Asian Journal of Social Science and Management Technology
ISSN : 2313-7410
Volume 6, Issue 3, May-June, 2024
Available at www.ajssmt.com

Complex Disasters and Economic Development in Northeast Asia

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ABSTRACT:
This paper analyzes the multi-façade consequences of complex disasters on the East-Asian economy from 1992 to 2021. A complex disaster is defined as any disaster that starts as a natural disaster followed by human-made mistakes and vice versa. Northeast Asian nations are defined in a narrow sense and comprise China, Mongolia, South Korea, and Japan. We exclude Hong Kong, Macao, North Korea, and Taiwan because their data are not comprehensive. Three types of disasters' damage used in this research comprise the number of deaths, the number of people affected, and the magnitude of direct damages. Data on disasters are from The Emergency Events Database (EM-DAT) website. Data on the macroeconomic variables are available from the World Bank website. The paper investigates the following sectors of the economy: primary, secondary, and tertiary. The results show that the effects of the number of mortalities on the primary and secondary sectors are mostly adverse and statistically significant. The impacts on the tertiary sector are mostly not statistically significant. However, the impacts of the number of people affected and the magnitude of direct damage differ for different economic sectors. We also compare across nations.

JEL classification: O40, Q54

Keywords: natural, human made, complex, disasters, Northeast Asia

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1. INTRODUCTION

January 2020 came with the shocking news of the new coronavirus epidemic in Wuhan, China. By the time international researchers roughly experimented with a vaccine, the pandemic had been wreaking havoc throughout the world through human contacts. Since then, the impacts of disasters have gained attention in policy analyses by all agents in world organizations, states, and local governments. This new tendency also calls for an examination of complex disasters.

Going through recent research on this topic, however, we find that most current researchers focus on natural disasters. Moreover, writings on complex disasters often focus on the damage caused by epidemics, pandemics, or technological hazards triggered by natural disasters. Few scholars spend time studying the economic effects of other complex disasters although data are available on the EM-DAT website. The lack of a comprehensive study on this topic inspires us to have a more thorough look at the complex disaster. The paper estimates disaster impact in terms of foregone production and capital formation for each of the above sectors using a panel dataset from 1989 to 2018 for these nations. We first analyze the determinants of these costs for Northeast ASias a group. We then compare the economic costs of disasters across nations. Data for three types of disaster damage are from the EM-DAT website: the number of people killed, the number of people affected, and the magnitudes of direct damage in U.S. dollars.

Section 2 discusses the existing research and outlines our goals in this paper. Section 3 introduces the methodology. Section 4 analyzes the results and extends the discussions to the impact of the COVID-19 Pandemic. Section 5 concludes and provides the economic implications of the findings.

2. EXISTING RESEARCH

The term "complex disasters" receives the following definition from the International Federation of Red Cross and Red Crescent Societies (IFRC) website:

"Some disasters can result from several different hazards or, more often, to a complex combination of both natural and man-made causes and different causes of vulnerability. Food insecurity, epidemics, conflicts and displaced populations are examples."

In this paper, we define complex disasters as anyone caused by a combination of natural and human forces with data provided by the EM-DAT database. Belonging to this category is any natural disaster that leads to a technological disaster, animal or insect infestations, famines, epidemics, and pandemics. In the next subsections, we review the existing literature complex disasters.

Northeast Asia has elevated exposure to complex disasters, especially biological ones such as contagions or infestations of insects or animals on an epidemic or pandemic level. The consistent exposure to complex disasters, combined with geophysical events such as earthquakes or tsunami, may generate different macroeconomic effects compared to regions that only experience infrequent but significant geophysical incidents.

Petrova and Krausmann (2011) introduce articles on the natural hazards that lead to technological disasters following a specially organized session named "Natural Hazards and Technological Disasters" at the General Assembly 2010 of the European Geosciences Union. The compile selected contributions from the attendants into a special issue focusing on natural disasters, which cause technological disruptions, and measures to mitigate their frequency and impact. The following seven paragraphs summarize articles in this issue.

Kepekci and Ozcep (2011) analyze mitigation efforts by selected cities in Turkey. They discuss the accident risk based on the earthquake damage reported by the cities. The authors perform a Poisson distribution to estimate the probabilistic seismic hazard for each city. They then categorize the risk levels based on each city's statistics: the number of houses, per-capita income, population, and ground-motion levels. Krausmann *et al.* (2011) discuss the efforts reported in European FP7 Project iNTeg-Risk regarding risk management against chemical disasters ignited by earthquakes, floods, and lightning. The authors then introduce new concepts and recommendations for risk rankings, risk evaluation, planning, and emergency warning.

Girgin (2011) carries out a case study of the 1999 İzmit earthquake, a typical natural disaster that induced a series of technological disasters (Natech), on August 17 in Turkey. The two most severe accidents were the fire at the Izmit refinery and the acrylonitrile spill at the acrylic fiber plant. The author emphasizes any lack of Natech emergency planning, or slow response to emergencies during an incident, or an inadequate assessment of the risk evolved as a factor that determines the severity of a disaster. Increasing communication with the public during and following the accident is crucial to mitigate the consequences of a disaster event.

Ozunu *et al.* (2011) present the Natech problem in Romania using data from a survey conducted by the Romanian authorities. The results show that the vulnerability of local communities and infrastructures raises the frequency and the severity of the Natech incidents. They also reveal that improved planning, adequate preparedness, appropriate implementation of safety codes, and frequent reports can decrease the number and adverse impact of these Natech accidents.

Besstrashnov and Strom (2011) discuss tools to mitigate disaster losses by reducing pipeline strains at active fault crossings**.** They analyze the importance of determining accurate locations and different types of active faults by observing fault activity to avoid surface rupturing. They point out that this method is quite efficient in any area belonging to Russia and other nations of the former Soviet Union with new oil and natural-gas fields in seismically active regions.

Petrova (2011) presents various types of technological disasters triggered by multiple hazards instead of a single Natech problem. They comprise weak infrastructures, unsafe production processes, and inadequate transport facilities. Using a web-based dataset, she calculates each natural incident's proportion among all incidents that cause technological disasters. She also compares across regions concerning the differences in their frequencies and magnitudes.

Frolova *et al.* (2011) have the last article published in the above special issue compiled by Petrova and Krausmann (2011). This last paper uses the Geographic Information System (GIS), a software that captures geographic data, analyzes the spatial aspects of seismic events that lead to technological accidents. The GIS enables these scientists to estimate various losses caused by the consequential disasters following an earthquake. The authors also present several case studies of Natechs in Russia.

Silei (2014) emphasizes that technological accidents triggered by natural disasters have become a global issue. The involvement of international society has led to an interdisciplinary approach to solving this problem. A rise in new hazardous substances and materials, as well as numerous opportunities for human errors during implementing processes, are the significant factors leading to technological accidents. A blur distinction between natural hazards and human-made accidents also calls for worldwide efforts to developing policies for collective security, public health, and environmental protection.

A geophysical disaster in a developed country can have more severe effects on developing nations surrounding the region than the impact on the host country. Vu *et al.* (2014) perform a data analysis of the Japanese earthquakes and tsunamis, some of which led to technological accidents and their impact on tourist flow to the surrounding countries. They use a panel dataset on natural disasters in Japan from the Center for Research on Disasters' Epidemiology and other data from the World Bank website. The results show that the adverse effects on tourism industries in these countries last longer than in Japan. The results also reveal that the arrival rates to the developing countries are different for different nations, thanks to various combinations of the private and public sectors' efforts to redirect capital to more efficient uses and risk reduction through resource diversification.

Many researchers of complex disasters focus on epidemics and pandemics. Bloom and Mahal (1997) examine the impact of the HIV/AIDS epidemic on economic growth. They find that the impact on the output growth is statistically insignificant. In contrast, Jamison *et al.* (2001) see a 1.7 percent drop in economic welfare and a 2.6 percent fall in the growth rate of wealth when analyzing a slightly different dataset.

Fan (2003) uses the Oxford Economic Forecasting (OEF) Model to perform an *ex-ante* prediction of the effects of the Severe Acute Respiratory Syndrome (SARS) on GDP growth. Guangdong province in southern China was the first region that experienced SARS in November 2002. The epidemic shared 80% of its genetic code with COVID-19 and ended in July 2003. SARS became a pandemic when it spread to 29 countries and caused 774 deaths globally. The estimation predicts that the composite growth rate of GDP in theses 29 countries will reduce by 0.2-1.8% if SARS persists for a quarter and 1.5-4.0% if SARS lasts for three quarters.

Nonetheless, an *ex-post* study carried out by Hanna (2004) shows that the *ex-ante* prediction by Fan (2003) was higher than the actual GDP loss. The growth rate was predicted at 1.5 percent during the peak of the SARS pandemic, while the actual fall was at 0.5 percent, although the pandemic did last three quarters. With *ex-post* research, mitigation activities by both governmental and private-sector measures led to less severe consequences than the ones predicted.

In a similar study, Chou (2004) also finds moderate loss from SARS. Using a computable general equilibrium model for 31 sectors and 16 regions in Taiwan, the author estimates the SARS outbreak's macroeconomic consequences. The results show that the fall in Taiwan's output growth was between 0.5 percent and 0.6 percent. The research compares two scenarios where there is complete disclosure of SARS cases versus a lack of public communication and finds the difference is 1.6% loss of GDP. Like the above authors, Keogh-Brown (2008) finds that SARS's economic consequences on affected nations turned out to be much smaller than forecast values conducted by contemporary models. These results call for the improvement of forecasting models to estimate the impacts of epidemics and pandemics more accurately.

Smith *et al.* (2009) examine the effects of the 2009 H1N1 (Swine Flu) pandemic that occurred from January 2009 to August 2010. According to the WHO, the Swine Flu caused over 284,000 deaths. The results predict a GDP reduction of 0.5-1 percent for low fatality and 3.3-4.3 percent for high fatality scenarios. They forecast a more extensive than 4.3 percent GDP loss if the recuperative effects of pre-vaccinations and prophylactic are absent. A qualitative analysis by Monterrubio (2010) also points out that the inclusion of industry information is quite valuable to locate the above efforts' impact on specific sectors such as tourism in Mexico during the Swine Flu pandemic.

Several papers show that complex disasters can have adverse effects on GDP per capita. Karlsson *et al.* (2014) discuss the Spanish flu epidemic, which became a pandemic in 1918 and affected 1/3 of the world's population due to the failure to promptly discover the source of the viruses and the timely finding of vaccines. The results find that for each one percent rise in mortality rate, there is a five percent fall in capita income in Sweden. No researcher has conducted a study on the aggregate effect of the 1918 Spanish flu worldwide, partly because it lasted close to two years, with roughly 17-50 million deaths, partly because data on the damage caused by this pandemic is not comprehensive.

This paper will be incomplete if we skip the specific effects of COVID-19, although there are very few new cases in NorthNortheast ASia. The World Health Organization (WHO, 2020) received the first reported COVID-19 case from Chinese health authorities on December 31, 2019, and subsequently labeled it a pandemic on March 11, 2020. By the time COVID-19 came into existence, the world had endured five diseases caused by a coronavirus. The WHO labeled each of them a type of "flu," including the SARS and 2009 H1N1 mentioned above. However, COVID-19 was rapidly spreading due to its much higher transmission rate than that of the other five. Also, whether the pandemic will become a permanent endemic remains unknown. The impact of the pandemic on the economy worldwide is certainly severe, but those on Northeast ASiamight be small. Thus, we will examine this pandemic toward the end of the paper.

Vu *et al.* (2017) study the correlations among global warming, hurricanes, and sustainable tourism in NorthNortheast ASia. The authors construct a dataset on the damaging impact of cyclones based on the Tropical Best Track Tables and the Annual Tropical Cyclone Reports provided by the United States National Climatic Data Center for 1995-2014. They point out evidence of a correlation between rising temperatures caused by tourist activities and the intensity of cyclones. They also find a two-way causality between hurricanes and sustainable tourism: hurricanes sharply reduce tourist-arrival growth rate, and sustainable tourism reduces the frequency and the magnitude of the hurricanes. The authors then provide policy suggestions to reduce tourist activities that lead to environmental degradation and subsequently achieve sustainable tourism in the region.

Tashanova et al. (2020) point out that he COVID-19 Pandemic has been causing significant losses due to governments' decisions to shut down production plants and businesses. Aifuwa *et al.* (2020) perform a linear regression of a surveyed dataset from private enterprises in Nigeria through questionnaires administered online. The results show that COVID-19 hurts both the financial and non-financial performance of private enterprises in this country. The authors propose that the Nigerian government include private firms in its stimulus packages to help private sectors run smooth operations once the economy reopens.

Based on the above literature review, thorough data analysis of all disasters in Northeast ASia is a compelling subject: its nations reveal differences in the levels of GDP per capita, infrastructure, and government involvement. On the other hand, they share similarities in cultural characteristics of Confucianism, high literacy rate, export growth policies, and increasing trade openness.

Our paper aims to describe the short-run dynamics of the macroeconomy following disasters. The long-run analysis raises questions of endogeneity in disaster impacts that are, to no small extent, absent in the short-run.

The involvement of all complex disasters helps us draw general conclusions in a realistic scenario, which otherwise might be absent in single-occurrent analyses.

3. METHODOLOGY

This section presents the data and the model. We will investigate the aggregate effects using each empirical model first and then examine country effects by adding dummy variables.

3.1 General model

Model (1) is a general model containing a system of equations to account for the possible feedback effects among the variables:

$$PERCA_{i,t} = \alpha_1 DAM_{i,t} + \sum_{k=1}^{K} \alpha_k DAM_{i,t-k} + \beta X_{i,t} + q_i + s_t + \varepsilon_{i,t} \qquad (1.1)$$
$$DAM_{i,t} = \varphi Z_{i,t} + \theta PERCA_{i,t} + \sum_{l=1}^{L} \gamma_l Z_{i,t-l} + v_i + w_t + \omega_{i,t} \qquad (1.2)$$

where *PERCA* is per capita output, which is the ratio of each sector's output to population, and *DAM* the ratio of damage caused by disasters to population. We will eliminate *Equation* (1.2) if our preliminary tests show the assumption of the weak exogeneity of the DAM measures used in Skidmore and Toya (2002) holds for a disaster type, implying there is no feedback effect. X and Z are two vectors of potential control variables that might affect the system's dependent variables. The subscript *i* is country index among EA countries, *t* is the time index measured in years, *k* and *l* are the numbers of lagged periods. The last three variables in each equation are country-specific effect, time-specific effect, and idiosyncratic disturbances.

Concerning data on disasters, while the “Country Profile” page on the EM-DAT website only provides data for two types: natural and technological, its “Advanced Search” has data for complex disasters but only comprises famines, animal/insect infestations, and lack of access to or availabilities of food. We hence move all datapoints presenting epidemics/pandemics, which spread out due to a combination of natural and humanmade causes, from EM-DATs’ “natural-disaster” category to “complex disaster” category. The same is true for any disaster that is a combination of natural and technological disasters. Thus, we construct data from 1989 to 2018 for China, Mongolia, South Korea, and Japan.

Data on the output for three essential sectors of the economy – primary, secondary, and tertiary – employment, trade, Foreign Direct Investment (FDI), infrastructure, human capital, and capital formation are from the World Development Indicators posted on the World Bank website. Data on interest rates, exchange rates, GDP deflators, and population are from the U.S. Department of Agriculture (USDA) Website and the International Monetary Fund (IMF) website. We calculate the sum of all school enrollments and divide by population to obtain a proxy for human capital in each country. To obtain a proxy for infrastructure, we calculate the sum of freights from rail lines, roads, and airlines, all in “million ton-km.” The term “ton-km” is the total volume measured in metric tons times kilometers traveled. We then multiply all nominal values in U.S. dollars with the GDP deflators and divide by population to obtain real per-capita values.

Figure 1 charts the real GDP per capita (RGDPPC) for the four countries. From this figure, we can see the starkly different levels of RGDPPC among these four countries, although they share many cultural characteristics.

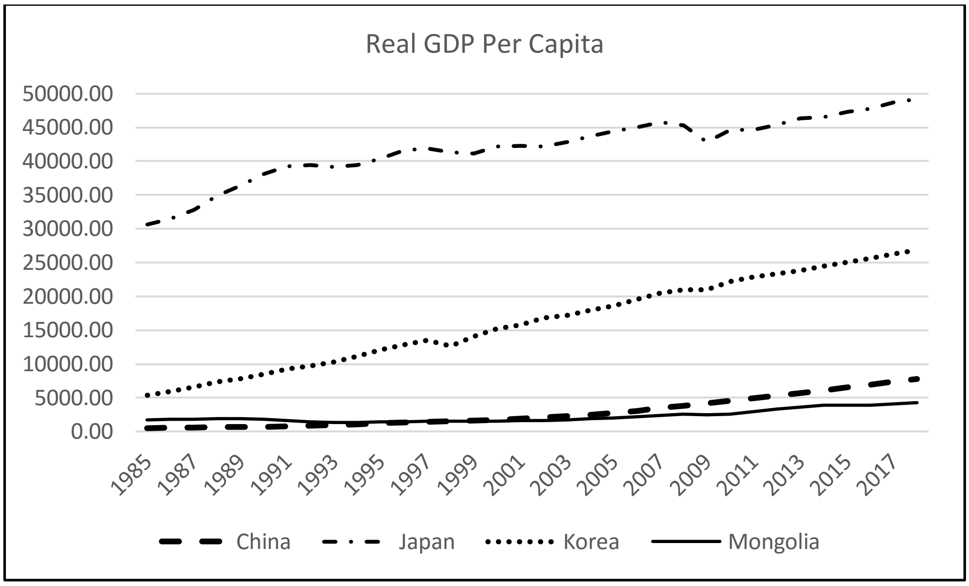

Figure 1. Real GDP per capita

Source: Constructed by Tam Vu based on data from USDA

The chart also shows Japan's real GDP per capita declined sharply in 2007-2009 in addition to the stagnation during 1991-2009. The sharp drop dragged Japan's economy back 5-6 years, to the 2003 level, where it started a new trajectory, which is parallel to the previous trend at a lower level. South Korea and China enjoyed high growth during this period, with South Korea growing faster in real terms. Mongolia 's economy did not start its growth until 1999, two years after joining the World Trade Organization (WTO). Note that the figure charts the real GDP per capita instead of the nominal one.

Table 1 shows that the average GDP composition for the three essential sectors in each country during the period 1989-1918 also extremely different among the four countries. This difference makes our study even more enjoyable.

Table 1. GDP composition for Northeast ASia(%)

Country	Primary	Secondary	Tertiary
China	15	45	40
Japan	8	30	62
Mongolia	41	33	25
South Korea	10	39	51

Since we select a model empirically for each type of disaster through a model-search process, more data discussions will come later.

We will perform downward piecewise regressions to avoid missing variables, starting with all available variables that might explain each of the dependent variables according to the existing literature. We then eliminate variables gradually, using multicollinearity tests. Gathering all available data on the NorthNortheast ASian economy, we have nine control variables: employment rate (EMP), physical capital (CAP), real interest rate (INT), human capital (HUM), the exchange rate (EXC), initial output (INI), and infrastructure (INF). There are missing observations, so we have unbalanced panels, and we will use binary dummies to control for missing observations.

As a preliminary step, we use Robust Ordinary Least Squares estimations (ROLS) instead of panel-data regressions to preserve information that might not reveal in a sophisticated estimation. We then carry out multicollinearity tests using the Variance Inflation Factors (VIF) approach discussed in Kennedy (2008). Kennedy recommends that we eliminate any variable with VIF greater than ten.

We use the Ramsey Regression Specification Error Tests (RESET) to detect omitted variables.
To detect possible endogeneity for each model, we employ the modified Hausman test called Omitted Variable (OV) variant of the Hausman test in Kennedy (2008). There are two versions of the OV variant of the Hausman test. We use the second version of this test, which helps us avoid all complications arisen using the original Hausman test for endogeneity discussed in Kennedy (2008), pages 144-154.
Next, we perform Granger-causality tests on each model. Theoretically, when a variable z does not "Granger causes" a variable y, then

$$E(y_t/y_{t-1}, z_{t-1}) = E(y_t/y_{t-1}).$$

Hence, we will regress the PERCA on its lags, the DAM lags, and the remaining variables in Model (1) and test the significance of the DAM lags. We will also regress DAM on its lags, PERCA lags, and the other variables, and test the significance of the PERCA lags. If any of the lags are statistically significant, then there is a possible two-way causality. However, the results for a Granger-Causality test come from single equation estimations and so sometimes fail to detect the two-way causality due to simultaneity biases. Therefore, we also carry out preliminary regressions of the system, including both Equations (1.1) and 1.2) using the Three-Stage Least Squares (3SLS) technique.
To control for the presence of lagged dependent variables in the model, we employ the Blundell-Bond System generalized method of moments (SGMM) procedure as described in Blundell and Bond (1998) and Bond (2002). The Blundell-Bond process is a refined application of the Arellano and Bond (1991) and the Arellano and Bover (1995) procedures.
To solve this problem, Blundell and Bond (1998) develop a modified process introduced in Arellano and Bond (1991 and Arellano and Bover (1995). In this approach, they add the difference of the instrumental variable (IVs) to make them exogenous to the fixed effects. To build this while retaining the original Arellano-Bonds for the transformed equation, they design a *system* GMM estimator that we follow in our paper.
For the number of lags to include in each model, we use the Akaike (1973) Information Criterion (AIC) and Schwarz (1978) Bayesian Information Criterion (BIC). We employ the Dickey-Fuller tests discussed in Kennedy (2008) to determine whether the series is stationary. A Hausman test for model specification will help us decide whether a random effect is more appropriate than a fixed-effect model and vice versa.
Figure 2 charts two series for complex disasters: numbers of events and numbers of deaths.

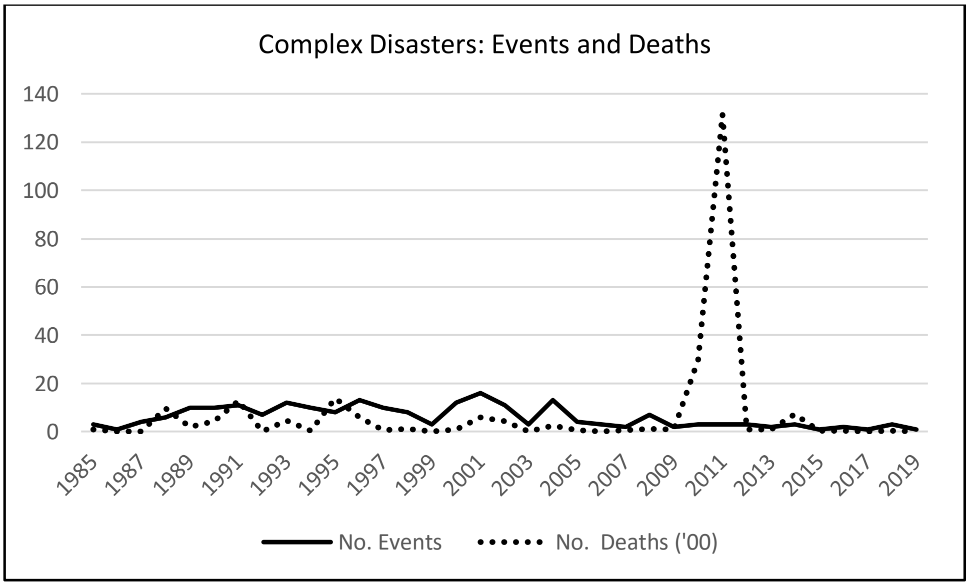

Figure 2. Complex disasters: numbers of events and numbers of deaths
Source: Constructed by Tam Vu based on EM-DAT data

Figure 3 charts the remaining series for complex disasters.

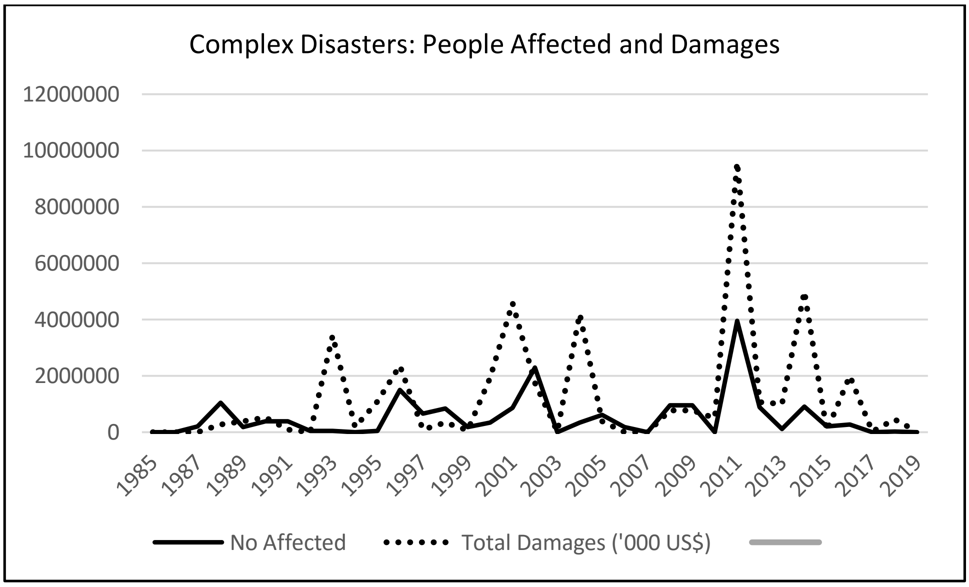

Figure 3. Complex disasters: numbers affected and total damages
Source: Constructed by Tam Vu based on EM-DAT data

The graphs disclose that numbers of deaths, numbers of people affected, and total damages all peaked in 2011. Observing the data, we see that these maximum values are due to the March 11 Earthquake in Tohoku that lead to a tsunami and a nuclear accident in Fukushima, Japan. Hence, we eliminate this outlier from our regressions. The preliminary tests on Model (1) with damage measures for complex disasters confirm the structural equations for System (2) as follows:

$$PERCA_{i,t} = \alpha_1 DAM_{i,t} + \alpha_2 DAM_{i,t-1} + \beta_1 INT_{i,t} + \beta_2 CAP_{i,t} + \beta_3 INI_{i,t} + s_t + \varepsilon_{i,t} \quad (2.1)$$

$$DAM_{i,t} = \theta_1 PERCA_{i,t} + \lambda_1 HUM_{i,t} + \lambda_2 INF + \lambda_3 EXC + r_i + u_t + e_{i,t} \quad (2.2)$$

After checking the order and rank conditions for System (2), we have System (3), which presents the reduced forms so that predicted values from the regression results of System (3) can serve as IVs for System (2):

$$DAM_{i,t-1} = \pi_{11} DAM_{i,t-2} + \pi_{12} INT_{i,t} + \pi_{13} HUM_{i,t} + e_{2i,t} \quad (3.1)$$

$$PERCA_{i,t} = \pi_{21} PERCA_{i,t-1} + \pi_{22} EXC_{i,t} + \pi_{23} INI_{i,t} + \pi_{14} CAP_{i,t} + e_{1i,t} \quad (3.2)$$

Having saved the IVs from estimating System (3), we then estimate System (2) using the RE3SLS approach.

4. RESULTS

This section discusses the estimation results for the model introduced in Section 3 regarding impact of complex disasters on economic development.

Table 2 shows the aggregate results for Model (2), which shows the two-way causality between complex disasters and per capita output.

(1) The severities of the disaster losses' effects on the output per person, ranging from the most to the least, are MORT, AFFT, and TERT.

(2) The tertiary helps the most among the three sectors in reducing the disaster's losses.
(3) The signs of the control variables are as expected.

The results in (3) make sense, as an increase in exchange rates reduces a company's quantity of exports and revenue, reducing a firm's resources needed to fight against disaster losses. As a result, the disaster impact's severities increase. Similarly, an increase in interest rates reduces a business's ability to borrow funds to cope with disaster losses.

Table 2. Aggegate effects of complex disasters

Panel (2.1) Dependent variable: Sectoral output per person			
Variable	Primary	Secondary	Tertiary
MORT	-2.78*** (.009)	-1.69** (.034)	-0.19** (.027)
MORTL	-0.25** (.046)	-0.09** (.033)	0.05** (.025)
COM-MORT	-3.03** (.031)	-1.78** (.028)	-0.24** (.028)
AFFT	-1.92** (.045)	-1.43** (.035)	-0.56 (.119)
AFFTL	0.14** (.031)	-0.12* (.065)	0.12 (.165)
COM-AFFT	-1.78** (.021)	-1.55* (.039)	-0.44 (.217)
DAMA	-1.19** (.039)	0.11*** (.007)	0.13* (.083)
DAMAL	0.05*** (.006)	0.02** (.013)	0.08* (.061)
COM-DAMA	-1.14** (.031)	0.13** (.025)	0.21* (.055)
INT	-0.08*** (.002)	-0.09** (.031)	-0.11** (.028)
CAP	0.31*** (.004)	0.32** (.048)	0.34** (.033)
INI	-0.06** (.029)	-0.07** (.041)	-0.08*** (.005)
Panel (2.2) Dependent variable: Ratio of damage measure to population			
Variable	MORT	AFFT	DAMA
PRIM	-0.07** (.022)	-0.08** (0.43)	-0.11** (.039)
SECOND	-0.12** (.031)	-0.15** (.031)	-0.18*** (.004)
TERT	-0.16** (.047)	-0.19*** (.003)	-0.20** (.028)
HUM	-0.06*** (.001)	-0.07** (.035)	-0.08** (.041)
INF	-0.15** (.036)	-0.13** (.050)	-0.14** (.042)
EXC	0.05* (.064)	0.02** (.012)	0.07** (.044)
p-value for F-test	0.006	.003	0.009
Average RMSE	0.206	0.218	0.184
p-value for AR (1)	0.276	0.312	0.251
p-value for AR (2)	0.247	0.301	0.324
Chi^2-Sargan	0.326	0.198	0.412
Chi^{2-}Hansen	0.501	0.377	0.255

Notes: ***, **, * indicate the significant level at 1, 5, and 10 percent, respectively, with p-values in parentheses. The p-value for AR(1) and p-value for AR(2) are from Arellano-Bond test for AR(1) and AR(2) in first differences and second differences, respectively.

These differences also make sense considering the complicated nature of complex disasters. For example, the earthquake and tsunami in northeastern Japan on March 11, 2011, which lead to Fukushima nuclear accident, caused such severe damage that took Japan several years to recover. Had we not removed this event from the dataset, outlier biases might have rendered unreliable results for our subsequent regressions.

Table 3 shows the country-specific effect of complex disasters. South Korea shows its superb ability to cope with disasters as the country with the least disaster losses.

One might wonder why Japan consistently ranked second in disasters' fighting even though it has achieved a developed country's status long before South Korea. The answer might come to terms with our studying period, which from 1991 to 2020. From 1991 through 2011, Japan was in two lost decades due to the problems of nonperforming bank loans and damaged balance sheets.

Table 3. Country-specific effects of complex disasters

Panel (3.1) Dependent variable: Sectoral output per person			
Variable	Primary	Secondary	Tertiary
MORT (China)	-2.98*** (.006)	-2.56** (.031)	0.67** (.025)
MOMORT	-0.52** (.028)	-0.49** (.029)	-0.35*** (.021)
KOMORT	1.38** (.017)	1.37*** (.004)	0.52** (.035)
JAMORT	1.16** (.021)	0.95**(.018)	0.43** (.015)
AFFT (China)	-1.67** (.043)	-1.49** (.031)	0.35** (.029)
MOAFT	-0.41** (.036)	-0.38** (.022)	-0.26** (.033)
KOAFFT	1.46** (.018)	1.37** (.050)	0.65** (.024)
JAAFFT	1.23** (.041)	1.21** (.028)	0.51** (.035)
DAMA (China)	-1.46** (.029)	-1.24*** (.005)	0.23*** (.008)
MODAMA	-0.54*** (.007)	-0.48** (.038)	-0.26** (.031)
KODAMA	0.96** (.016)	0.85** (.029)	0.72** (.037)
JADAMA	0.67** (.032)	0.61** (.024)	0.54** (.022)
Panel (3.2) Dependent variable: Ratio of damage measure to population			
Variable	MORT	AFFT	DAMA
PRIM (China)	-0.04** (.043)	-0.05** (.032)	-0.07** (.034)
Mongolia	0.02 **(.038)	0.01** (.015)	0.03** (.037)
South Korea	-0.04** (.041)	-0.03** (.028)	-0.06** (.035)
Japan	-0.03** (.034)	-0.02** (.044)	-0.05** (.018)
SECND (China)	-0.11** (.026)	-0.13** (.018)	-0.12** (.023)
Mongolia	-0.01** (.031)	-0.02** (.026)	0.02** (.027)
South Korea	-0.06** (.034)	-0.04** (.041)	-0.07** (.049)
Japan	-0.05*** (.004)	-0.03** (.046)	-0.06**(.029)
TERT (China)	-0.11** (.045)	-0.12** (.024)	-0.16** (.015)
Mongolia	0.04*** (.026)	0.05*** (.006)	0.06** (.047)
South Korea	-0.06** (.038)	-0.07** (.024)	-0.08*** (.045)
Japan	-0.05** (.016)	-0.06** (.042)	-0.07** (.025)
p-value for F-test	0.000	0.003	0.006
Average RMSE	0.247	0.112	0.205
p-value for AR (1)	0.528	0.315	0.414
p-value for AR (2)	0.286	0.268	0.203
Chi^2-Sargan	0.342	0.265	0.325
Chi^{2-}Hansen	0.371	0.413	0.364

Notes: ***, **, * indicate the significant level at 1, 5, and 10 percent, respectively,
with p-values in parentheses. The p-value for AR(1) and p-value for AR(2) are from Arellano-Bond test for AR(1) and AR(2) in first differences and second differences, respectively.

The Tokyo Nikkei average index plunged from its peak of the 9300s in 1990 to its trough of the 6900s in 2009. By the time the Tohoku Earthquake struck on March 11, 2011, the Nikkei average index had not completely recovered from that loss, trading in the range of 9000s. Japanese authority has tried to lower the real interest rate to stimulate the economy since 1991. However, the low rate has caused the so-called “monetary trap.” The deflation has caused Japanese consumers to delay buying durable goods or investing in real estate, worrying that their prices will fall in the future. Moreover, the deflation hurt any borrower who had taken out a long-term loan before the deflation. Thus, the Japanese economy has been stagnating for a long time, making it difficult to cope with disasters.

During this same period, South Korea enjoyed substantial growth, especially in the secondary sector. The South Korean government has also promptly implemented rules and regulations against disasters. Moreover, South Korean is the most disciplined people in embracing large-scale interventions. This phenomenon might have roots in the South Korean experience of rapid industrialization and national development in the past forty years.

Both panels reveal the struggles of these countries. In Panel (3.1), most countries endure more severe losses from complex disasters than from technological ones. In Panel 3.2), an increase in output reduces the severity of a complex-disaster loss less than that of the other ones. One detail worth attention in Panel (3.2) is Mongolia’s secondary sector, which reduces disasters’ losses more than China’s. The results might imply the severity of environmental degradation in China as the manufacturers extend their production without appropriate measures against the pollution caused by the careless industrialization.

5. CONCLUSION

From the above estimation and forecast results, the following lessons are crucial to mitigate the disaster losses.

For complex disasters, our estimation results support the recent lock-down of business, public communication, and testing to locate and confine the infected areas in the recent pandemic.

Experiences from the recent incidents reveal that most countries still implement more reactive measures than preventive ones. Governments should develop plans to prevent a human-made disaster from occurring after any natural disaster instead of waiting until an accident occurs and then try to fix it.

For epidemics and pandemics, provide people with information in ways to improve their immune systems and distribute masks free of charge among workers to reduce the number of contractions. Monitoring each company's workers is essential in keeping the production lines open. An insect infestation is also preventable if researchers can find and nurture another type of insect that is unfavorable to the harmful one.

In brief, this paper examines the effects of complex disasters on economic development of three essential sectors —primary, secondary, and tertiary—in four NorthNortheast ASian countries. We find that the effects of human losses are the most severe for all four countries. The effects of the number of people affected are the second. The adverse effects of the total damages in U.S. dollars are very mild and even favorable for some sectors in certain countries, depending on the level of development, government policies, and private sectors' efforts. The results reveal the importance of tracking each disaster by the governmental agencies and refinancing private sectors for replenishing lost capital due to any disaster.

The less severe or favorable results from all disasters in South Korea compared with those in Japan were a result of the measures to prevent and mitigate the disaster losses carried out by federal and local governments as well as the public seriousness in fighting against disasters in each country.

This paper only examines three essential sectors of the economy. The inclusion of broken-down sectors such as exports, imports, and transportation can also prove extremely valuable in finding out the most vulnerable sectors and allocating resources accordingly to mitigate the adverse effects of disasters. Future researchers should employ this approach when studying one type of disaster or a single disaster event.

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How to cite/reference this article: Tam Bang Vu, PhD, Complex Disasters and Economic Development in Northeast Asia, Asian. *Jour. Social. Scie. Mgmt. Tech*. 2024; 6(3): 64-76.