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Growth Resilience to Large External Shocks in Emerging Asia: Measuring Impact of Natural Disasters and Implications for COVID-19

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Abstract

This study examines the extent to which Emerging Asian countries show resilience to large external shocks. Its main objective is to estimate the impact of large-scale natural disasters (LNDs). Recent large-scale natural disasters (LNDs) in four Emerging Asian countries: China, India, Indonesia and the Philippines are examined. LNDs have a large negative impact on GDP growth in India, Thailand and the Philippines, although the speed at which the impact wanes differs, with a more persistent impact in the Philippines. Growth resilience to large external shocks will be determined by economic systems and policy considerations. These analyses will provide a useful reference to consider the impact of COVID-19 pandemic.

JEL Classification: E17, O53, O20, Q54

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Growth Resilience to Large External Shocks in Emerging Asia:
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1. Introduction

This paper examines the extent to which Emerging Asian countries show resilience to large external shocks. The growth resilience to external shocks is estimated for four Emerging Asian countries, namely, China, India, Indonesia and the Philippines. The analysis employs a structural vector autoregression (SVAR) model, which is well suited to capture both the size and the speed of the impact. The analysis is based on data from large-scale natural disasters (LNDs) that the four countries have experienced in recent decades, as a sort of proxy variable for large external shocks. Insights on the size and speed of external shocks are derived from impulse response functions. Our empirical results show that LNDs have a negative impact on real GDP growth in all four economies, although the speed at which the impact wanes is different across countries. Furthermore, our estimates show that a prolonged external shock stretching over several periods will lead to a more lasting effect on economic activity than a single-hit scenario. Finally, the model is extended to a non-linear case by an Autoregressive (AR) Markov regime-switching model, to examine the similar impacts.

Thorough knowledge of the underlying impact of the COVID-19 crisis on growth is of particular importance for the region’s policy makers. Since the data on past pandemics are very scarce, information on natural disasters can act as a reference for large external shocks. Though economic analysis of natural disasters may supplement that of pandemics, results must be interpreted with care due to differences between the two types of events.

2. Methodology and Data

2.1. Assessing the Economic Costs of Large Exogenous Shocks of Natural Disasters

A review of the literature shows that there are several approaches to measuring the direct and indirect costs of natural disasters and large-scale external shocks. Measuring resilience to

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external shocks is far from straightforward for several reasons. Defining and identifying resilience poses challenges. In addition, gauging how countries will differ in their shock absorption capacity must take into account a variety of parameters that pertain to countries' economic structures. Moreover, large exogenous shocks tend to occur less frequently, thus limiting the potential for comparative studies.

A large number of studies have assessed both the short-term and long-term economic impact of large exogenous shocks of natural disasters. Numerous studies ascribe negative growth to a natural disaster via various factors such as human capital and technology. For instance, Noy and Nualsri (2007) show that a natural disaster that destroys human capital has a negative impact on growth, while they do not find any statistically significant effect on output with regard to natural disasters leading to a reduction in physical capital. Raddatz (2007), Noy (2009) and Rasmussen (2004) also find that natural disasters can have short-term adverse effects on the economy. Analysing a panel of countries simultaneously, they consider various indicators for measuring the magnitude of a disaster. Their estimation shows that the costs of natural disasters in direct damage are associated with a 0.5% to 3% decrease of the same-year real GDP growth rate. Furthermore, some studies suggest that affected countries are relegated to a lower growth path permanently (Hsiang and Jina, 2014). Growth appears to be more sensitive to natural disasters in developing countries than in developed ones, with more sectors affected and the effects larger and more economically meaningful (Loayza et al., 2012; Klomp and Valckx, 2014).

Several studies explore the impact of natural disasters through case studies. In a comparative cross-country event study, Cavallo et al. (2013) construct a counterfactual that illustrates what would have happened to the path of GDP of the affected country had the natural disaster not occurred. The results show that only very large disasters display an impact on GDP growth in the affected countries in both the short and the long term. For instance, ten years after the disaster, the average GDP per capita of the affected countries is 10% lower on average than at the time of the disaster, whereas it would be approximately 18% higher in the counterfactual scenario in which the disaster did not take place. For their part, Heger and Neumayer (2019) identify the causal economic impacts of the 2004 Indian Ocean tsunami by observing differences in economic activity between flooded districts/sub-districts and non-flooded districts/sub-districts in the Indonesian province of Aceh. The study provides compelling evidence that the tsunami depressed growth only in the first year following the disaster, while the reconstruction effort boosted growth in subsequent years.

Another strand of literature emphasises the effects of natural disasters on economic growth (Hallegatte and Dumas, 2009). For instance, Albala-Bertrand's (1993) paper assessed the impact of 28 natural disasters on 26 countries between 1969 and 1970. The author found that, in most cases, GDP growth increases after a disaster, partly due to the replacement of the destroyed capital by more efficient capital. Similarly, Skidmore and Toya (2002) count the frequency of natural disasters over the 1960-90 period for each country and conduct an empirical analysis of the correlation of this measure with average measures of economic growth, physical and human capital accumulation, and total factor productivity. The results show that a one-standard-deviation increase in climatic disasters, defined as "floods, cyclones, hurricanes, ice storms, snow storms, tornadoes, typhoons, and storms" results in a 22.4% increase in the average annual rate of economic growth. In addition, the empirical analysis concludes that total factor productivity is the primary route through which disasters affect growth. Fomby et al. (2013) bring an important contribution to this strand of literature by showing that the timing of the growth response varies: negative effects tend to occur close to the time of a disaster's occurrence, while positive effects tend to materialise with some delay.

2.2. Recent Attempts to Measure the Economic Costs of COVID-19

A growing number of studies are focusing on the specific impact of the COVID-19 pandemic on growth. Maliszewska et al. (2020) use a computable general equilibrium (CGE) model to simulate the size of the negative impact of the pandemic on output and trade growth in both advanced and developing economies. Their results indicated that GDP would decline by 2% below the benchmark for the world, 2.5% for developing countries, and 1.8% for advanced economies. In a time series-based framework, Caggiano et al. (2020) found a peak negative response of world industrial production of about 1.6%, and a cumulative output loss over one year of approximately 14%. Finally, Gupta et al. (2020) use a time-varying parameter structural vector autoregressive (TVP-SVAR) model to analyse the dynamic impact of uncertainty due to pandemics on output growth. The study considers the impact of the SARS, avian flu, swine flu, MERS, Ebola, and COVID-19 on output growth in the United States and advanced and emerging economies. The authors show that the negative effect of COVID-19 on the output growth rate in these economies is unparalleled, with only MERS causing a comparable, albeit considerably smaller, deterioration of output growth. Furthermore, among the three country groupings considered, emerging markets appear to be the worst hit in the wake of COVID-19.

Several other modelling frameworks could be used to evaluate the impact of the COVID-19 pandemic on growth, as discussed hereafter. Understanding how an epidemic develops once it has emerged is primordial. Modelling epidemics is a classical problem in mathematical biology and modelling methods are diverse. A widely used model in epidemiology is the 'SIR' model (Atkeson, 2020), where individuals can be classed in one of three groups: S, or healthy and susceptible to infection; I, or infected and therefore capable of transmitting the disease; and R, or recovered and immune, or deceased. Other models focus on the direct costs of pandemics, including mortality risk and the costs faced by health care systems. To assess the economic losses associated with mortality risk, several studies focus on the concept of "value of a statistical life" (Viscusi, 2018; Kniesner and Viscusi, 2019). Other papers attempt to estimate resource use and direct medical costs per infection (Xiao et al., 2004; Bartsch et al., 2020). Furthermore, several studies specifically explore the impact of lockdown-type restrictions on welfare (Keogh-Brown et al., 2009; Mesnard and Seabright, 2009; Barrett et al., 2011; Fenichel et al., 2011; Fenichel, 2013). The COVID-19 pandemic will also have indirect economic costs, such as lost productivity. Studies that aim to quantify the indirect costs of pandemic outbreaks include, inter alia, work by Gupta et al. (2005) and Luh et al. (2018).

Several studies use a structural vector autoregressive method for assessing the impact of external shocks due this method's versatility (Bordo and Murshid, 2002; Canova, 2005; Mackowiak, 2006; Ludvigson et al. 2020). The sectoral impact of external shocks can be assessed by using input-output tables (Timmer et al., 2015). Another method widely used in economic impact assessment is the event-study approach. While this methodology is typical in the field of financial markets, several studies have used it for gauging the impact of pandemics on various sectors (Chen at al., 2007).

2.3. Analytical Framework

To estimate the macroeconomic impact of COVID-19 in Emerging Asian countries, we examine a baseline framework, by the following p-lag vector autoregression (VAR) model, in a similar vein as Ludvigson et al (2020) and Tanaka (2021):

$$X_t = \sum_{i=1}^{p} \beta_i X_{t-i} + \eta_t$$

β_i are 3x3 matrices containing estimation coefficients and η_t is a 3x1 vector of error terms. Denoting X_t as a vector of three variables including, in this order, measurements of large-scale natural disaster (LND_t), real economic growth (g_t) and economic uncertainty index (U_t):

$$\mathrm{X_t} = \begin{bmatrix} \mathrm{LND_t} \\ \mathrm{g_t} \\ \mathrm{U_t} \end{bmatrix} = \begin{bmatrix} \text{Large} - \text{scale natural disaster} \\ \text{Real economic growth} \\ \text{Economic uncertainty index} \end{bmatrix}$$

The reduced form innovations η_t relate to mutually uncorrelated structural shocks e_t by:

$$\eta_t = Be_t \text{ , } e_t \ N \ (0, \Sigma)$$

In this equation, Σ is a diagonal matrix with the variance of the shocks, and diag(B) = 1. For identification, B is assumed to be lower triangular. The covariance matrix of VAR residuals is orthogonalised using a Cholesky decomposition with the variables ordered as above, i.e. from the most exogenous to the most endogenous. The resulting structural VAR (SVAR) has the following structural moving average representation:

$$X_t = \mu + \psi_0 e_t + \psi_1 e_{t-1} + \psi_2 e_{t-2} + \cdots$$

with μ is deterministic or steady state value of X_t. ψ_j, 3x3 matrices including the standard deviation of shocks. The impact effect of shock i is measured in the i-th diagonal entry of ψ_j. The dynamic responses of X_{t+h} to one-time change in e_t are summarized by ψ_h, matrices that can be estimated directly from the VAR using Ordinary Least Squares (OLS).

2.4. Data and Methodology

Macroeconomic data

Quarterly data on real economic activity[2] are collected from the IMF's International Financial Statistics database. The annual real GDP data come from the World Bank’s World Development Indicators database, interpolated at quarterly frequency over a period of about

[2] Industrial production, unemployed persons, real GDP.

six decades from 1960 to the last updated quarter.[3] As a measure of economic uncertainty, we use the quarterly Economic Policy Uncertainty Index (EPU) constructed by Baker, Bloom and Davis (2016). The EPU spanning the period of 1960 Q1 to 2020 Q1 for all Southeast Asian countries except Brunei Darussalam, for which data are not available.

Measuring large-scale natural disasters

Natural disasters are a common occurrence in Emerging Asia, often with a devastating impact on lives and economies. The EM-DAT database from the Centre for Research on the Epidemiology of Disasters records the nature, scope and costs of major disasters globally. Monthly natural disaster data are collected from the Emergency Events Database. We use the monetary costs (not the value of lives lost) of frequently occurring natural disasters in Emerging Asia over the period Q1 1960 to Q1 2020 as a measure of natural disasters in units of billions of US dollars. These are disasters such as earthquakes, landslides, floods, storms, droughts, and results of volcanic activity.[4] Quarterly data by country are obtained by summing up the monthly damage costs of all such natural disasters. The resulting observations highlight 660 quarters with disasters, of which 164 occurred in the Philippines alone, 120 in China and 113 in India.[5]

The analysis focuses on disruptive natural disasters, i.e., large-scale natural disasters coinciding with a drop in real GDP during the same quarter or the next one. Only four countries experienced such events during the period studied are included in this study: 14 quarters in the Philippines, 8 quarters in Thailand, 8 quarters in India and 4 quarters in China. Taking account of annual economic growth, four natural disasters coincide with a decline in real GDP in Myanmar, and only one in Cambodia and Indonesia. However, these countries are not included in our empirical investigation, as we are focusing on countries with available quarterly data for a longer period.

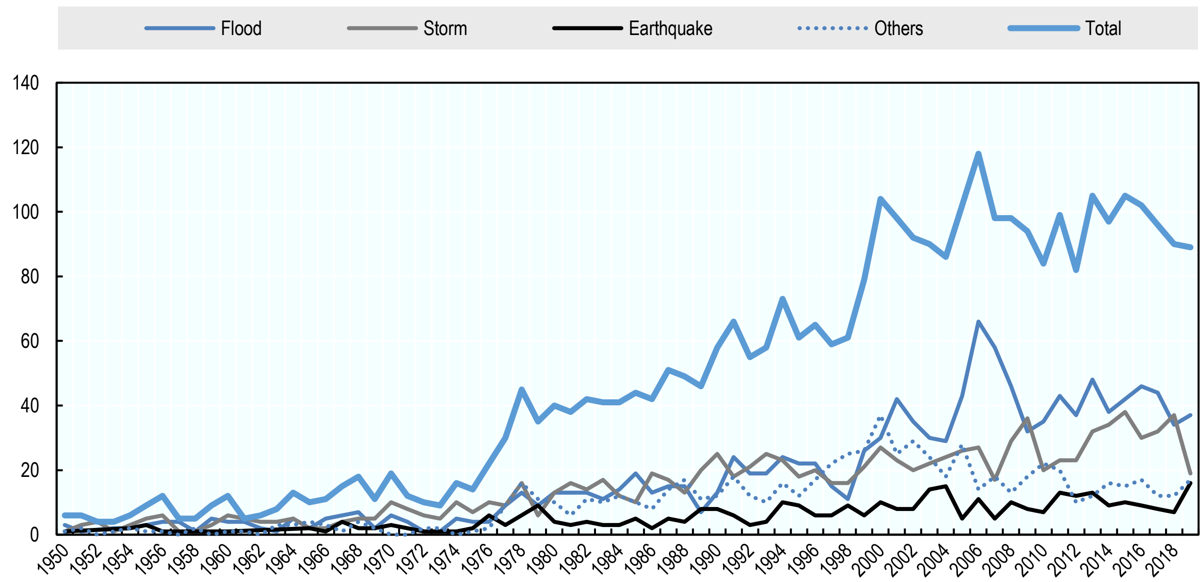
3. Large-Scale Natural Disasters in China, India, the Philippines and Thailand

Emerging Asia is prone to natural disasters. Major natural disasters in the region include meteorological disasters such as storms, geophysical disasters such as earthquakes and volcanic

[3] We use constant rather than quadratic interpolation. The date of the latest available observation differs from one country to another.
[4] No costs in damages are reported for epidemics for the selected countries.
[5] This corresponds to quarters and not the number of events.

activity, hydrological disasters such as flood and landslide, or climatological disasters such as drought. The number of floods and storms has steadily increased in recent decades. The region has suffered 57% of its natural disasters and 59% of its floods and storms in the last 20 years of the seventy-year time period observed. Other extreme weather conditions such as droughts and wildfires have also occurred more often in last 20 years. 52% of other disasters have also occurred in the last 20 years (Figure 1). A clear increase in the trend of natural disasters occurred in the late 1970s and another one in the late 1990s. Earthquakes, which are not climate-related, have remained roughly on a similar level the whole period of observation.

Figure 1. Recorded Occurrences of Natural Disasters in Emerging Asia, 1950-2019



Note: Other disasters include drought, epidemics, volcanic activity, landslides, extreme temperature, insect infestation, wildfire and mass movements (dry). Events are categorised as disasters if they meet at least one of four criteria: 10 or more persons killed; 100 or more persons affected, injured, or left homeless; an appeal for international assistance; or an official declaration of a state of emergency.
Source: CRED (2020)

Damage from natural disasters in Emerging Asia may take many forms. In addition to life damage (death or injury), severe disasters also typically damage infrastructure, household property and arable land. Tsunamis, earthquakes and other volcanic-activity derived disasters are very common in the region, since the Emerging Asian region lies at the intersection of multiple tectonic plates. While in general various natural disasters occur in the region, frequency of each disaster type varies by country, depending on geographical characteristics. Numerous large-scale natural disasters have hit China, India, the Philippines and Thailand over the past six decades. Table 1 provides some examples of typical large-scale natural disasters in these countries.

Table 1. Examples of Large-Scale Natural Disasters in Selected Emerging Asian Countries

Country	Starting month	Disaster type	Description
China	July 1976	Earthquake	242 000 deaths, 164 000 injured. Damage: USD 5.6 billion.
	September 2011	Flood	117 deaths. Damage: USD 4.25 billion.
India	October 1971	Tropical cyclone	9 658 deaths, two million homeless. Damage: USD 30 million.
	July 1979	Flood	100 deaths. Damage: USD 100 million.
	1972-73	Drought	Damage: USD 100 million.
Philippines	September 1984	Tropical cyclone	1 399 deaths, 2 565 injured, 547 076 homeless. Damage: USD 216.7 million.
	November 1990	Tropical cyclone	503 killed, 1 274 injured, 1 110 020 homeless. Damage: USD 388.5 million.
	December 1990	Drought	Damage: USD 64 million.
Thailand	August 2011	Flood	813 deaths. Damage: USD 40 billion.
	September 2013	Flood	61 deaths. Damage: USD 482 million.
	January 2015	Drought	Damage: USD 3.3 billion.

Source: EM-DAT database.

China experienced the Great Tangshan earthquake in July 1976 that occurred in northeastern China. It is considered as one of the biggest catastrophic quakes in the country in 20th century. The earthquake and its aftershocks contributed to approximately 242 000 deaths and more than 160 000 people being injured, with total damage of USD 5.6 billion, according to the EM-DAT database. The disaster severely damaged infrastructure and agriculture. In September 2011, riverine flood occurred in the country, causing 117 deaths and USD 4.25 billion in damage. The flood was caused by heavy downpours, which were preceded by a series of abnormally heavy rainfalls and floods starting from June. It affected a number of provinces, including Sichuan, Shaanxi, Henan, Chongqing, Hubei, Shandong, Shanxi and Gansu.

Cyclones and flooding are the main disaster threats faced by **India**. A very severe tropical cyclone that struck Orissa (now Odisha) and surrounding states in October 1971 killed almost 10 000 people, left 2 million people homeless and caused damage of USD 30 million. The disaster disrupted infrastructure including rail, road, electricity and communications. In July 1979, a low-pressure monsoon depression caused a flash flood of the Luni basin, following several days of heavy rainfall. It took 100 lives and caused USD 100 million in damage. The flood affected more than 1000 villages, damaging infrastructures and crops (Sharma, 1997). Maharashtra faced a severe drought in 1972-73, which caused USD 100 million in damage according to the EM-DAT database. It is considered one of the most severe droughts in the history of Maharashtra state. Monsoon rainfall was 24% below average. The drought led to a large shortage of food grains.

The **Philippines'** position as an archipelago near an area of significant tectonic movement, known as the Ring of Fire, makes the country prone to earthquakes, tropical weather systems and volcanic eruptions. In September 1984, the Philippines suffered from a tropical cyclone that killed 1 399 people, injured more than 2 500, left more than 540 000 people homeless and caused USD 216.7 million in damage. The Surigao del Norte province was one of the most affected by Typhoon Ike (known as Typhoon Nitang in the Philippines), together with several other provinces. Typhoon Mike (Ruping) occurred in November 1990, killing more than 500 people, leaving more than 1 200 injured, approximately 1.1 million people homeless, and causing USD 388.5 in damage. The typhoon went across several provinces including Samar and Leyte, Cebu, and Negros, causing massive damage. A severe drought started in December 1990 and lasted until July 1992. The drought affected several areas, including Mindanao, Central and Western Visayas and Cagayan Valley, and caused a 20% shortfall in Metro Manila water supply.

Extreme precipitation events are relatively common in **Thailand**. The 2011 flood inundated 9.1% of the country's total land area (Poaponsakorn and Meethom, 2013) and triggered landslides, killing 813 people and causing approximately USD 40 billion in damage through January 2012. The severe flood was caused by a series of irregular conditions: anomalously high rainfall in the pre-monsoon season, especially during March; record-high soil moisture content throughout the year; elevated sea level in the Gulf of Thailand, which constrained drainage; and other water management factors (Promchote P. et al., 2016). Damaged areas were dispersed in 69 provinces, with most damage and loss concentrated in the industrial estates and residential areas of Bangkok, the adjacent provinces to the north and west of Bangkok, and the farm areas in some provinces in the Lower Northern region and Central Plains (Poaponsakorn and Meethom, 2013). In September 2013, the country faced another flood that killed 61 people and caused USD 482 million in damage. Less than two years afterwards, a drought hit the country, starting in January 2015 and lasting until May 2017, causing USD 3.3 billion in damage. The drought was considered as one of the worst in decades and water rationing taking place in almost a third of the country.

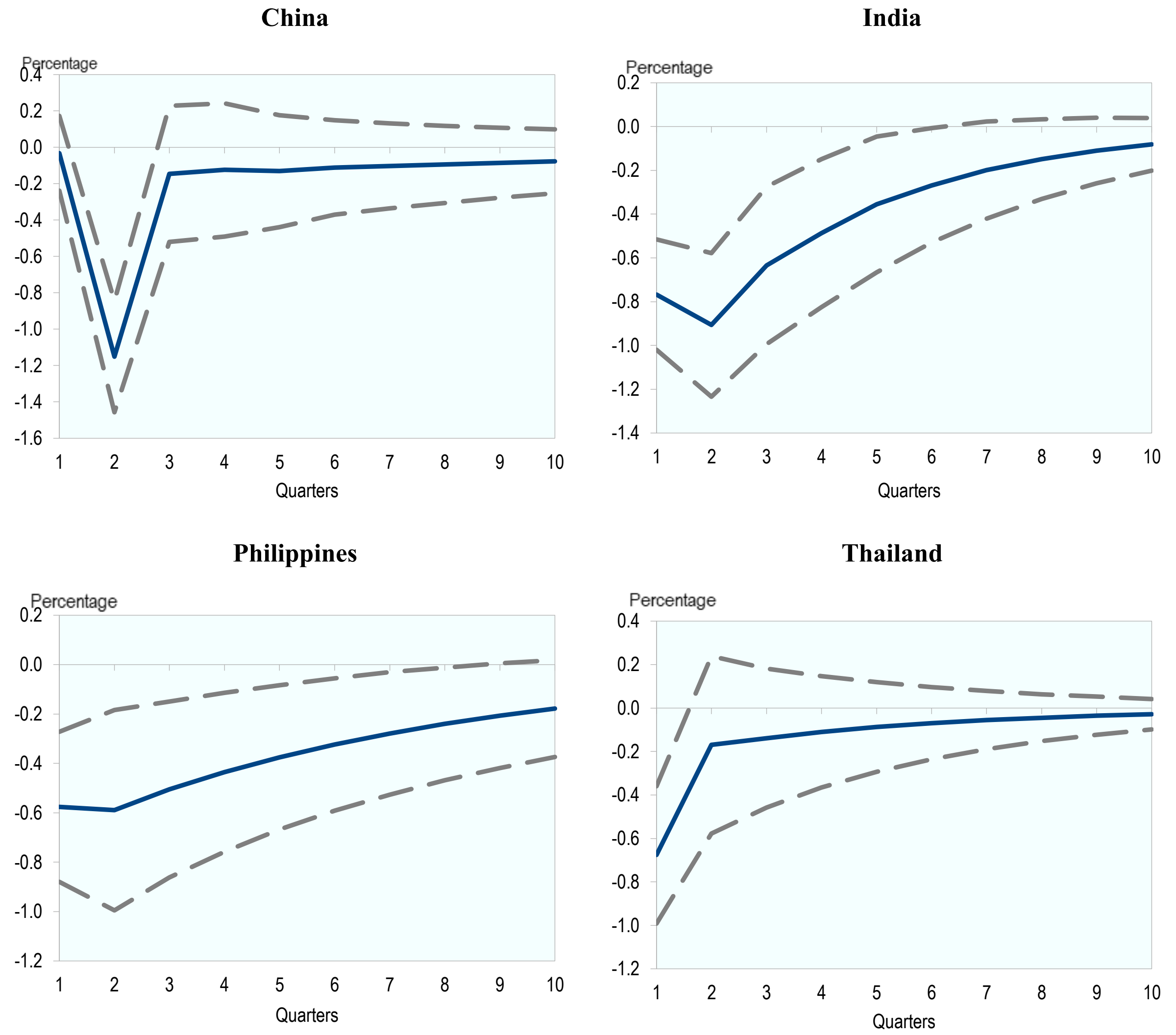
4. Empirical Results

4.1. Examining Growth Resilience via Analysis of Impulse Response Functions

In this section, we examine the dynamic responses of real economic growth to a single-period shock of a magnitude of one standard deviation. Information on the size and speed of the pass-through of external shocks on economic growth can be derived from impulse response functions (IRFs). In other words, growth resilience could be interpreted as the magnitude and speed of recovery in the aftermath of an external shock, as can be inferred from the analysis of IRFs.

Our results point to a negative impact on real GDP growth in all countries following the shock (Figure 2). Indeed, during the first quarter, the exogenous shock of LNDs would reduce economic growth most severely in India, followed by Thailand (0.68%) and the Philippines (0.58%). During the following quarter, a more significant negative effect is observed mainly in China and India: during this period, the negative impact on real economic growth reaches 1.15% in China and 0.91% in India. However, from the third quarter onwards, the impact becomes statistically insignificant. In Thailand and China, the negative effect lasts only one period and becomes statistically insignificant, while in India and the Philippines the effect on growth is more persistent and lasts up to seven quarters.

Figure 2. Response of Real Economic Growth to Large Scale Natural Disasters, Innovation using Cholesky (d.f. adjusted) Factors (±2 S.E)



Source: Author's calculations.

Note: The dotted grey lines are the error bands (lower bound and upper bound) and the dark blue line in the middle is the impulse response function.

4.2. Analysing the Economic Effects of Large and Prolonged Shocks

We analyse the dynamic responses of the real economic growth of selected countries to unexpected, large and prolonged shocks produced by large-scale natural disasters. This could be a reference to capture the impact of the COVID-19 pandemic on economic activity in the Emerging Asia region.

The COVID-19 pandemic differs from historical disasters in several dimensions. First, the magnitude of the economic damaged caused by the COVID-19 pandemic seems to be larger than that of other past natural disasters. Second, the COVID-19 pandemic could be a multi-period shock: a second wave has already materialised and the possibility of repeated waves cannot be excluded. To explore these two features, we estimate multi-period shocks and large shocks based on our SVAR models taken as baselines.

For two consecutive shocks of one standard deviation, the dynamic response of $Xt+h$[6] is:

$$\mathrm{E}[X_{t+h}|e_{1t} = \sigma, e_{1t-1} = \sigma, X^t] - \mathrm{E}[X_{t+h}|e_{1t} = 0, e_{1t-1} = 0; X^t] = \psi_h + \psi_{h+1}$$

X^t contains all information in X at time t and at all lags. The left side of the equation denotes the difference between the forecasted variables under and in the absence of a shock of one standard deviation.

In what follows, we consider two scenarios: *i)* a single-hit scenario corresponding to a one-period shock (the results under this scenario are presented and discussed in the previous section); and *ii)* a double-hit scenario in which the economy is hit by a two-period shock, the first occurring during the first quarter and the second occurring in the third quarter following the first shock. Since the model is linear, IRFs are linear in the size of shocks. Mention should be made about the non-endogeneity of policy response to the first shock. Indeed, our results highlight the sequence shocks impact on growth in the absence of policy responses.

Table 2 reports the dynamic responses of real economic growth in both a single-hit and a double-hit scenario. It shows that a one-time shock of a magnitude of 10xσ has a negative impact on real economic growth of 7% in India, 5.3% in the Philippines, 3.6% in China and 2.7% in Thailand. Nevertheless, if the economy were hit by a two-period shock of the same magnitude, the impact would be more disruptive in all countries. Growth would be reduced by around 8.4 % in India, 6% in the Philippines and China, 4.2% in Thailand.

[6] *h* is the horizon for which the impulse responses are computed.

Table 2. Annual real economic growth response to large scale natural disaster shock (average)

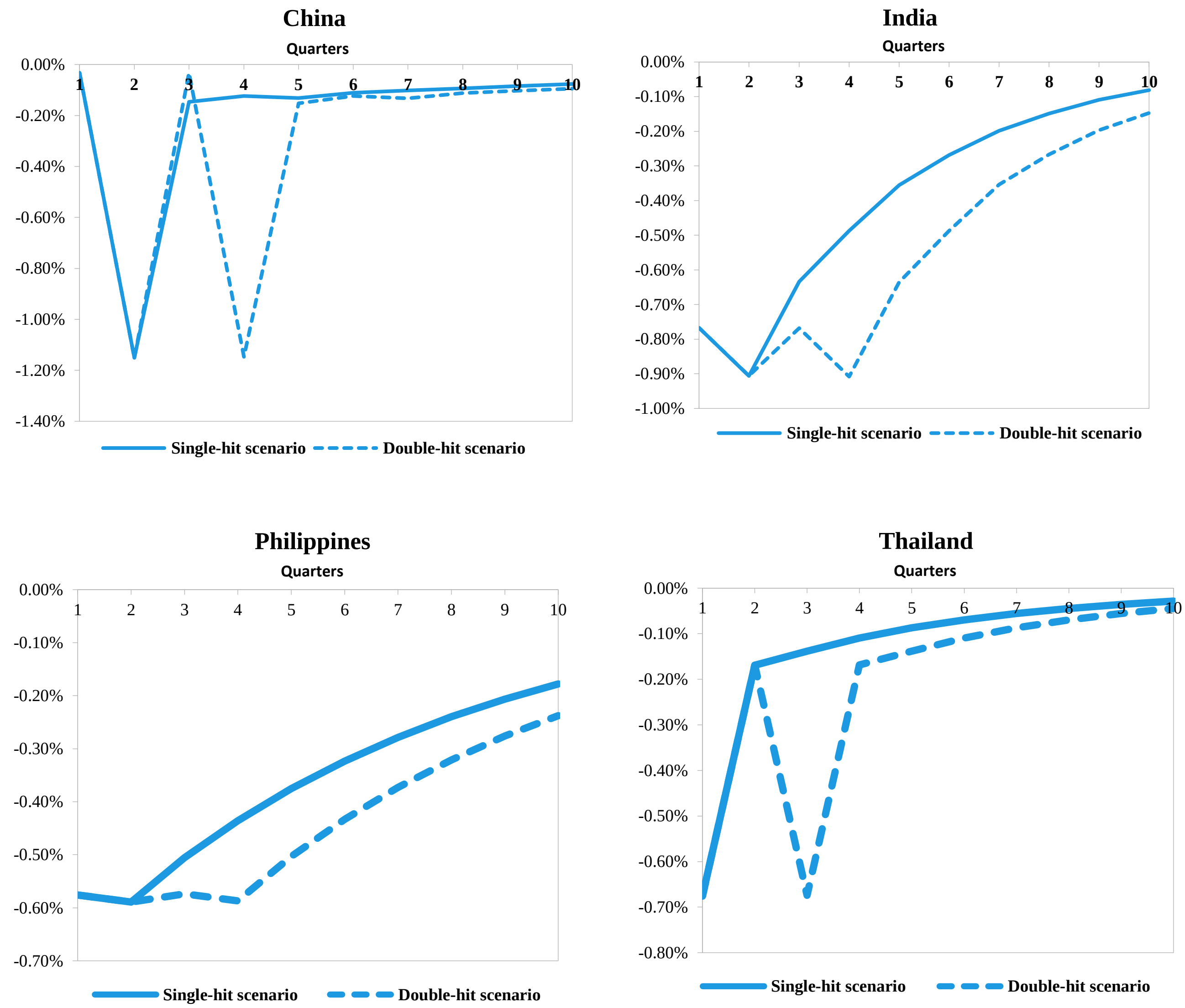
	China	India	Philippines	Thailand
Shock size		Single-hit scenario		
1	-0.36%	-0.70%	-0.53%	-0.27%
5	-1.82%	-3.49%	-2.63%	-1.37%
10	-3.63%	-6.99%	-5.27%	-2.73%
15	-5.45%	-10.48%	-7.90%	-4.10%
		Double-hit scenario		
1	-0.59%	-0.84%	-0.58%	-0.42%
5	-2.95%	-4.19%	-2.91%	-2.11%
10	-5.91%	-8.38%	-5.81%	-4.22%
15	-8.86%	-12.56%	-8.72%	-6.33%

Note: σ: Cholesky standard deviation.
Source: Authors calculations.

Two-period shocks affect the selected economies in an additional way. A second wave of shocks will probably cause a second significant drop in output in the same quarter or the next one, and it will lead to a more prolonged effect on economic activity (Figure 3). In the case of a double-hit scenario, the negative effect of LND shocks on China's economy will start to fade from the fifth quarter following a disaster, rather than the third quarter in the case of a single-hit scenario. Similarly, the impact of a two-time shock on India's economic growth will be disruptive during the entire current year. Concerning the Philippines, the impact of a second shock will probably plunge the country into a more severe recession, lasting eight quarters instead of six.[7] In Thailand, a double-hit shock will significantly push down the economic growth during the four quarters of the current year, and its effect becomes statistically insignificant from the beginning of next year.

[7] Taking account of only statistically significant quarters.

Figure 3. Multi-Period Impulse Responses for Selected Emerging Asian Economies



Source: Author's calculations.

5. A Non-Linear Approach: The Regime-Switching Model

5.1. Estimating Growth Using the Markov Switching Model

To account for potential non-linearities in the relationship between real economic growth and LNDs, we estimate an Auto Regressive (AR) Markov regime-switching model for the growth rate series. We introduce as an exogenous explanatory variable a dummy variable taking value 1 when the $LND_t \neq 0$ and zero otherwise. The AR Markov regime-switching model of order 1 and two states takes the following form:

$$y_t = \begin{cases} \alpha + \alpha_1 y_{t-1} + \beta\ dummy_t + \varepsilon_t, & when\ s_t = 0 \\ \alpha' + \alpha_1' y_{t-1} + \beta'\ dummy_t + \varepsilon_{t'}, & when\ s_t = 1 \end{cases}$$

Where y_t denotes real economic growth, $\alpha_1 < 1, \alpha_1^{'} < 1$ and $\{\varepsilon_t, \varepsilon_t^{'}\}$ are i.i.d. random variables with mean zero and their respective variance $\{\sigma_1^2, \sigma_2^2\}$. The AR(1) is a stationary process with coefficients $\{\alpha, \alpha_1, \beta\}$ when $s_t = 0$, and it switches to another stationary AR(1) process with different coefficients $\{\alpha^{'}, \alpha_1^{'}, \beta^{'}\}$ when s_t changes from 0 to 1. When the two sets of coefficients are significantly different from one state to another, y_t is then governed by two distributions with distinct means, and s_t determines the switching between these two distributions (regimes). We assume that s_t follows a first order Markov chain with the following transition matrix:

$$P = \begin{bmatrix} P(S_t = 0|S_{t-1} = 0) & P(S_t = 1|S_{t-1} = 0) \\ P(S_t = 0|S_{t-1} = 1) & P(S_t = 1|S_{t-1} = 1) \end{bmatrix} = \begin{bmatrix} P_{00} & P_{01} \\ P_{10} & P_{11} \end{bmatrix}$$

The transition probabilities satisfy $p_{i0} + p_{i1} = 1$ for $i = 0,1$.
We estimate the model employing a maximum likelihood technique assuming normally distributed errors and using the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm.

5.2. Results from Applying the Markov Model

Table 3 reports the outputs for Markov-switching regression. Two regimes of the Markov switching models are considered in this study. A Marquardt step is used to estimate the parameters of an unobserved state. The findings emphasise the presence of two distinct regimes: a regime characterised by a high negative impact of LNDs, and a low autoregressive coefficient. In the second regime, the negative effect of a LND is small, while the autoregressive parameter is significantly close to 1. Consequently, the negative effect of LNDs on economic growth in the contraction period is greater, while this effect during the expansion period is either small or non-significant.

During contraction periods, the negative impact of LNDs ($dummy_t$=1) on growth is around 0.12 in China and 0.11 in Thailand. In the Philippines, the effect of LNDs on growth is negative in both regimes but non-significant. Due to lack of non-interpolated data, India is excluded. In fact, original quarterly economic growth series are only available from 2005 while the associated LNDS took place before 1980.

Table 3. Markov Switching Regression Results

Number of states: 2

Method: Markov Switching Regression (BFGS / Marquardt steps)

Initial probabilities obtained from ergodic solution

Huber-White robust standard errors and covariance

	Regime 0		Regime 1		Included observations
	$dummy_t$	AR(1)	$dummy_t$	AR(1)	
China	-0.12***	-0.15	-0.00	0.97***	160
	[0.02024]	[0.72569]	[0.00650]	[0.18154]	
Philippines	-0.04	0.74***	-0.01	0.87***	144
	[0.034292]	[0.07227]	[0.010896]	[0.103078]	
Thailand	-0.11**	0.24	-0.00	0.98***	234
	[0.034403]	[0.145515]	[0.007275]	[0.055441]	

Note: Standard errors appear in parentheses.
*** Significant at 1% level
** Significant at 5% level
* Significant at 10% level
Convergence achieved

Source: Authors' calculations.

These results highlight the same shock persistence on growth as when using the SVAR approach. Indeed, the transition probability (Table 4) in China for switching from regime 0 to regime 1 is higher than the transition probabilities from regime 1 to regime 0. This means that the economic recovery takes place rapidly, with an expected duration of one quarter in regime 0 and 14 quarters in regime 1. Then, the second regime of expansion periods is more prevalent than the first regime corresponding to low economic growth.

The same conclusion is observed in the case of Thailand. However, the probability of switching from low economic growth to recovery is smaller compared to the same for China. The expected duration in crisis regime is six quarters against only one quarter for China.

Table 4. Transition Probabilities and Expected Duration

	China	Philippines	Thailand
p_{00}	0.00	0.96	0.94
p_{01}	1.00	0.04	0.06
p_{10}	0.07	0.06	0.17
p_{11}	0.93	0.94	0.83
Constant expected duration			
Regime 0	1.00	25.90	6.00
Regime 1	14.05	14.76	15.88

Source: Authors' calculations.

6. Conclusion

In this paper, we provide empirical evidence on impact of external shocks on the growth resilience of four Emerging Asian economies: China, India, the Philippines and Thailand. The analysis is performed using a structural vector autoregressive (SVAR) approach. Information on the size and speed of the impact of external shocks on growth resilience is derived from impulse response functions.

According to our results, large-scale natural disasters have a negative impact on real GDP growth in all four countries. LNDs have a large negative impact on GDP growth in India, Thailand and the Philippines, although the speed at which the impact wanes differs, with a more persistent impact in the Philippines. Growth resilience to large external shocks will be determined by economic systems and policy considerations. In addition, our estimates show that a prolonged external shock that stretches over several periods will lead to a more lasting effect on economic activity than a single-hit scenario. In addition, the model is extended to a non-linear case by an Auto Regressive (AR) Markov regime-switching model, to examine the similar impacts.

While the results derived in this paper need to be interpreted with necessary caution, this analysis could provide a reference on assessment of the impact of the COVID-19 shock on growth.

References

ADRC (2002), "Natural disasters in Myanmar", *20th Century Asian Natural Disasters Data Book*, Asia Disaster Reduction Centre

Albala-Bertrand, J.M. (1993), *The Political Economy of Large Natural Disasters: With Special Reference to Developing Countries*, Clarendon Press, Oxford.

Atkeson, A. (2020), "What will be the economic impact of COVID-19 in the US? Rough estimates of disease scenarios", *NBER Working Papers*, No. 26867.

Baker, S.R., N. Bloom and S.J. Davis (2016), "Measuring economic policy uncertainty", *Quarterly Journal of Economics*, Vol. 131/4, pp. 1593-1636.

Barrett, C., et al. (2011), "Economic and social impact of influenza mitigation strategies by demographic class", *Epidemics*, Vol. 3/1, pp. 19-31.

Bartsch, S.M., et al. (2020), "The potential health care costs and resource use associated with COVID-19 in the United States", *Health Affairs*, Vol. 39/6 pp. 1-7.

Bordo, M.D. and A.P. Murshid (2020), "Globalisation and changing patterns in the international transmission of shocks in financial markets", *NBER Working Papers*, No. 9019.

Caggiano, G., E. Castelnuovo and R. Kima (2020), "The global effects of COVID-19-induced uncertainty", *Economics Letters*, Vol. 194, pp. 109392.

Canova, F. (2005), "The transmission of US shocks to Latin America", *Journal of Applied Econometrics*, Vol. 20, pp. 229-251.

Cavallo, E., et al. (2013), "Catastrophic natural disasters and economic growth", *Review of Economics and Statistics*, Vol. 95/5, pp. 1549-1561.

Chen, M-H., S.C. Jang and W.G. Kim. (2007), "The impact of the SARS outbreak on Taiwanese hotel stock performance: An event-study approach", *International Journal of Hospitality Management*, Vol. 26/1, pp. 200-212.

Chen, Q., et al. (2020), "Livelihood vulnerability of marine fishermen to multi-stresses under the vessel buyback and fishermen transfer programs in China: The case of Zhoushan City, Zhejiang Province", *International Journal of Environmental Research and Public Health*, Vol. 17/3, pp. 765.

Dolley, J. C. (1933), "Open market buying as a stimulant for the bond market", *Journal of Political Economy*, Vol. 41/4, pp. 513-529.

ESSA (1967), *Mariners Weather Log*, Vol. 11/2, Environmental Science Services Administration, US Department of Commerce.

Fang, W.S. and S.M. Miller (2009), "Modeling the volatility of real GDP growth: The case of Japan revisited", *Japan and the World Economy,* Vol. 21/3, pp. 312-324.

Fenichel, E.P. et al. (2011), "Adaptive human behaviour in epidemiological models", *Proceedings of the National Academy of Sciences of the United States of America,* Vol. 108/15, pp. 6306-6311.

Fenichel, E.P. (2013), "Economic considerations for social distancing and behavioural based policies during an epidemic", *Journal of Health Economics,* Vol. 32/2, pp. 440-451.

Fomby, T., Y. Ikeda and N. V. Loayza (2013), "The growth aftermath of natural disasters", *Journal of Applied Econometrics,* Vol. 28/3, pp. 412-434.

Gupta, R., et al. (2020), "Time-varying impact of pandemics on global output growth", *Finance Research Letters,* pp. 101823.

Hallegatte, S. and P. Dumas (2009), "Can natural disasters have positive consequences? Investigating the role of embodied technical change", *Ecological Economics,* Vol. 68/3, pp. 777-786.

Heger, M.P. and E. Neumayer (2019), "The impact of the Indian Ocean tsunami on Aceh's long-term economic growth", *Journal of Development Economics,* Vol. 141, pp. 102365.

Hsiang, S.M. and A.S. Jina (2014), "The causal effect of environmental catastrophe on long-run economic growth: Evidence from 6 700 cyclones", *NBER Working Papers,* No. 20352.

IMF (2020), *World Economic Outlook, April 2020: The Great Lockdown*, International Monetary Fund.

Jie, Y. (2011), "Six survive gas blast in Hunan mine", *China Daily,* 31 October 2011.

Keogh-Brown, M., et al. (2009), "The possible macroeconomic impact on the UK of an influenza pandemic", *University of Oxford Department of Economics Discussion Paper Series,* No. 431,.

Klomp, J. and K. Valckx (2014), "Natural disasters and economic growth: A meta-analysis", *Global Environmental Change,* Vol. 26, pp. 183-195.

Kniesner, T.J. and W.K. Viscusi (2019), "The value of a statistical life", *Oxford Research Encyclopaedias: Economics and Finance,* Oxford University Press, pp. 142-146.

Loayza, N.V., et al. (2012), "Natural disasters and growth: Going beyond the averages", *World Development,* Vol. 40/7, pp. 1317-1336.

Ludvigson, S.C., S. Ma, and S. Ng (2020), "COVID-19 and the macroeconomic effects of costly disasters", *NBER Working Papers,* No. 26987.

Luh, D-L., et al. (2018), "Economic cost and burden of dengue during epidemics and non-epidemic years in Taiwan", *Journal of Infection and Public Health,* Vol. 11/2, pp. 215-223.

Mackinlay, A. C. (1997), "Event studies in economics and finance", *Journal of Economic Literature,* Vol. 35/1, pp. 13-39.

Mackowiak, B. (2006), "External shocks, US monetary policy and macroeconomic fluctuations in emerging markets", *SFB 649 Discussion Paper,* No. 2006,026.

Maliszewska, M., A. Mattoo and D. Van der Mensbrugghe (2020), "The potential impact of COVID-19 on GDP and trade: A preliminary assessment", *World Bank Group Policy Research Working Paper,* No. 9211.

Mesnard, A. and P. Seabright (2009), "Escaping epidemics through migration? Quarantine measures under incomplete information about infection risk", *Journal of Public Economics*, Vol. 93/7-8, pp. 931-938.

Noy, I. (2009), "The macroeconomic consequences of disasters", *Journal of Development Economics,* Vol. 88/2, pp. 221-231.

Noy, I. and A. Nualsri (2007), "What do exogenous shocks tell us about growth theories?", *University of Hawaii Economics Working Papers,* No. 07-28.

Poaponsakorn, N. and Meethom P. (2013), *Impact of the 2011 Floods, and Flood Management in Thailand*, ERIA Discussion Paper Series ERIA-DP-2013-34.

Promchote, P., Simon Wang, S.-Y., & Johnson, P. G. (2016), The 2011 Great Flood in Thailand: Climate Diagnostics and Implications from Climate Change, Journal of Climate, 29 (1), 367-379. Retrieved Dec 15, 2020.

Raddatz, C. (2007), "Are external shocks responsible for the instability of output in low-income countries?", *Journal of Development Economics,* Vol. 84/1, pp. 155-187.

Rasmussen, T.N. (2004), "Macroeconomic implications of natural disasters in the Caribbean", *IMF Working Papers*, WP/04/224.

ReliefWeb (2011), "China: Floods-Jun 2011", OCHA ReliefWeb with information from Xinhua News Agency.

Riskianingrum, D. (2016), The Historical Overview Of Quake Management Policy In China: From Tangshan, Sichuan, To Yunnan. *Jurnal Kajian Wilayah*, *6*(2), pp. 149-160.

Sharma K.D. (1997), *Flash floods and their control in the Indian arid zone,* Destructive Water: Water-Caused Natural Disasters, their Abatement and Control (Proceedings of the Conference held at Anaheim, California, June 1996). IAHS Publ. no. 239, 1997.

Schumpeter, J.A. (1934), "The theory of economic development: An inquiry into profits, capital, credit, interest, and the business cycle", *Harvard Economic Studies*, No. 46.

Sharma, K.D. and N.S. Vangani (1982), "Flash flood of July 1979 in the Luni basin—A rare event in the Indian desert", *Hydrological Sciences Journal*, Vol. 27/3, pp. 385-397.

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

Tanaka, K (2021), "Forecasting Developing Asian economies during normal times and large external shocks: Approaches and challenges", *OECD Development Centre Working Papers, No.345.*

Timmer, M.P., et al. (2015), "An illustrated user guide to the world input-output database: The case of global automotive production", *Review of International Economics, Vol. 23/3,* pp. 575-605.

UNDRO (1985), "Philippines Typhoon Oct 1985 UNDRO Information Reports 1-3", United Nations Disaster Relief Organization.

UNDRO (1991), "Philippines Typhoon Mike Nov 1990 UNDRO Situation Reports 1-6", United Nations Disaster Relief Organization.

Viscusi, W.K. (2018), "Best estimate selection bias in the value of a statistical life", *Journal of Benefit-Cost Analysis,* Vol. 9/2, pp. 205-246.

World Bank (2020), "East Asia and Pacific in the time of COVID-19", *World Bank East Asia and Pacific Economic Update, April 2020,* World Bank, Washington, DC.

Xiao, F., et al. (2004), "Analysis on the cost and its related factors of clinically confirmed Severe Acute Respiratory Syndrome cases in Beijing", *Zhonghua Liu Xing Bing Xue Za Zhi*, Vol. 25/4), pp. 312-316.

Xuequan, M. (2019), "Typhoon Mitag lands in east China", *Xinhua News Agency*, 1 October 2019.

Yang Zhang et al. (2014), *Planning and Recovery Following the Great 1976 Tangshan Earthquake*, Journal of Planning History 2015, Vol. 14(3), pp. 224-243.

Zingales, L. (13 March 2020), "Captured Western governments are failing the coronavirus test", Promarket blog.