is not meaningful to aggregate the data across the countries. Since the five variables are so varied in its absolute number, it is later indexed to 2000 value of the particular country.

The second set of geographic variables, land area, and latitude are also involved directly in the regression estimating weights. Since the variation in these two variables is minimal if not none, 2008 value is used and is indexed to the target country in the analysis. The mean latitude for the countries in the synthetic cohort is 19 and it varies from 72 to -41 degrees, thus a wide geographic area of selection. The land area variable has a mean of 621,000 sq. km, and is also varied from 2 to 1.64x10^7 sq. km. The last set of variables are disaster-related variables, and they are only used in the selection of I and J countries. We can see the mean occurrence of disaster each year is 2 times with a standard deviation of 2. The minimum number of occurrences is 1 while the maximum goes up to 27 times a year for a single country. Moreover, the number of death has a mean of 510 and a significant standard deviation of 7166, suggesting the large variation in the human-based destruction. This great variation is also observed in the range of 1 to 300,000 people killed per disaster year.

From Appendix.10, all of the five regressions for the I countries have around 100-110 observations with one exception of Indonesia due to the secondary education attainment GDP predictor. And the R-square suggests that over 90% of the variance in GDP can be explained by all the GDP and GDP predictor variables of synthetic countries. Each country has a different set of synthetic countries that are statistically significant, indicating the uniqueness of each synthetic cohort and the similar secular trends of these selected countries.

Regression Results

The five countries show three different impacts that partially coincide with the conclusion of Cavallo *et al*. Firstly, the case of Luxemburg shows a significant negative impact by the natural disaster, which fits the finding of Cavallo for the 99th percentile (fig.10). Secondly, the case of Sri Lanka and Pakistan both illustrate that the disasters have no significant impact on the economy, with Pakistan having a very small positive impact over the short- and medium-run. This finding agrees with the conclusion by Cavallo et al. for large disasters above 90th and 75th percentile (fig.11&12). Lastly, both cases of Spain and Indonesia show a strong economic boost after the disaster over the medium and long-term. This result demonstrating the "creative destruction" by Albala-Bertrand (1993) contradicts the conclusion of Cavallo *et al*.

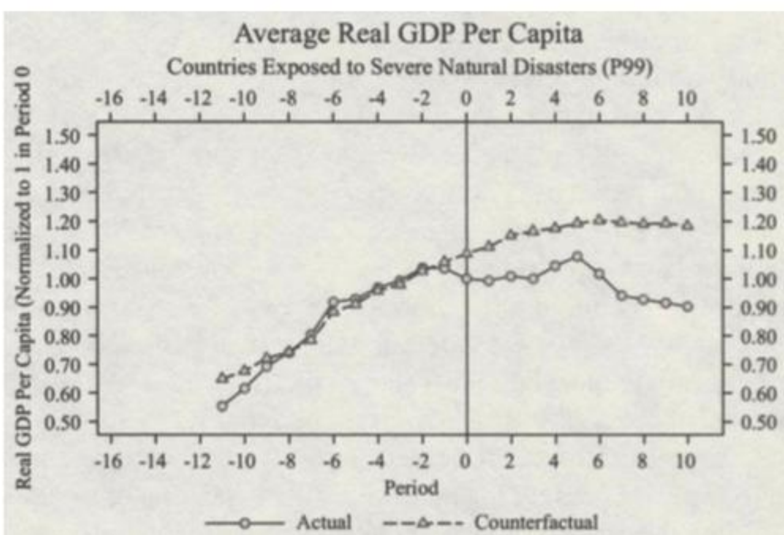
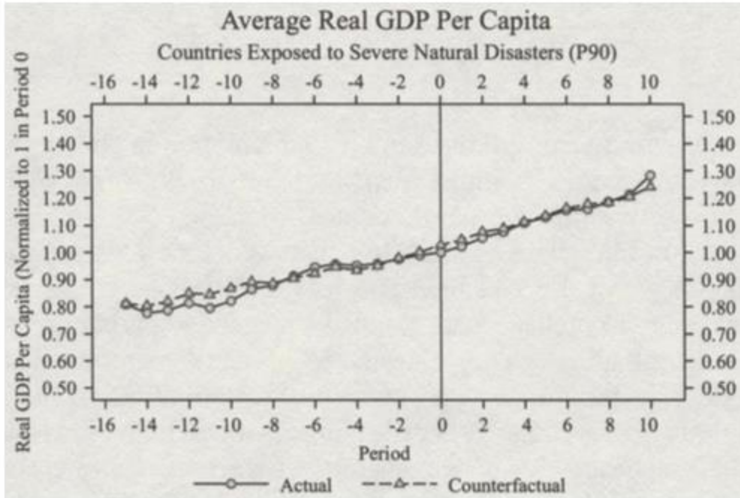
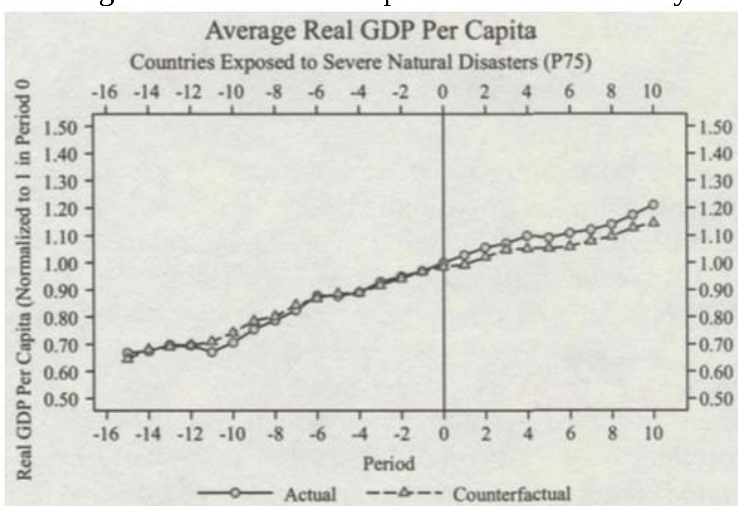


Fig.10 the impact of large disaster above 99th percentile concluded by Cavallo et al (2013)



Average taken across large disaster countries without missing data.

Fig.11 the impact of large disaster above 90th percentile concluded by Cavallo et al (2013)



Average taken across large disaster countries without missing data.

Fig.12 the impact of large disaster above 75th percentile concluded by Cavallo et al (2013)

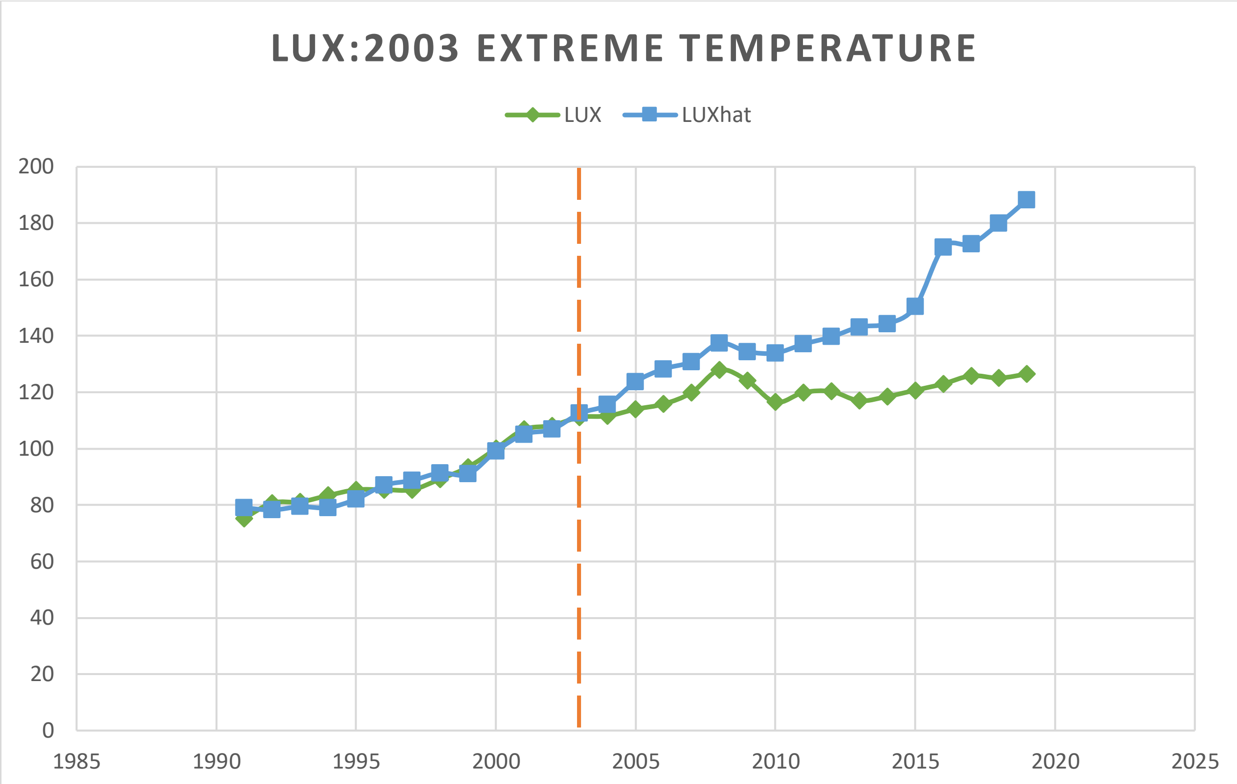


Fig. 13 Growth path of Luxemburg after the 2003 extreme temperature (green: actual growth path, blue: counterfactual growth path from synthetic cohort)

The case of Luxemburg (Fig.13) is perhaps aligns the best with the conclusion by Cavallo *et al.*, where the direction of the is negative in both short- and long-term. Though, in the short run, there was no apparent decline in GDP, the medium- to long-term growth is suppressed after the disaster. The brake by the disaster caused the rate of growth to be significantly slower and the first four years immediately after the disaster, especially in the second year. The gap between the actual and counterfactual diverges even more after the financial crisis in 2008 as the actual growth stagnates after 2008, while the counterfactual has grown more substantially. Seemingly, though there was no initial decline, the post-disaster growth model for Luxemburg fits scenario C (Fig.2) as the damped growth never recovered as the counterfactual growth suggested.

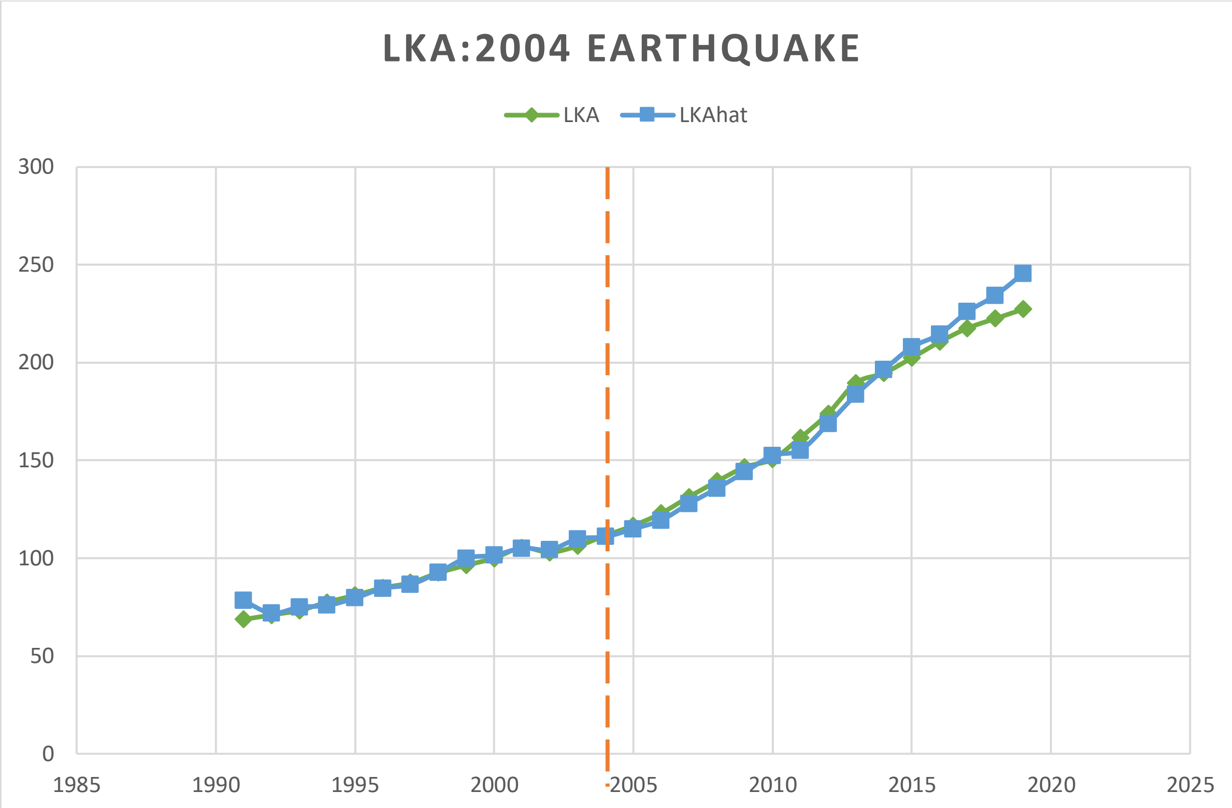


Fig. 14 Growth path of Sri Lanka after the 2004 earthquake (green: actual growth path, blue: counterfactual growth path from synthetic cohort)

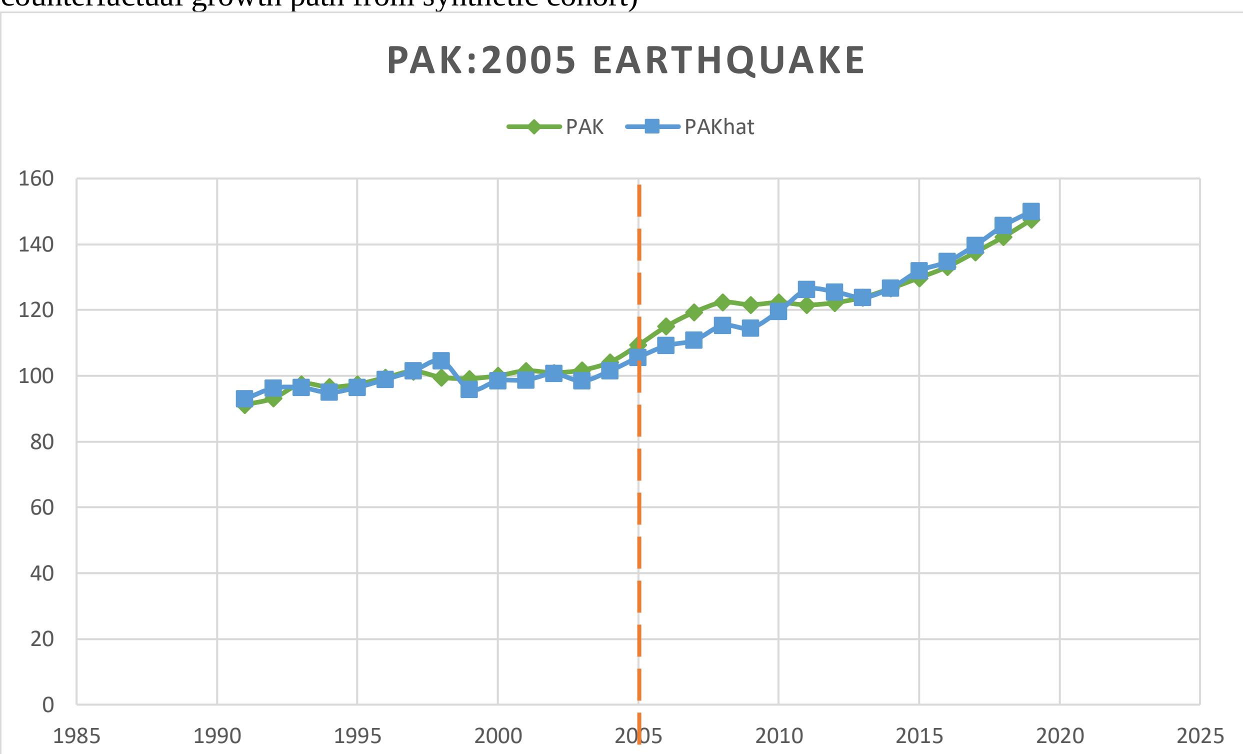


Fig. 15 Growth path of Pakistan after the 2005 earthquake (green: actual growth path, blue: counterfactual growth path from synthetic cohort)

Both Sri Lanka (Fig.14) and Pakistan (Fig.15) did not experience significant effects due to the earthquakes as the counterfactual growth paths closely align with their actual growth paths. This conclusion coincides with those of Cavallo et al for the large disasters of 90th and 75th percentile (Fig.11&12). Especially for Sri Lanka, the paths are almost identical until 2015, where counterfactual slightly outgrows the actual. However, since this change happened a decade later, it is unlikely related to the disaster. However, though not as visible as the phenomenal post-disaster growth of Indonesia, Pakistan still shows a slight boost in the economy in the medium rum (5 years period) where the actual growth outperforms the counterfactual. This small positive effect is a little more visible as the actual growth departs from the counterfactual immediately after the year of the earthquake. The divergence increased until 2008 and slowly decreased to the counterfactual growth level in 2010.

Interestingly, Pakistan shows only a medium-run small positive growth and this growth disappeared after 2010, as illustrated in scenario B (Fig.2). This difference might suggest that the reconstruction in both countries has not been a strong boost to the economy like that of Indonesia. The transitory effect of reconstruction only lasted five years and did not help the countries to boost their productivity fundamentally. Once the international aids were exhausted and the construction was finished, the stimuli dissipated, and the economy went back to the equilibrium. The economy going on the same path as it used to be. However, these two cases also show that there was no initial decrease in growth due to the disaster as shown in scenario B (Fig.2).

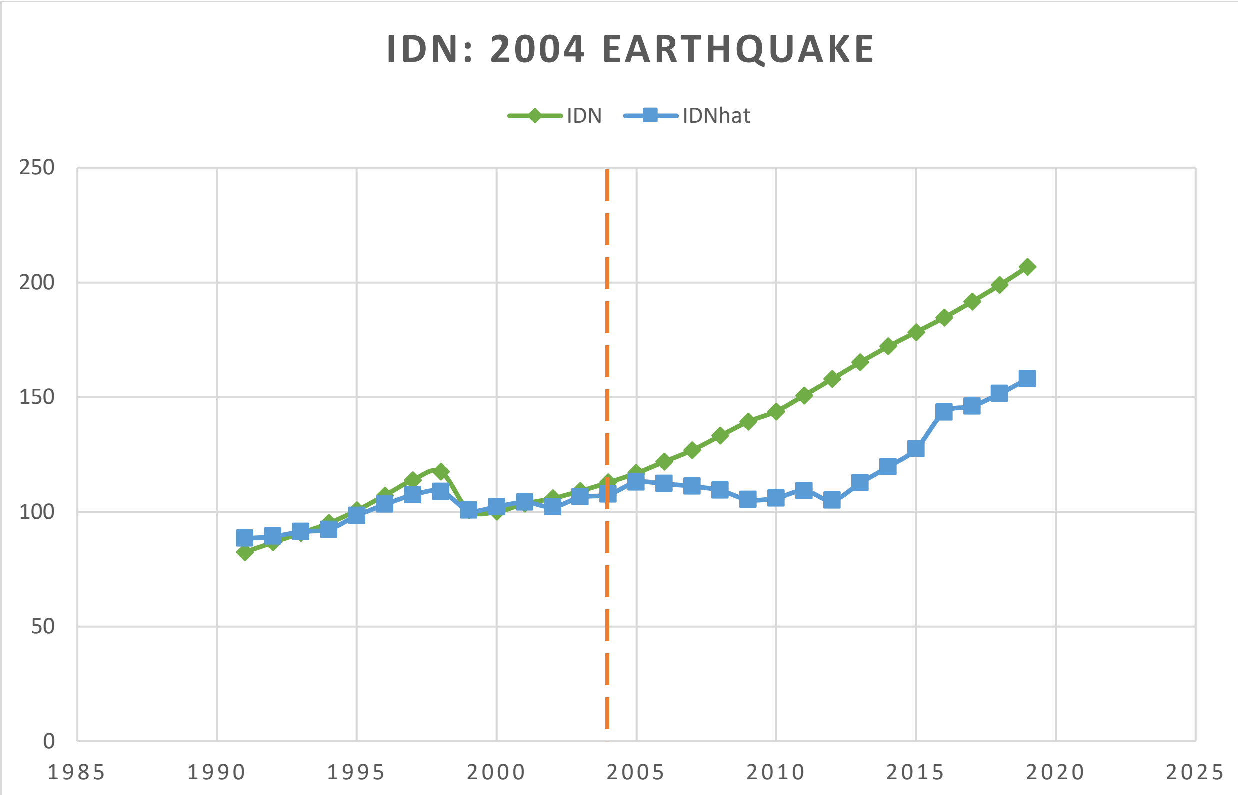


Fig. 16 Growth path of Indonesia after the 2004 earthquake (green: actual growth path, blue: counterfactual growth path from synthetic cohort)

Indonesia (Fig.16) experienced phenomenal growth after two years of the 2004 Earthquake and it greatly exceeded the synthetic counterfactual growth path. The counterfactual growth shows that the growth will be stagnated at the 1990-2004 level of around 100-110 points without much fluctuations or growth. However, the actual growth picked up rapidly after the year of the disaster. This generally positive impact the second year after the disaster suggests that reconstruction and international aids might have boosted the economy greatly. The rapid growth diverges even more from the counterfactual from 2006 to 2010 and is only reduced after 2012 as the counterfactual growth path experiences a drastic growth. However, the gap between the actual and counterfactual remained constant between 2016 to 2019, suggesting that the disaster might have permanently increased the productivity in the country due to technology transfers.

This after-disaster growth experienced by Indonesia is aligned with the creative destruction theoretical model. The economic stimuli due to the disaster have enabled Indonesia to grow faster than its original path. The international aids pouring in, the capital stock purchased, the employment created as well as the government spending for reconstruction have all played a role in the souring economic performance of the country in the first five years after the disaster. The sustained growth in the long-run has suggested scenario D (Fig.2) where the growth has been sustained by the increase in capital flexibility and marginal productivity of factor due to technology transfer. It is, however, intriguing that how Indonesia did not experience an initial decrease in the growth at all in the very short term like scenario D suggested. This pattern is also observed in most other cases and will be explained later.

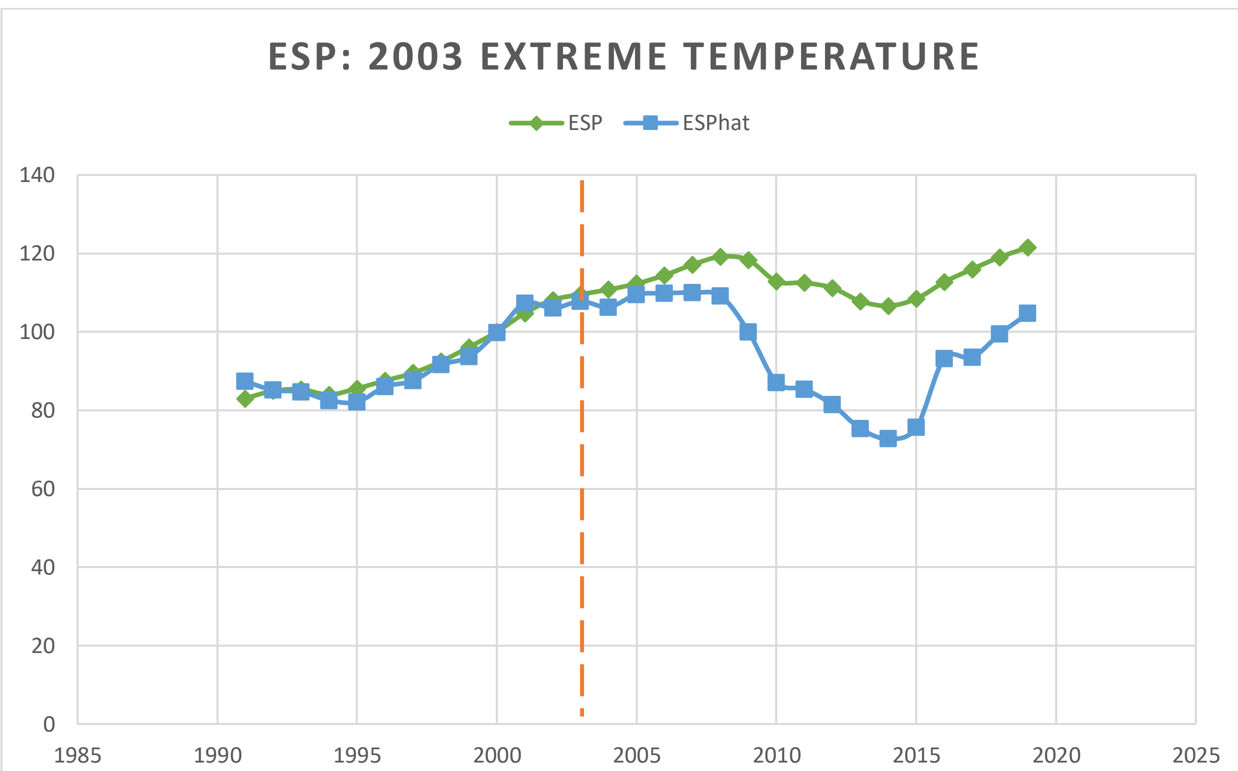


Fig. 17 Growth path of Spain after the 2003 extreme temperature (green: actual growth path, blue: counterfactual growth path from synthetic cohort)

The 2003 extreme temperature in Spain (Fig.17) also left a small positive effect on growth in the short and medium run and a persistent large growth impact in the long run. The pattern is similar to that of Indonesia: in the short run, there is no decrease in growth caused by the disaster; in the medium run, the economic stimuli, though smaller than that of Indonesia, caused the GDP to grow significantly and increasingly diverged from the counterfactual path. However, the abnormality is that for Spain, the counterfactual growth path seems to suggest a drastic economic decline since 2008, probably due to the financial crisis. Nevertheless, the actual growth is more resistant to the financial crisis and only shows a smaller decline over the period of 2008 to 2015. This might suggest that the economic stimuli and increase in flexibility and productivity of capital stocks due to disaster have cushioned the economic recession during this period. Nevertheless, the overall effect of the disaster follows the scenario D (Fig.2) just like Indonesia did, despite that Spain is a more developed economy and the reconstruction after the extreme temperature event is not as significant in terms of physical assets as compared to the earthquake. This difference in economic development and type disaster will be discussed later in this section.

In general, most cases except for one (Luxemburg) showed a positive impact of the disasters on economic growth. Two cases (Indonesia and Spain) indicate a strong boost in the economy in both medium- and long-run. The creative destruction model for these two countries generally satisfies scenario D (Fig.2). There was an immediate stimulus because of the reconstruction and aids and the effect caused short- and medium-term increases in growth. In the long run, the technology transfer into the country helped to better flexibility and productivity for capital and thus permanently increased the growth of the economy.

For the two cases (Sri Lanka and Pakistan) where there is only a slight increase in medium-run growth, scenario B in fig.2 is a better fit where the economy eventually returns to equilibrium. The transitory effect of reconstruction might have only lasted five years and did not help the countries to boost their productivity fundamentally. In the discussion section, the model of reconstruction and aid will be analyzed to see if these differences in approach are the caused by the lack of long-run stimuli as compared to Indonesia and Spain.

All five cases did not show an initial decline in GDP immediately after the natural disaster despite its extremely large human-based destruction. This observation fairly different from the finding by Cavallo et al. (2013) and other studies suggesting the negative impact on growth in both short and long term. One major distinction between the cases chosen for this study and those of Cavallo et al. (2013) is that Cavallo aggregates the effect of all countries in each percentile cohort and averaged the effect. Since the regression results for individual I countries was not shown, it might be that Cavallo et al. also experienced a variation for different countries while the averaged effect for all I countries shows an overall negative impact. Therefore, a few questions arise from this difference in the effects of the disaster on GDP: What caused the difference in the effects of disaster? Are aids, both international and domestic, public and private, more immediate and sufficient in response to some countries than the others? These questions will be briefly analyzed in the discussion section.

Discussion

The five cases show three different impacts of natural disasters for both direct and indirect costs in the long run. While the case of Luxemburg illustrates the conclusion with the 99th percentile large disasters by Cavallo et al. for a negative impact and Sri Lanka with the 90th and 75th percentile for an insignificant impact, the rest of the cases indicate an economic stimulus caused by the disaster. This country- and disaster-based case study might not be as representative as the method of Cavallo *et al*. where all the impact by disasters during the period were aggregated and averaged. Nevertheless, these individual cases still can shed light on how the different disaster responses and different initial conditions of the affected country could affect or mediate the impact of disasters.

Due to the availability of data, the cases chose coincidently fall into two of the major types of disasters – earthquakes and extreme temperature events. As suggested by the literature, different types of disasters would mean different effects on the economy. Earthquakes result in a more significant loss in physical assets like houses and infrastructure and production capacity like factories while has little effect on crops. On the other hand, the extreme temperature would most likely have a predominant human-based effect and agricultural effect. Hence, the positive effect would likely be bigger for earthquakes due to more massive reconstruction and the productivity effect by the more rapid embodiment of new technology in the rapid turnover of capital (Murlidharan and Shah, 2003). Hence, the earthquake in Indonesia resulted in a long-run positive effect and Pakistan and Sri Lanka experienced an insignificant or small positive impact in the medium run.

However, it also remains a question of how much of the cost of reconstruction was through international aids, government spending or simply debt. The latter two could cause the fiscal deficit, inflation as well as the debt crisis, especially in less developed countries. Some scholars suggest that this fiscal and trade imbalance can be perpetual (Hochrainer, 2009). However, there is also evidence that these effects are only transitory where the impact will become statistically insignificant in two years (Murlidharan and Shah, 2003). As for five cases, the latter conclusion by Murlidaharan and Shah is more applicable - richer countries like Luxemburg experienced a more negative impact in a long run while poorer countries like Indonesia, Pakistan and Sri Lanka that are likely to experience the perpetual post-disaster fiscal imbalance and debt did not show any economic distress.

Likewise, the scale of the disasters is significantly bigger for the 2004 Indian Ocean Tsunami and the 2005 Kashmir Earthquake than the European heatwave based on life-loss. It would likely have a larger strain on the economy. Nevertheless, Indonesia, Sri Lanka, and Pakistan did not show a larger impact on the economy than Luxemburg and Spain. Ultimately, the impact depends on the size of disasters, the size of the economy and the prevailing economic conditions (Hochrainer, 2009). Further studies will need to look into the composition of the payment of disaster reconstruction cost of individual disasters to better assess the impacts on the different economies.

Another factor that might explain the variation of results in the two groups of countries is the phase of development by the countries. The five cases coincidently also fall into two categories for the level of development. According to Hallegatte and Pryluski (2010), for countries of high growth, thus using its factors of production at their full capacity, the disaster is detrimental through "diverted resources, production capacity scarcity, and accelerated inflation". This coincides with the case of Luxemburg as its GDP grew rapidly from 1990 to 2000. While for the other countries like Indonesia and Pakistan, it is apparent that the GDP growth was slow during the pre-disaster period. Thus, idle resources in those economies were mobilized due to the economic stimuli of the disaster.

The variations in the conclusion and the many inconsistencies with existing literature also propose some limitations of this study. First, although the five cases are chosen with the intention to vary the pre-disaster economic conditions and the type of disasters, they are still not representative to illustrate the different impacts of natural disasters on different conditions. Further studies should be done to also compare the impact of other types of disasters of flood, storm, etc. Moreover, one crucial assumption in the study is the static weight distribution for each country for the synthetic cohort. This assumption might not hold for a lot of countries with a volatile economic condition or frequent change of leadership and public policies. Thus, further studies can be done with a more careful selection of cohort countries with stable and similar secular trends with the disaster country. More dynamic time series regression can also be done to monitor the weight change over time, thus creating a more accurate predicted counterfactual growth path.

Moreover, the composition of reconstruction spending needs to be analyzed to further the understanding of the process of "creative destruction" as most cases in this study suggest. The tradeoff between economic boom due to reconstruction spending and the fiscal and trade imbalance is largely related to the amount and timing of international aids given. However, repeatedly we hear the report of the uncommitted pledge of aids that either is given late or never realized (OCHA, 2005). Sometimes, aids were also given in an unwanted form like the case of Sri Lanka where food aids were wasted due to a large harvest of the year (BBC, 2005). Therefore, the actual composition of aids and the effectiveness of aids should be further analyzed in relation to the reconstruction cost.

Finally, this study sheds light on the rich variations in the impact of natural disasters due to the pre-disaster conditions of the economy and the type and intensity of disasters. The three theoretical models are all valid in explaining both short- and long-term impacts depending on the country and the disaster.

Conclusion

The five cases show three different impacts of natural disasters for both direct and indirect costs in the long run and agree with the conclusions of Cavallo et al. (2013) at various degrees. All of the five cases did not show a short-run economic decline as most theories suggest. For the medium- and long-run, Luxemburg suffered permanent loss as its GDP never recovered from the heatwave since 2003. While Sri Lanka and Pakistan did not show any long-run impact of disasters, Pakistan experienced a small positive growth in the medium-run, suggesting that the reconstruction period has given a boost to the economy and the effect dissipated after the reconstruction finished. Both Indonesia and Spain saw a significant positive permanent growth which might be caused by the permanent increase in capital productivity due to technology transfer during reconstruction.

This country- and disaster-based case study might not be as representative as the method of Cavallo et al where all the impact by disasters during the period were aggregated and averaged. Nevertheless, these individual cases still can shed light on how the different disaster responses and different initial conditions of the affected country could affect or mediate the impact of disasters. Since the intensity of disaster is limited to the top 99th percentile and within the same two types of disasters there are different responses to the disaster, the type of disasters thus did not matter as much as the initial economic condition of the country. The level of economic development also shows very distinct consequences within the less developed and developed groups, suggesting the initial absolute value of development also did not affect the economic responses by different countries. Thus, this study proposes that one crucial factor that caused the different impact is the idle production capacity before disasters. This study also proposes future studies on the actual composition of aids and the effectiveness of aids should be further analyzed in relation to the reconstruction cost.

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Appendix

Introduction

Appendix 1 introduces the initial list of I countries in the top 99th percent cohort before selecting the five case studies.
Appendix 2 introduces the list of variables and their sources respectively.
Appendix 3-9 are descriptive statistics for all the variables – GDP predictors, geographic variables and disaster variables.
Appendix 10 shows the List of J countries in the synthetic cohort with weights for different I country

Appendix.1 top 99th percentile of countries that suffered disaster from 2000 to 2010

list of I countries in top 99th percentile	Death per million population	Disaster type	Year of disaster
SLV	195.5456	earthquake	2001
PRT	257.7728	extreme temperature	2003
HTI	294.5703	Flood	2004
VGB	304.2905	Storm	2017
HTI	304.7393	Storm	2004
FRA	313.1181	extreme temperature	2003
MDV	327.695	earthquake	2004
NPL	327.695	earthquake	2015
BTN	338.3975	Flood	2000
ITA	350.5126	extreme Temperature	2003
ESP	357.6877	extreme Temperature	2003
GRD	373.753	Storm	2004
LUX	376.4143	Extreme Temperature	2003
RUS	390.341	extreme temperature	2010
FSM	439.1292	Storm	2002
PAK	457.4933	Earthquake	2005
ASM	599.8271	Earthquake	2009
IDN	742.6182	Earthquake	2004
WSM	801.9246	Earthquake	2009
DMA	895.631	storm	2017
SOM	1660.594	Drought	2010
LKA	1825.9	Earthquake	2004
MMR	2771.22	Storm	2008
HTI	22370.37	Earthquake	2010

Appendix.2 Variable, source and definition

Dataset	Variable name	Definition	Variable name original
WDI	educ	Enrollment includes Individuals officially registered in a given educational programme, or stage or module thereof, regardless of age. Data on education are collected by the UNESCO Institute for Statistics from official responses to its annual education survey. All the data are mapped to the International Standard Classification of Education (ISCED) to ensure the comparability of education programs at the international level.	Secondary education, general pupils
	trade	Trade is the sum of exports and imports of goods and services measured as a share of gross domestic product.	Trade (% of GDP)
	pop	Total population is based on the de facto definition of population, which counts all residents regardless of legal status or citizenship. The values shown are midyear estimates.	Population, total
	GDP	GDP per capita based on purchasing power parity (PPP). PPP GDP is gross domestic product converted to international dollars using purchasing power parity rates. An international dollar has the same purchasing power over GDP as the U.S. dollar has in the United States. GDP at purchaser's prices is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. Data are in constant 2011 international dollars.	GDP per capita, PPP (constant 2011 international $)
ICRG	ICRG	This is an assessment both of the government's ability to carry out its declared program(s), and its ability to stay in office. Including 3 sub components: government unity, legislative strength, popular support 12 points: 12 – low risk, 0 – high risk	Government stability

PWT	cn	Capital stock at current PPPs (in mil. 2011US$)	
Geography2	lat	Latitude above equator +above, - below	
EM-DAT	distype	Description of the disaster according to a pre-defined classification.	Disaster type
	death	Number of people who lost their life because the event happened.	Total deaths
area	area	Land area (sq.km)	

Appendix.3 **Descriptive Statistics for GDP per capita, PPP constant 2011 USD**

Variable	Obs	Mean	Std.Dev.	Min	Max
AUS	29	37286.11	5781.945	27968.4	45377.75
AUT	29	39763.88	4854.541	31341.9	46260.38
BEL	29	37484.39	4378.699	30188.79	43582.13
BRA	29	12593.8	1800.402	10092.97	15535.63
CMR	29	2792.773	295.504	2343.861	3358.591
CHL	29	16465.63	4365.682	8969.838	22873.81
CHN	29	6796.211	4602.787	1521.964	16181.78
DNK	29	42074.07	4330.948	33785.65	48419.44
ECU	29	8709.4	1233.745	7357.015	10868.12
SLV	29	5930.675	795.365	4512	7393.007
FIN	29	35643.87	5767.851	25618.62	42657.77
HKG	29	40790.95	9651.75	26974.37	57318.06
IND	29	3623.751	1492.909	1886.977	6888.188
IRL	29	42153.22	12988.06	22409.33	70855.33
ITA	29	35270.32	2194.263	31216.86	38700.63
JPN	29	34802.15	2379.857	30582.43	39293.69
KEN	29	2361.196	288.366	2073.087	3076.845
KOR	29	24434.22	7760.407	11632.6	36776.52
MYS	29	18611.98	4869.485	10556.63	28201.06
MLI	29	1657.89	244.053	1274.093	2055.623
MEX	29	15858.69	1329.157	13452.23	18133.7
NLD	29	42055.34	5498.518	32305.19	49787.07
NOR	29	58059.02	7118.834	42770.19	65389.18
PRY	29	9059.687	1321.395	7616.971	12067.54
PER	29	8280.246	2609.418	5133.096	12793.5
PHL	29	5065.823	1224.905	3800.095	7942.51
PRT	29	25201.3	2525.099	20144.04	28999.37
THA	29	11430.68	2944.854	6653.336	16904.7
TGO	29	1263.762	139.027	984.707	1574.02
TUR	29	16521.19	4432.268	11289.9	25357.72
GBR	29	34403.36	4758.146	26181.77	40522.25
URY	29	14624.22	3591.946	9841.948	20916.15

Appendix.4 **Descriptive Statistics for secondary school attainment**

Variable	Obs	Mean	Std.Dev.	Min	Max
AUS	38	1380000	151000	1100000	1680000
AUT	38	477000	38915.9	427000	583000
BEL	30	503000	72439.14	433000	668000
BRA	30	1.87e+07	6050000	8440000	2.63e+07
CMR	33	648000	460000	154000	1730000
CHL	32	1070000	148000	801000	1240000
CHN	34	6.12e+07	1.42e+07	4.40e+07	8.59e+07
DNK	37	349000	35689.18	306000	423000
ECU	31	907000	419000	476000	1650000
SLV	28	364000	118000	163000	522000
FIN	38	309000	18270.86	281000	345000
HKG	36	445000	42252.93	342000	507000
IND	33	7.08e+07	3.02e+07	3.00e+07	1.30e+08
IRL	37	315000	32422.79	263000	373000
ITA	38	3110000	340000	2640000	3830000
JPN	35	7780000	1290000	6280000	9920000
KEN	32	2100000	1110000	767000	4990000
KOR	38	3490000	319000	2780000	4100000
MYS	38	1910000	520000	1070000	2580000
MLI	37	335000	309000	54964	919000
MEX	38	7440000	1960000	3730000	1.03e+07
NLD	36	815000	99730.69	668000	1030000
NOR	38	276000	23714.49	243000	322000
PRY	33	312000	163000	112000	533000
PER	39	2090000	523000	1150000	2730000
PHL	33	4980000	1560000	2920000	8440000
PRT	36	605000	119000	398000	829000
THA	34	3200000	1370000	1530000	6070000
TGO	38	292000	192000	85745	712000
TUR	36	4480000	2150000	1680000	8690000
GBR	38	4380000	345000	3830000	5120000
URY	33	233000	37756.46	162000	304000

Appendix.5 **Descriptive Statistics for Trade as a percentage of GDP**

Variable	Obs	Mean	Std.Dev.	Min	Max
AUS	39	37.714	4.783	28.582	45.798
AUT	39	82.594	15.936	62.472	107.79
BEL	39	133.733	18.752	103.055	165.315
BRA	39	21.663	4.605	14.391	29.678
CMR	39	48.199	9.225	26.453	65.025
CHL	39	59.364	9.31	39.865	80.79
CHN	39	37.02	13.881	12.425	64.479
DNK	39	81.493	15.192	61.353	105.236
ECU	39	47.099	10.022	29.915	68.057
SLV	39	63.103	12.176	36.928	80.666
FIN	39	65.88	11.355	43.488	86.184
HKG	39	285.243	84.648	169.173	442.62
IND	39	29.689	14.756	12.219	55.794
IRL	39	147.388	39.791	93.857	226.041
ITA	39	46.424	7.523	33.878	60.408
JPN	39	24.714	6.69	16.014	37.546
KEN	39	55.007	8.173	36.181	72.858
KOR	39	69.805	17.581	47.587	110
MYS	39	157.482	36.811	104.683	220.407
MLI	39	53.993	6.336	42.103	64.839
MEX	39	47.868	16.574	22.117	80.448
NLD	39	119.731	18.894	95.674	157.817
NOR	39	70.974	3.494	65.508	79.484
PRY	39	75.496	22.324	25.142	123.079
PER	39	40.247	9.478	22.537	58.434
PHL	39	72.985	19.378	45.909	108.25
PRT	39	65.524	8.671	54.02	86.957
THA	39	98.323	32.291	47.384	140.437
TGO	39	85.008	15.358	51.399	118.102
TUR	39	41.63	10.003	17.09	60.157
GBR	39	52.931	4.701	45.074	62.305
URY	39	44.835	8.793	31.617	65.208

Appendix.6 **Descriptive Statistics for ICRG**

Variable	Obs	Mean	Std.Dev.	Min	Max
AUS	35	8.04	1.885	5.125	10.917
AUT	35	7.961	1.165	5.583	10
BEL	35	7.769	1.251	5.083	10
BRA	35	6.965	1.641	4.667	10.333
CMR	35	7.958	2.194	4	11.083
CHL	35	7.225	2.079	2	10.708
CHN	35	8.82	2.194	4	12
DNK	35	7.682	1.286	5.667	9.792
ECU	35	6.8	1.319	4.75	9.75
SLV	35	6.944	2.204	3	10
FIN	35	8.423	1.461	5.5	10.75
HKG	35	7.504	2.408	1.25	11
IND	35	6.869	1.831	2.167	10.083
IRL	35	8.15	1.67	4.958	10.833
ITA	35	7.061	1.66	3.167	9.833
JPN	35	7.823	1.71	4.583	10.417
KEN	35	6.921	1.59	4	9.917
MYS	35	7.945	2.221	2	11
MLI	35	7.213	2.08	4	11
MEX	35	7.379	1.326	5	10.667
NLD	35	7.99	1.352	6.167	11
NOR	35	7.757	1.301	5.333	10.333
PRY	35	6.638	1.302	3.083	9.417
PER	35	6.12	1.773	3	9.833
PHL	35	6.604	2.447	1	11
PRT	35	7.711	1.479	5.333	10.833
KOR	35	7.474	1.12	4.667	10
THA	35	7.505	1.457	4.333	10.292
TGO	35	7.38	2.275	3	10.667
TUR	35	7.605	1.634	3.667	10.083
GBR	35	7.912	1.708	4.667	11.083
URY	35	7.496	1.663	4.417	10.75

Appendix.7 **Descriptive Statistics for capital stock from PWT**

Variable	Obs	Mean	Std.Dev.	Min	Max
AUS	38	2410000	1270000	995000	5420000
AUT	38	1110000	604000	362000	2520000
BEL	38	1420000	778000	679000	3030000
BRA	38	5800000	4700000	1270000	1.58e+07
CHL	38	544000	417000	141000	1530000
CHN	38	2.44e+07	2.90e+07	2320000	1.06e+08
CMR	38	89134.67	59368.8	27973.98	227000
DNK	38	743000	353000	382000	1500000
ECU	38	379000	268000	120000	958000
FIN	38	656000	257000	361000	1110000
GBR	38	6140000	3390000	2850000	1.34e+07
HKG	38	864000	624000	115000	1970000
IND	38	9020000	9680000	1590000	3.34e+07
IRL	38	453000	375000	115000	1300000
ITA	38	7980000	4070000	3540000	1.68e+07
JPN	38	1.57e+07	5860000	6850000	2.35e+07
KEN	38	145000	101000	49728.55	394000
KOR	38	3590000	2640000	443000	8900000
MEX	38	3810000	2360000	1370000	9270000
MLI	38	16247.43	15037.31	2580.029	55200.41
MYS	38	1030000	754000	203000	2810000
NLD	38	2050000	1120000	957000	4590000
NOR	38	743000	397000	358000	1570000
PER	38	469000	329000	84246.14	1200000
PHL	38	1040000	746000	232000	2880000
PRT	38	1130000	708000	279000	2510000
PRY	38	79411.31	58652.51	11747.07	189000
SLV	38	51632.69	41858.93	11504.17	130000
TGO	38	20450.87	13730.96	11533.83	55997.17
THA	38	2190000	1590000	264000	5100000
TUR	38	2670000	2240000	1140000	8340000
URY	38	135000	72651.73	66043.06	302000

Appendix.8 **Descriptive Statistics for geographic variables**

Variable	Obs	Mean	Std.Dev.	Min	Max
latitude	206	19.104	24.005	-41	72
Landarea (yr2008)	209	621000	1780000	2	1.64e+07

Appendix.9 **Descriptive Statistics for disaster variables**

Variable	Obs	Mean	Std.Dev.	Min	Max
occurrence	5123	1.933	1.974	1	27
death	5123	509.57	7165.893	1	300000
pop	5123	1.23e+08	2.78e+08	29577	1.39e+09
percentkilled	5123	0	0	0	.022

Appendix.10 List of J countries in synthetic cohort with weights for different I country

VARIABLES	LUX	ESP	LKA	PAK	IDN
AUS	0.121	-0.04	0.493**	-0.156	0.259
AUT	0.619***	-0.126	0.165	-0.280*	-0.073
BEL	0.324**	-0.056	-0.406	0.315	-0.53
BRA	-0.117**	0.042	-0.04	-0.008	0.183
CHL	-0.09	-0.113	0.045	0.065	-0.176
CHN	-0.132	-0.209**	0.546***	-0.185	0.432*
CMR	0.309***	0.142*	0.049	-0.012	-0.107
DNK	-0.671***	0.054	0.487	-0.816***	0.006
ECU	0.192**	0.003	0.065	-0.119	-0.816**
FIN	-0.025	-0.019	-0.377	-0.044	-0.716**
GBR	-0.131	0.223**	0.620***	-0.145	-0.338
HKG	0.213***	0.174*	-0.181	0.546***	-1.088***
IND	0.224**	0.064	-0.148	0.420***	1.282***
IRL	0.742***	0.634***	-0.207	-0.088	0.109
ITA	-0.06	0.105	-0.058	0.043	0.05
JPN	-0.154*	-0.068	-0.319**	0.095	0.705***
KEN	0.002	-0.035	0.171	0.230***	-0.419**
KOR	0.160***	-0.104*	-0.134	0.185**	0.207
MEX	-0.176***	-0.001	-0.014	-0.181**	0.324*
MLI	-0.169	-0.184	-0.444*	0.156	0.461
MYS	0.05	0.098	0.157	0.177**	-0.393*
NLD	0.153	0.410***	-0.328	0.105	-0.206
NOR	-0.306***	-0.577***	0.415**	0.357**	1.380***
PER	0.120***	0.002	-0.058	-0.158***	-0.265**
PHL	-0.271***	0.013	0.342***	0.202**	0.720***
PRT	-0.394***	0.390***	0.266	0.082	-0.121
PRY	-0.031	-0.051	-0.204**	0.082	0.630***
SLV	-0.248***	-0.071	0.619***	-0.104	-0.539**
TGO	-0.034	0	0.133	0.157**	0.294**
THA	0.245***	0.06	-0.504***	-0.115	0.031
TUR	-0.058	0.103	-0.004	-0.126	-0.735***
URY	0.159***	-0.063	-0.264**	0.039	0.563***
Constant	42.532***	19.887**	13.275	26.540**	-10.857
Observations	104	105	110	110	80
R-squared	0.975	0.971	0.915	0.974	0.937
Standard errors in parentheses					
*** p<0.01, ** p<0.05, *p<0.1					