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QUALITY INFRASTRUCTURE AND NATURAL DISASTER RESILIENCY

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Abstract

A review of the academic literature on the topic has proved that most studies have been focused on how to finance the risk and indemnify the damages caused by an earthquake, rather than on mitigation measures. This study assessed the impact of quality infrastructure, development indicators and corruption on damages caused by a natural disaster using a panel data from 14 Asia and Pacific countries for 2007–2017. Using the generalized method of moments and vector error correction model, the study quantified the role of quality infrastructure in disaster impact mitigation. The empirical results suggest that increasing the quality of infrastructure may have a large impact on decreasing costs arising from natural disasters, and that policy makers should use public–private cooperation and schemes introduced by the study to prompt the construction of quality infrastructure. Because quality infrastructure development suffers from a lack of financing, several financing schemes are presented.

Keywords: disaster resiliency, disaster risk financing, quality infrastructure, disaster risk management

JEL Classification: Q54, H54, O18, H84

Contents

1. INTRODUCTION 1

2. LITERATURE REVIEW 2

2.1 Determinants of Society's Resiliency to Disasters 2
2.2 Role of the Government in Developing and Financing Quality Infrastructure.. 3

3. EMPIRICAL ANALYSIS 5

3.1 Data and Variables 5
3.2 Generalized Method of Moments 7
3.3 Robustness Check 10

4. CONCLUDING REMARKS AND POLICY RECOMMENDATIONS 14

REFERENCES 15

1. INTRODUCTION

Extreme disasters have become more frequent in recent years, with some observers believing that this effect is partially due to climate change (Kousky 2014). Although fewer natural disasters happened in 2017, evidence showed increased costs from said disasters, estimated to be around 49% above the previous average of $141 billion (UCL and CRED 2018). In 2017, 335 natural disasters affected over 95.6 million people, killing 9,697 and costing a total of $335 billion (UCL and CRED 2018). Asia appeared to be the most vulnerable continent for floods and storms, with 44% of all disaster events, 58% of the total deaths, and 70% of the total people affected (UCL and CRED 2018).

In order to reduce the impact of natural disasters, many studies have been conducted on the effect of prevention and mitigation policies (OECD Development Centre 2006; McDaniels et al. 2015; Havko et al. 2017). While risk prevention seeks to reduce the probability of the risk happening, mitigation policies aim at reducing the damages associated with the disaster after its occurrence. Preventive measures tend to have an effect on the number of dead and injured, as natural hazards are hardly preventable. Mitigation measures, on the other hand, generally affect the level of damages after a disaster. Examples of prevention policies include education and disaster drills, while mitigation policies generally refer to infrastructure development.

The role of quality infrastructure in mitigating the impact of natural disasters has been highlighted by many authors throughout the academic literature (Hosoya 2016, 2019; Havko et al. 2017; Marto et al. 2018; Rahman 2018). Developing infrastructure resilience was even one of the seven global targets of the Sendai Framework for Disaster Risk Reduction (DRR) 2015–2030 (UNISDR 2019). The importance of quality infrastructure is highlighted by the fact that two out of the four priorities directly relate to resilient infrastructure development, namely "investing in DRR for resilience" through collaboration between public and private entities and "enhancing disaster preparedness for effective response and to "Build Back Better" in recovery, rehabilitation, and reconstruction" (UNISDR 2019). Of the few studies that have been published on the subject, most do not assess quantitatively the impact of infrastructure on mitigating disasters' impacts (McDaniels et al. 2015; Havko et al. 2017; Marto et al. 2018). While Hosoya (2016, 2019) quantified the effect of infrastructure on the recovery after the occurrence of a disaster, the studies did not assess mitigation practices in reducing damages. Rahman (2018) did quantify the impact of infrastructure on earthquakes, but only considered urbanization without assessing the quality of infrastructure nor the role of other development indicators. Hence, this research aims at filling the gap in the literature by assessing quantitatively the impact of infrastructure on reducing the damages after a disaster occurs, through a comprehensive framework of analysis.

The empirical part of this research will evaluate the impact of quality infrastructure, DRR progress, and economic factors on damages by using a panel data analysis. The rest of the paper is structured as follows: Section 2 summarizes the relevant academic literature about the factors that impact society's resilience against disasters, and then proposes some schemes for the development and financing of quality infrastructure. Section 3 presents the data and statistical method used and discusses the results of the study. Finally, section 4 is for the concluding remarks and policy implications.

2. LITERATURE REVIEW

2.1 Determinants of Society's Resiliency to Disasters

In order to quantify the impact of quality infrastructure on the mitigation of natural disasters, this section provides an analysis of the causes that impact society's resilience in front of disasters by reviewing the literature on the topic.

As previously stated, some authors have highlighted that quality infrastructure has a positive impact on disaster resilience. Both McDaniels et al. (2015) and Havko et al. (2017) highlighted the need to make cities more resilient to disasters. Analyzing the Great East Japan Earthquake and Tsunami of 2011, Hosoya (2016, 2019) studied the impact of public infrastructure in the recovery after disasters. Both studies concluded that infrastructure substantially accelerated the recovery, the speed of which depended on the estimation methodology used (Hosoya 2016, 2019). Focusing on earthquakes, Rahman (2018) analyzed a panel of countries across 60 years and proved that governments could significantly reduce casualties by focusing on the quality, rather than the quantity, of infrastructure.

In addition, the magnitude of the disaster is a decisive factor increasing the total amount of losses after a disaster. Academic studies seem to reach a consensus in affirming that more severe disasters tend to increase the overall costs and economic losses (Bergholt and Lujala 2012; Kousky 2014; Bahinipati et al. 2015). Using a normalizing methodology, Neumayer and Barthel (2011) argued that there was no significant increase in economic losses even though disasters became more severe, although such result may be due to mitigation practices which were not assessed in their methodology. Studies also seemed to concur on whether the increased frequency and intensity of natural disasters is due to anthropogenic climate change or not. Bergholt and Lujala (2012), Kousky (2014), and Bahinipati et al. (2015) argued that climate change would increase the severity of climate-related disasters, and hence would result in increased economic losses and negative effects on growth. Therefore, it is crucial to take into account the severity and intensity of a natural disaster.

The level of development is also a factor affecting the disaster's impact and, later, the recovery from said disaster. Shoji (2010), Clarke and Grenham (2013), and Sawada and Takasaki (2017) argued that disasters are particularly devastating when they affect low-income households. In particular, Sawada and Takasaki (2017) insisted that poverty and natural disasters form a nexus. The relationship between poverty and natural disasters is unclear, as there is also a lack of consensus on whether rising income decreases disaster damages. By reviewing the literature, Kellenberg and Mobarak (2008) concluded that most empirical studies found a negative relationship between income per capita and measures of risk from natural disaster, thanks to DRR policies. However, the authors argued that the relationship between the two factors is non-linear, and that the risks increase with income before they decrease. Schumacher and Strobl (2011) found that the relationship between wealth and disasters is mainly shaped by the exposure to disaster hazards. The study proved that countries facing low hazards from disasters first witness increasing losses then decreased ones as they grow more developed, while it is the opposite for countries facing high disaster hazards.

Finally, a decisive factor in disaster resilience is the quality of institutions. Spence (2004) concluded that improved or new regulations have a significant impact in DRR, even in poorer and middle-income countries. In a more recent study, Breckner et al. identified in 2016 that the quality of institutions is one of the two main determinants of society's resilience in the face of disasters. In addition, several studies have been published on the impact of corruption on recovery after natural disasters. Mahmud and Prowse (2012) showed that 90% of households reported losses from corrupt practices, and that post-disaster interventions suffered from greater levels and worse types of corruption. In particular, the poorest households were the most affected by corruption in pre-disaster interventions. Using an inter-country panel data, Yamamura (2014) showed that natural disaster increased the corruption in the public sector. Rahman et al. (2017) observed an increase of corruption levels after natural disasters, which in turn impeded the efficiency of post-disaster measures. In conclusion, the academic literature showed that corruption and natural disasters act as an interaction: natural disasters increase corruption, and corruption in turn impedes the efficiency of DRR and post-disaster recovery.

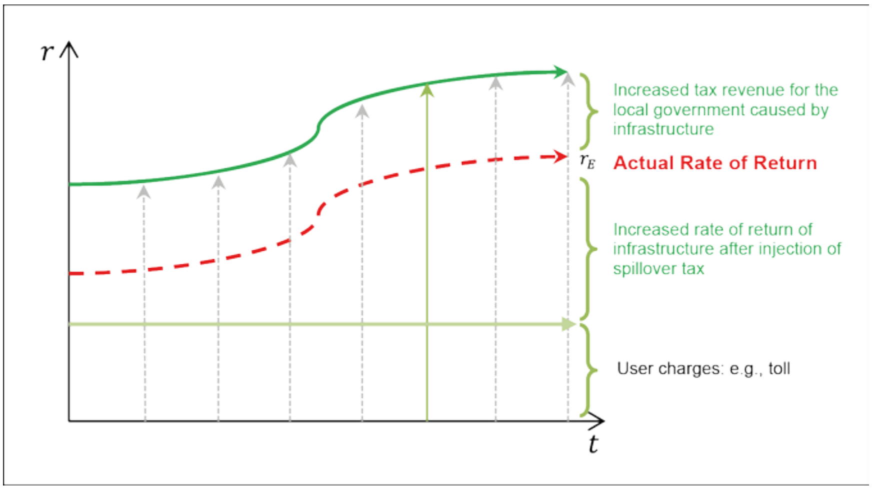
2.2 Role of the Government in Developing and Financing Quality Infrastructure

Quality infrastructure has been proved to mitigate the impact of natural disasters (Havko et al. 2017; Marto et al. 2018), but financing of that infrastructure remains an issue in many aspects. Mostafavi, Abraham, and Vives (2014) argued that the fiscal space in the government budget for infrastructure development in the United States is not sufficient to create resilient infrastructure. Jain (2015) emphasized the need for private investors for large-scale infrastructure projects in India and identified some obstacles for their participation in the regulatory environment, as well as a lack of information about insurance premiums available for private investors. Finally, Macaskill and Guthrie (2018) argued that the main issue in reconstruction is the availability of capital, as well long negotiations between the public and private sector for the construction of resilient infrastructure. It is certain that the public sector alone cannot carry the burden of building resilient infrastructure, and that there is a need for cooperation between the public and private sector.

One way to promote the development of quality infrastructure is public–private cooperation for projects that are highly risky. Infrastructure projects, in particular, suffer from a large variety of risks, such as a political regime change that may affect the project through subsidy cuts or even stoppage, cost increases due to the extension of the construction period or delays in land acquisition, and an unexpected decrease in revenue. Additional burdens, for example, compensation for noise after the completion of the project, can add to costs for completing infrastructure projects. Private investors apply various strategies to avoid or reduce the possibility of the aforementioned risks and maximize their benefits. In doing so, some investors may force the transfer of risks onto the public sector. This is especially the case in Japan, where infrastructure projects have been carried out by third-party entities established by various regional governments. As a consequence, there has been a budget deficit in the public sector. It is thus essential to determine beforehand how risks should be shared between the public and private sector. A viability fund coming from tax revenues created by the spillover effects of infrastructure, such as highways and railways, could be an ideal solution to solve this issue, in particular for infrastructure projects which are indispensable for the public, but do not offer enough benefits to represent interesting opportunities for the private sector. Figure 1 illustrates this effect. The figure clearly shows that the rate of return for the private sector for this project will be increased, hence making it more attractive. Private funds can also be introduced in projects thanks to toll revenue.

However, if the toll revenue is too low, there is a possibility that the private sector would not put their money into the project at all (Nakahigashi and Yoshino 2016).[1]

Figure 1: Spillover Effect of Infrastructure and Actual Rate of Return



Source: Authors' compilation based on Yoshino, Taghizadeh-Hesary, Nakahigashi (2019).

In another study Yoshino and Pontines (2015) identified an increase in tax revenues of regions along the Philippine highway STAR (Southern Tagalog Arterial Road). In particular, they evaluated the change rates of business and property tax revenue thanks to the operation of the STAR highway. To compare the change rate of tax revenues in affected regions with that in unaffected regions, the authors applied a difference-in-differences methodology broadly used for policy analysis.

Credit Guarantee Scheme (CGS) is another type of instrument that can be used to reduce the risk of investment in infrastructure projects (Yoshino and Taghizadeh-Hesary 2019). CGS has been used in many countries and in various forms over the decades to increase the flow of funds to targeted sectors and segments of the economy, mainly for small and medium-sized enterprises. CGS is especially effective as it absorbs, or shares, the risks associated with initial lending, and hence can increase the amount of funds lent to enterprises beyond the collateral limits (Yoshino and Taghizadeh-Hesary, 2019). Bearing the role of loan assessor and monitor, CGS can improve the quality of lending. Fees associated with the guarantee funds are born by the government or a third-party institution through fees or subsidies. Taghizadeh-Hesary and Yoshino (2019) proposed the Green Credit Guarantee Scheme (GCGS) to low-carbon infrastructures (renewable energy projects), as it can help by reducing information asymmetry and the expected default losses. As loans are guaranteed by the credit guarantee corporation (government), banks are more likely to lend money to low-carbon projects. However, the GCGS proposed by Taghizadeh-Hesary and Yoshino (2019) does not imply an increased budget burden on the public sector. Indeed, the CGS is financed through premiums collected from green project investors who are seeking credit guarantees. The spillover effect of green energy supply also provides a source of funding from local governments, and a portion of the increase in tax revenue is to be returned to private investors, directly or through contribution to GCGS, allowing the investor to use the GCGS for collateral when getting a new loan. CGS is more applicable in the beginning

[1] Under this framework, a revenue bond is one of the measures for raising private funds. See Yoshino (2010, 2012) for more information about revenue bonds.

part of establishment of the infrastructure when the spillover effect is low. As the spillover effect gradually increases, governments can collect more taxes from the region and refund a portion of it to the private investors, shifting from CGS to spillover tax refund.

Through the literature review, the study identified several determinants that help mitigate the impact of natural disasters, namely infrastructure, disaster intensity, poverty and development, and institutions. While most factors remain uncontrollable by public institutions, infrastructure development and control of corruption are one of the few channels of action for governments. However, infrastructure financing remains an issue. For this purpose, the study offered several innovative solutions through public–private cooperation and CGS.

3. EMPIRICAL ANALYSIS

The empirical part of this study aims at assessing the impact of mitigation policies, and, in particular, of quality infrastructure on the reduction of damages caused by natural disasters. For this purpose, the study used the Generalized Methods of Moments (GMM) and a Panel Vector Error Correction Model (VECM) to estimate the impact. Section 3-1 will introduce the variables and the data, Section 3-2 will present the results, and Section 3-3 will provide a robustness check.

3.1 Data and Variables

As introduced in section 2-1, the study explored various determinants of society's resilience against natural disasters, using a panel dataset from 2007 to 2017. Because Asia and the Pacific are repeatedly struck by natural disasters (UCL and CRED 2018), the panel is composed of 14 countries from Asia and the Pacific, namely Australia; Bangladesh; the People's Republic of China (PRC); India; Indonesia; Japan; Malaysia; Myanmar; Nepal; Pakistan; the Philippines; Sri Lanka; Thailand; and Viet Nam. Countries were chosen on the basis of data availability and by how regularly they are affected by natural disasters. Variables used in the analysis are detailed in Table 1.

The total estimated damages as a result of disasters as a percentage of GDP (DAMAGE) was used as the dependent variable, in line with Toya and Skidmore (2007). Data was provided by the EM-Dat Database of the Center for Research on the Epidemiology of Disasters (CRED), a database regularly used by researchers on this topic, and hence considered as reliable[2] (e.g., Toya and Skidmore 2007; Loayza et al. 2012; Cavallo et al. 2013; Rahman 2018; Panwar and Sen 2019). In addition, few studies used the total estimated damages as a dependent variable (Toya and Skidmore 2007; Cavallo et al. 2013).

Determinants of a society's resilience to natural disasters were identified through the literature. First of all, the quality of infrastructure appeared to be important to mitigate the impact of natural disasters. For this purpose, the study selected three variables to reflect it: Quality of Overall Infrastructure (INFRA); the Logistics Performance Index (TRADE); and the Quality of Port Infrastructure (PORT) from the World Economic Forum (WEF) reports. All three variables were retrieved from the World Bank database. INFRA

[2] Despite being used in many studies, it is important to acknowledge three major shortcomings of the EM-DAT database. First, the data for many events is not reported, hence making it difficult to decide whether it is missing or that no damages were associated with the event. Second, a bias may arise from the fact that recent disasters are better documented than earlier ones. Finally, the accuracy of data collection highly depends on the primary agency that provides data to EM-DAT and may highly vary depending on countries.

assesses the quality of general infrastructure (e.g., transport, telephony, energy) in a country on a scale of one (underdeveloped) to seven (extensive and efficient). TRADE is based on surveys conducted by the World Bank in partnership with academic and international institutions, as well as private companies. Respondents were asked to evaluate the quality of trade and transport on a scale of one (low) to five (high) (World Bank 2019). The second infrastructure variable, reflecting PORT, was also retrieved from the World Bank database, and is a compilation of the results of surveys from WEF reports. It summarizes business executive perceptions of country port facilities, ranking from one (underdeveloped) to seven (efficient). Although these three indicators assess the quality of public infrastructure, this study assumes that countries with efficient public infrastructure must have a similar level of residential infrastructure.

Table 1: Description of Variables

Notation	Variable	Unit	Group	Source
DAMAGE	Total estimated damages (in 000'US$ current value) as a percentage of GDP (in 000'US$ current value)	2000 US$ current value	Dependent Variable	EM-Dat Database; World Bank Database
INFRA	Quality of overall infrastructure	/	Quality Infrastructure	World Bank Database
SEV	Severity of disaster, as the total number of affected people (killed and injured) as a percentage of the population	%	Intensity of the disaster	EM-Dat Database; World Bank Database
TRADE	Quality of trade and transport-related infrastructure, as measured by the Logistic Performance Index	/	Quality Infrastructure	World Bank Database
PORT	Quality of port infrastructure, as measured by the WEF	/	Quality Infrastructure	World Bank Database
POVGAP	Poverty gap at $1.90 a day (2011 PPP)	% (2011 PPP)	Poverty	World Bank Database
GDPPC	GDP per capita, PPP (constant 2011 international $)	constant 2011 international $	Development	World Bank Database
CORRUPCON	Control of Corruption, as measured by the Worldwide Governance Indicators (WGI)	/	Institutional Quality	Worldwide Governance Indicators

Note: The variable DAMAGE was provided by EM-DAT: The Emergency Events Database—Université Catholique de Louvain (UCL)—CRED, D. Guha-Sapir, www.emdat.be, Brussels, Belgium.

Source: Author's compilation.

As identified in the literature, the intensity of disasters is also to be considered and is expected to play a significant role in increasing total damages from disasters. Following Noy (2009), Cavallo et al. (2013), and Panwar and Sen (2019), we used the total number of people affected or killed as a percentage of the population to measure a disaster's severity.

A low level of development and high levels of poverty were regularly highlighted in the literature as factors that worsen the impact of natural disasters. Therefore, two variables were assigned to reflect such effect: GDP Purchasing Power Parity (PPP) Per Capita (GDP PPPPC), and the Poverty Gap as a percentage of the poverty line

(POVGAP), with the poverty line set at $1.90 a day using 2011 PPP. All indicators were retrieved from the World Bank database.

Finally, a last determinant for a society's resilience toward damages is the presence of good institutions and low levels of corruption. For this reason, the study used the results of the index on the Control of Corruption (WGI 2019). The index reflects the perceptions on the extent of corruption of public power, for both petty and grand forms of corruption. The index assesses the governance performance on a scale from –2.5 (weak) to 2.5 (strong) (WGI 2019). Higher corruption could lead to a waste of public funds for DRR and mitigation practices, and overall increase the damages.

3.2 Generalized Method of Moments

3.2.1 Estimation Method

There exists many panel data analysis techniques, and this section aims at providing a rationale for the selection of one of them. In the case of a dynamic panel model, certain estimation methods might decrease the robustness of the results. For instance, endogeneity can affect the consistency of the results of the Ordinary Least Square (OLS) estimates. Despite the scarcity of studies on the impact of mitigation practices, many authors have used the EM-DAT database to assess the impact of natural disasters on economic growth. These studies report issues of endogeneity, which might be associated with the use of EM-DAT (Panwar and Sen 2019), hence preventing the use of the OLS estimates. Another issue that arises when using fixed effects in dynamic panel models is called the "Nickell bias," a negative bias in estimators (Nickell 1981). For this purpose, Loayza, Olaberria and Christiaensen (2012), Klomp (2016) and Panwar and Sen (2019) have used the generalized method of moments (GMM) as a main estimator to solve both the Nickell bias and endogeneity issues. In line with these studies, we chose GMM as our main estimation method.

3.2.2 Results

In order to evaluate the determinant factors of damages caused by natural disasters, we used Panel Generalized Method of Moments (GMM) with fixed effects (Holtz-Eakin, Newey, and Rosen 1988; Arellano and Bond 1991). This model is well designed for panel data with significant number of cross-sections and a short time series, which is the case in our study.

The lagged values of explanatory variables are used as instruments in the study. Due to the short period of study, we only used one lag for dependent variable as regressors. In addition to the lagged dependent variable (DAMAGE), we used INFRA, SEV, TRADE, PORT, POVGAP, GDPPC, and CORRUPCON as independent variables. In addition, we used period dummy variables to control for period fixed effects. A transformation is applied to the specification of a dynamic panel model to remove cross-section fixed effects; we used first difference in the regression for this purpose. However, we did not apply the transformation to the period dummy variable. We used 2-step iteration and, as for the GMM weighting matrix, White (diagonal) was used as innovations present time series correlation that varies by cross-section. The results are presented in Table 2.

Table 2: Results Using the Panel Generalized Method of Moments (GMM)

Variable	Expected Sign	Coefficient	t-Statistic	p-Value
D(DAMAGE)	(+)	0.42	16.78***	0.00
INFRA	(–)	–5.91	–5.71***	0.00
SEV	(+)	11.52	5.50***	0.00
TRADE	(–)	–7.55	–1.98**	0.05
PORT	(–)	–3.76	–1.46	0.14
POVGAP	(+)	0.01	0.01	0.98
GDPPC	(–)	–5.75	–1.68*	0.09
CORRUPCON	(–)	–4.22	–1.94**	0.05
Hansen Test for overidentified Restrictions				0.40
Arellano-Bond Test for AR (1) in First Differences				0.01
Arellano-Bond Test for AR (2) in First Differences				0.80

Note: *, **, *** denotes significant results with 10%, 5%, and 1%. respectively. Dependent variable: DAMAGE, Method: Panel generalized method of moments (GMM).

Source: Authors' compilation from Eviews 9.0.

As shown in Table 2, all the coefficients are in line with our assumptions, although some of them are not statistically significant, namely PORT and POVGAP.

As highlighted before, the intensity of a disaster remains the factor that has the highest impact on total damages of disasters. Both D(DAMAGES) and SEV are shown to increase the total estimated amount of damages. Given that natural disasters, such as hurricanes, cyclones, earthquakes, mudslides, floods, wildfires, volcanic eruptions, and weather events, are likely to increase in frequency and intensity due to climate change (Bergholt and Lujala 2012; Kousky 2014; Bahinipati et al. 2015), it is crucial to increase protective measures in order to reduce the adverse effect linked with disasters. Indeed, these events bring with them a host of issues, including humanitarian, public health, environmental, and infrastructural damages.

Infrastructure variables come second in terms of magnitude, and all coefficients show a negative sign, meaning that the quality of infrastructure does indeed contribute to reducing the total amount of damages associated with a natural disaster. These results quantitatively confirm the studies of McDaniels et al. (2015), Havko et al. (2017), and Rahman (2018). In particular, TRADE represents the largest impact, followed by INFRA and then PORT, which is not statistically significant. It is interesting to note that the quality of trade and transport-related infrastructure tends to have more effect than port ones when it comes to mitigation. Results show that not only does the quality of infrastructure matter, but also the type of infrastructure.

Development variables have a large impact on total estimated damages. Per capita GDP bears a negative sign and its coefficient is statistically significant, meaning that a higher level of development leads to lessened damages, probably as a consequence of DRR practices. This finding is in line with Kellenberg and Mobarak (2008). However, given that all the countries studied in the panel face high disaster hazards, our results contradict the findings of Schumacher and Strobl (2011), as these authors argued that countries facing high disaster risks see their damages increase with development. Albeit statistically not significant, the coefficient associated with poverty shows a positive sign, quantitatively proving the findings of Shoji (2010), Clarke and Grenham (2013) and Sawada and Takasaki (2017).

Finally, our study proved that the quality of institutions, and the level of corruption in particular, tends to affect the total amount of damages after a disaster. Higher control of corruption tends to decrease the estimated damages, although its magnitude is not as large as previously mentioned factors. These results are in line with Mahmud and Prowse (2012) and Rahman et al. (2017). However, given that the magnitude of institutional quality is reduced compared to other variables, our findings contradict Breckner et al. (2016).

3.2.3 Diagnostics

There are several assumptions behind the use of GMM, and each needed to be tested. First, we assumed that there is no serial correlation in the error terms, that regressors are not correlated with the error term, and that the error term is weakly exogenous with regressors. As with other instrumental variable estimators, the validity of the instruments needed to be tested. For this purpose, the Hansen test for overidentified restrictions was considered, with the null hypothesis being that the instruments are valid during the estimation. As shown in Table 2, we failed to reject the null hypothesis, meaning that our instruments are valid. Finally, it was necessary to check whether the error terms were serially correlated. For this purpose, the Arellano–Bond test for AR (1) and AR (2) was used. The results of the test support our model.

In addition, the stationarity of the variables needed to be assessed. To this end, we performed a panel unit root test, namely the Fisher- Augmented-Dickey-Fuller (Fisher-ADF) test. Furthermore, two additional tests were performed for robustness, namely the Philips-Perron-Fischer Chi-square and Levin, Lin & Chu panel unit root. The results of Fisher ADF test and robustness checks are presented in Table 3. Each test was performed on variables at levels and first differences.

Table 3: Unit Root Tests

Variable	Fisher ADF	Probability	Philips-Perron-Fischer Chi-Square	Probability	Levin, Lin and Chu Panel	Probability	Stationarity
Damage	73.29	0.00	120.87	0.00	–123.96	0.00	Yes
D(Damage)	87.20	0.00	258.23	0.00	–37.28	0.00	Yes
Infra	43.54	0.03	44.70	0.02	–3.43	0.00	Yes
D(Infra)	68.31	0.00	93.08	0.00	–5.74	0.00	Yes
Sev	33.45	0.22	98.47	0.00	–0.80	0.21	No
D(Sev)	57.51	0.00	235.81	0.00	–1.90	0.03	Yes
Trade	52.29	0.00	53.07	0.00	–4.90	0.00	Yes
D(Trade)	66.41	0.00	25.34	0.61	–8.35	0.00	Yes
Port	42.78	0.04	68.55	0.00	–5.06	0.00	Yes
D(Port)	62.85	0.00	85.93	0.00	–6.47	0.00	Yes
PovGap	59.38	0.00	63.64	0.00	–8.20	0.00	Yes
D(PovGap)	32.73	0.02	23.05	0.19	–35.82	0.00	Yes
GDPPC	1.58	1.00	0.99	1.00	4.11	1.00	No
D(GDPPC)	83.86	0.00	62.56	0.00	–10.27	0.00	Yes
CorrupCon	24.79	0.64	18.77	0.91	–1.49	0.07	No
D(CorrupCon)	48.60	0.01	70.93	0.00	–5.44	0.00	Yes

Note: D (X) denotes the first differences; Fisher-ADF =Fisher-Augmented- Dickey-Fuller.

Source: Authors' compilation from Eviews 9.0.

The panel unit root tests imply that all variables are stationary in first differences, with DAMAGES, INFRA, TRADE, PORT, and POVGAP also being stationary in levels. Hence, the data is suitable for analysis.

Finally, we used the Chow Test to assess the poolability of the data.

3.3 Robustness Check

In addition to GMM, a robustness test was also conducted. Given the impossibility of using OLS estimator due to endogeneity issues, a VAR model was used in the study. The following subsections detail the necessary tests conducted before using the model and present the results of the Impulse Response Function and Variance Decomposition.

3.3.1 Cointegration Analysis

Because series were non-stationary in level and integrated of order one or I(1), we needed to assess the presence of cointegration. To this end, the results of a Kao Residual Cointegration Test are presented in Table 4.

Table 4: Kao Residual Cointegration Test

Series: Damage, Infra, Sev, Trade, Port, PovGap, GDPPC, CorrupCon		
	t-Statistic	**Probability**
ADF	–4.80	0.00

Source: Authors' compilation from Eviews 9.0.

The results of Kao Residual Cointegration show the presence of cointegration among variables. With a p-value of 0.00, we failed to accept the null hypothesis of no-cointegration. In addition, the Pedroni Residual Cointegration test was conducted in parallel as a robustness check. The results of this test are presented in Table 5. Most statistics indicate the presence of cointegration in line with the results of the Kao Residual Cointegration Test. Variables present a long-run correlation among each other. Therefore, it is highly recommended to use a Vector Error Correction Model (VECM) rather than a VAR model in this case, as it allows for the combination of both short-term and long-term relationship.

Table 5: Pedroni Residual Cointegration Test

	Statistic	**Prob**	**Weighted Statistic**	**Prob**
Panel v-Statistic	–0.58	0.72	–2.34	0.99
Panel rho-Statistic	1.54	0.93	1.86	0.96
Panel PP-Statistic	–5.54	0.00*	–9.05	0.00*
Panel ADF-Statistic	–3.90	0.00*	–4.09	0.00*
Group rho-Statistic	3.13	0.99		
Group PP-Statistic	–11.63	0.00*		
Group ADF-Statistic	–5.36	0.00*		

Note: (*) shows statistical significance at 5% level.

Source: Authors' compilation from Eviews 9.0.

Because of the presence of cointegration among variables, it was also necessary to conduct additional cointegration tests in order to assess the number of cointegration equations that would be used in the VECM. For this purpose, the study provides two tests, the Trace Test and Maximum Eigen Value, whose results are presented in Table 6 and 7, respectively. The null hypothesis is that, for each row, there exists at most the number of cointegrating equations written. Both tests indicate the presence of two cointegrating equations at the 5% level.

Table 6: Unrestricted Cointegration Tank Test (Trace)

Hypothesized		Trace	0.05	
No. of CE(s)	Eigenvalue	Statistic	Critical Value	Prob.**
None *	0.47	198.97	159.53	0.00
At most 1 *	0.36	127.30	125.62	0.04
At most 2	0.24	77.63	95.75	0.45
At most 3	0.19	46.21	69.82	0.79
At most 4	0.12	22.64	47.86	0.97
At most 5	0.05	8.63	29.80	0.99
At most 6	0.02	2.49	15.49	0.99
At most 7	0.00	0.35	3.84	0.55

Trace test indicates 2 cointegrating equation(s) at the 0.05 level.

* Denotes rejection of the hypothesis at the 0.05 level.

** MacKinnon-Haug-Michelis (1999) p-values.

Source: Authors' compilation from Eviews 9.0.

Table 7: Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized		Max-Eigen	0.05	
No. of CE(s)	Eigenvalue	Statistic	Critical Value	Prob.**
None *	0.47	71.67	52.36	0.00
At most 1 *	0.36	49.67	46.23	0.02
At most 2	0.24	31.41	40.08	0.34
At most 3	0.19	23.57	33.88	0.49
At most 4	0.12	14.01	27.58	0.82
At most 5	0.05	6.14	21.13	0.98
At most 6	0.02	2.14	14.26	0.99
At most 7	0.00	0.35	3.84	0.55

Max-eigenvalue test indicates 2 cointegrating equation(s) at the 0.05 level.

* Denotes rejection of the hypothesis at the 0.05 level.

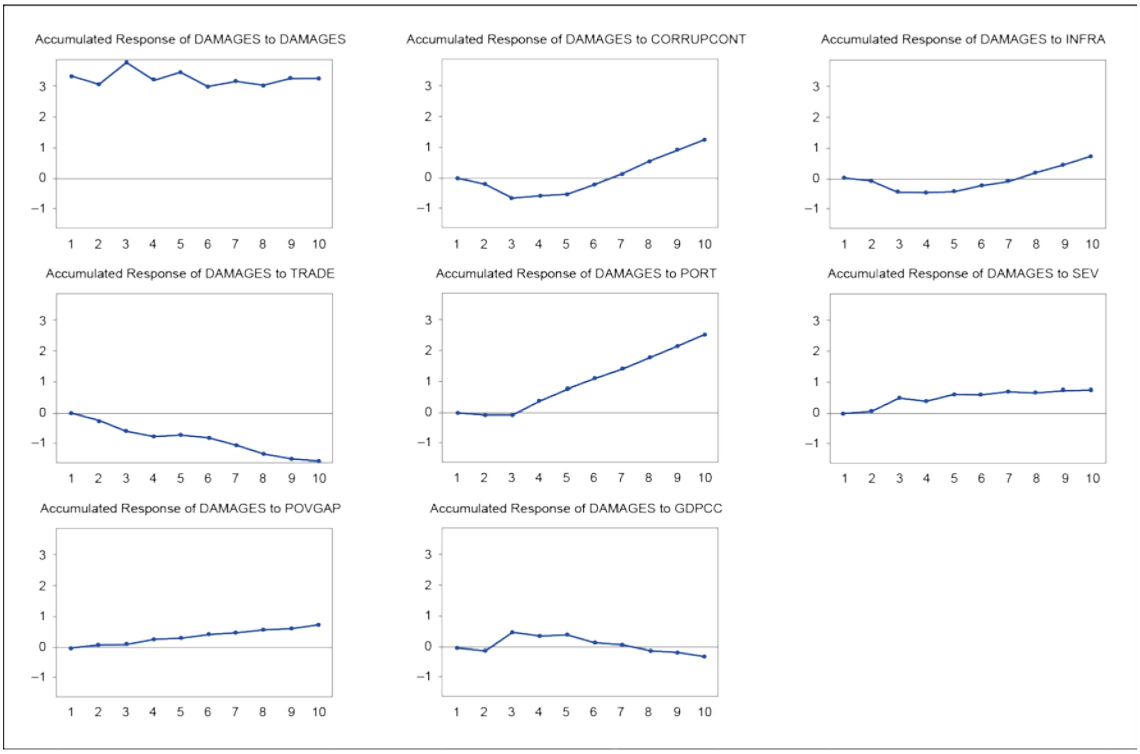
** MacKinnon-Haug-Michelis (1999) p-values.

Source: Authors' compilation from Eviews 9.0.

3.3.2 Impulse Response Function

The following sub-sections provide the detailed results of the VECM, including dynamics between the variables and the variance decomposition. The following ordering of variables was kept throughout the empirical analysis: DAMAGES, CORRUPCONT, INFRA, TRADE, PORT, POVSEV, POVGAP, GDPCC. Based on the Johansen's cointegration results, the number of cointegrating equations was set to two, with intercept and without trend. The results of the Impulse Response Function are shown in Figure 2.

Figure 2: Accumulated Response to Cholesky One S.D. Innovations



Note: Impulse response standard errors are not available for VECM; Cholesky ordering is: DAMAGES, CORRUPCONT, INFRA, TRADE, PORT, POVSEV, POVGAP, GDPCC.

Source: Authors' compilation from Eviews 9.0.

Figure 2 shows the accumulated response of DAMAGES to impulses or exogenous shocks to CORRUPCONT, INFRA, TRADE, PORT, POVSEV, POVGAP, and GDPCC, in this order. In line with the results of GMM, the accumulated response of DAMAGES to exogenous shocks of CORRUPCONT is negative and significant for 6 period, meaning that corruption control activities have statistically significant impact on reducing the damages caused by natural disaster and for increasing the resiliency. The response of DAMAGE to infrastructure variables INFRA, TRADE and PORT are negative and statistically significant in the first 7, 10 and 3 periods, respectively. Once again, the robustness check confirmed the results of the GMM estimates. Transport infrastructures tended to have a more stable and larger impact on reducing the damages due to natural disasters. The intensity of a disaster, as measured by SEV, bears a positive sign, like the GMM estimates. The response is significant in all 10 periods, showing the impact of disaster intensity on total damages. Finally, if the response of DAMAGE to POVGAP is positive and statistically significant, the response of DAMAGE to GDPPC is not even significant in one period. These results are in line with Kellenberg and Mobarak (2008), who argued that the relationship between income and loss from disaster is not linear.

3.3.3 Variance Decomposition

The next section details the results of the forecast error variance decomposition (FEVD) for the DAMAGES using Cholesky, and results are shown in Table 8. We used *Monte Carlo error* (MCE), implemented using 100 repetitions. The variance decomposition is a method that helps determine the magnitude of each variable in creating fluctuations in other variables.

Table 8: Forecast Error Variance Decomposition (FEVD) of DAMAGES

Period	DAMAGES	CORRUPCONT	INFRA	TRADE	PORT	SEV	POVGAP	GDPCC
1	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	99.02	0.28	0.06	0.02	0.41	0.04	0.08	0.09
3	91.04	1.90	1.05	0.01	1.26	1.64	0.09	3.01
4	89.34	1.85	1.00	1.50	1.43	1.63	0.26	3.00
5	88.05	1.84	0.99	2.60	1.41	1.89	0.27	2.97
6	86.24	2.45	1.16	3.25	1.40	1.82	0.34	3.33
7	84.43	3.16	1.32	3.80	1.80	1.85	0.35	3.29
8	81.43	4.33	1.77	4.63	2.21	1.78	0.40	3.45
9	79.60	4.96	2.14	5.41	2.31	1.78	0.42	3.38
10	77.78	5.57	2.58	6.13	2.36	1.74	0.46	3.39
11	76.47	5.96	2.85	6.68	2.48	1.74	0.49	3.33
12	74.95	6.41	3.13	7.26	2.70	1.71	0.53	3.30
13	73.62	6.76	3.36	7.86	2.88	1.71	0.56	3.24
14	72.28	7.14	3.62	8.49	2.98	1.69	0.60	3.21
15	71.10	7.47	3.84	9.05	3.07	1.68	0.62	3.16
16	69.86	7.84	4.07	9.59	3.19	1.67	0.66	3.14
17	68.66	8.19	4.28	10.10	3.33	1.65	0.69	3.10
18	67.46	8.55	4.51	10.61	3.45	1.64	0.71	3.07
19	66.35	8.88	4.72	11.11	3.54	1.63	0.74	3.03
20	65.26	9.20	4.93	11.58	3.64	1.61	0.77	3.01

Note: Cholesky Ordering is DAMAGES, CORRUPCONT, INFRA, TRADE, PORT, POVSEV, POVGAP, GDPCC.
Source: Authors' compilation from Eviews 9.0.

Results show that after ten periods, almost 77.75% of forecast error variance is accounted for by its own innovations, although this is reduced to 65.26% after 20 periods. In addition, after 10 periods, 13.64% of the variance of damages is explained by infrastructural innovations (INFRA, TRADE, PORT). The magnitude of this impact increases over time, and after 20 periods is 20.15%. This shows the importance of quality infrastructure for increasing the resiliency in front of natural disasters and reducing the natural disaster. Once again, transport infrastructures (INFRA and TRADE) were shown to have a larger impact than PORT. It is interesting to note that the intensity of disasters, SEV, is relatively small, explaining at most 1.89% of the variance of DAMAGE. Such magnitude is quite surprising, especially compared to the coefficient obtained through GMM. Moreover, the impact of disaster intensity is maximized after 5 periods, while the effect of infrastructure variables keeps increasing. These results imply that, while the effects of the intensity of a disaster is rather short-lived, infrastructure decreases damage in the long-term. The variable whose magnitude is the smallest is POVGAP, in line with the results of GMM, explaining at most 0.77% of the variance of DAMAGE. A higher level of poverty is shown to increase total damages, although its effect is not as large as other variables.

4. CONCLUDING REMARKS AND POLICY RECOMMENDATIONS

This study explored innovative financing schemes in infrastructure development and disaster risk financing and compensation, quantifying the impact of infrastructure and other factors on disaster mitigation.

Through the literature review, the study determined several factors that impact a society's resilience to natural disasters. While disaster intensity, poverty, and corruption are thought to increase damages linked with natural disasters, infrastructure and mitigation practices in general were praised in the literature for their capacity to strengthen society's resilience in front of disasters. The relationship between disaster and income remains subject to debate among authors, although the majority of studies have found a negative relationship between income per capita and measures of risk from natural disaster. Therefore, public institutions are strongly encouraged to strengthen DRR practices and increase the quality of infrastructures. Because financing is the main obstacle for infrastructure development, the study introduced several schemes and models of public–private cooperation, including public–private partnerships and CGS, a type of scheme that absorbs or shares the risk associated with initial lending and allows private investors to find funds for infrastructure projects.

Despite being largely praised for contributing to disaster impact mitigation, no study has quantified the role of quality infrastructure on disaster impact mitigation. The empirical part of this study attempted to assess this effect through the use of two methods, GMM and VECM, on a panel data of 14 countries from Asia and the Pacific between 2007 and 2017. Using measures of intensity and infrastructure, as well as development indicators and institutional quality, the study attempted to identify the weight of mitigation practices in reducing damages from disasters. Various diagnostics and robustness checks were also conducted to ensure the stability of our model. To the best of our knowledge, such a comprehensive framework of analysis is unprecedented.

The results of this study showed that, while disaster intensity remains the largest factor explaining the total amount of damages, its effects are short-lived. On the other hand, infrastructure components have the second largest impact on total damages and have a long-term effect on damages. In particular, transport infrastructures are shown to have a robust impact on damages. A higher GDP per capita and control of corruption were also associated with a decrease of the adverse effect of disasters. Finally, while a higher level of poverty is shown to increase the estimated amount of total damages, it is the indicator with the lowest magnitude in both GMM and VECM. The empirical results from this research suggest that increasing the quality of infrastructure has a large impact on decreasing costs arising from natural disasters, even larger than development or poverty indicators. Therefore, policymakers should prioritize quality infrastructure for the mitigation of disasters by using, for instance, public–private cooperation and schemes introduced in the study to prompt the construction of quality infrastructure.

REFERENCES

Arellano M. and S. Bond, (1991). Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *Review of Economic Studies*, 58 (2): 277–297.

Bahinipati, Chandra Sekhar, Unmesh Patnaik, and P. K. Viswanathan. 2015. "What Causes Economic Losses from Natural Disasters in India?" In *Handbook of Research on Climate Change Impact on Health and Environmental Sustainability,* edited by Soumyananda Dinda, 157–175. United States: Information Science Reference.

Bergholt, Drago, and Päivi Lujala. 2012. Climate-related natural disasters, economic growth and armed civil conflict. *Journal of Peace Research* 49(1): 147–162. https://www.jstor.org/stable/23141285.

Breckner, Miriam, Florian Englmaier, Till Stowasser, and Uwe Sunde. 2016. Resilience to natural disasters—insurance penetration, institutions, and disaster types. *Economics Letters* 148: 106–10. http://dx.doi.org/10.1016/j.econlet.2016.09.023.

Cavallo, Eduardo, Sebastian Galiani, Ilan Noy, and Juan Pantano. 2013. Catastrophic natural disasters and economic growth. *The Review of Economics and Statistics* 95(5): 1549–1561.

Clarke, Daniel J., and Dermot Grenham. 2013. Microinsurance and natural disasters: Challenges and options, *Environmental Science & Policy* 27(Supplement 1): S89–S98. https://doi.org/10.1016/j.envsci.2012.06.005.

Havko, Jan, Veronika Mitasova, Tomas Pavlenko, Michal Titko, and Jana Kovacova. 2017. Financing the disaster resilient city in the Slovak Republic. *Procedia Engineering* 192: 301–306. https//doi:10.1016/j.proeng.2017.06.052

Holtz-Eakin D., Newey W., and Rosen H.D. (1988). Estimating Vector Autoregressions with Panel Data. *Econometrica*, 56(6):1371–1395.

Hosoya, Kei. 2016. Recovery from natural disaster: A numerical investigation based on the convergence approach. *Economic Modelling* 55: 410–420. http://dx.doi.org/ 10.1016/j.econmod.2016.02.029.

Hosoya, Kei. 2019. Importance of a victim-oriented recovery policy after major disasters. *Economic Modelling* 78: 1–10. https://doi.org/10.1016/ j.econmod.2018.09.011.

Jain, Garima. 2015. The role of private sector for reducing disaster risk in large scale infrastructure and real estate development: Case of Delhi. *International Journal of Disaster Risk Reduction* 14: 238–55. http://dx.doi.org/10.1016/ j.ijdrr.2014.09.0 06

Kellenberg, Derek K., and Ahmed Mushfiq Mobarak. 2008. Does rising income increase or decrease damage risk from natural disasters? *Journal of Urban Economics* 63(3): 788–802. htpps//doi:10.1016/j.jue.2007.05.003.

Klomp, Jeroen. 2016. Economic development and natural disasters: A satellite data analysis. *Global Environmental Change* 36: 67–88. http://dx.doi.org/10.1016/ j.gloenvcha.2015.11.001.

Kousky, Carolyn. 2014. Informing climate adaptation: A review of the economic costs of natural disasters. *Energy Economics* 46: 576–592. http://dx.doi.org/10.1016/j.eneco.2013.09.029.

Loayza Norman V., Olaberria Eduardo, Rigolini Jamele, and Christiaensen Luc. 2012. Natural disasters and growth: Going beyond the averages. *World Development* 40(7): 1317–1336. http://dx.doi.org/10.1016/j.worlddev.2012.03.002.

Macaskill, Kristen, and Peter Guthrie. 2018. Funding mechanisms for disaster recovery: Can we afford to build back better? *Procedia Engineering* 212: 451–458. https://dx.doi.org/10.1016/j.proeng.2018.01.058.

Mahmud, Tanvir, and Martin Prowse. 2012. Corruption in cyclone preparedness and relief efforts in coastal Bangladesh: Lessons for climate adaptation? *Global Environmental Change* 22(4): 933–43. http://dx.doi.org/10.1016/j.gloenvcha.2012.07.003.

Marto, Ricardo, Chris Papageorgiou, and Vladimir Klyuev. 2018. Building resilience to natural disasters: An application to small developing states. *Journal of Development Economics* 135: 574–86. https://doi.org/10.1016/j.jdeveco.2018.08.008.

McDaniels, Timothy L., Stephanie E. Chang, David Hawkins, Gerard Chew, and Holly Longstaff. 2015. Towards disaster-resilient cities: An approach for setting priorities in infrastructure mitigation efforts. *Environment Systems and Decisions* 35(2): 252–63. https://dx.doi.org/ 10.1007/s10669-015-9544-7.

Mostafavi, Ali, Dulcy Abraham, and Antonio Vives. 2014. Exploratory analysis of public perceptions of innovative financing for infrastructure systems in the U.S. *Transportation Research Part A* 70: 10–23. http://dx.doi.org/10.1016/j.tra.2014.10.002.

Nakahigashi, M., and N. Yoshino. 2016. Changes in economic effect of infrastructure and financing methods. *Public Policy Review, Policy Research Institute, Ministry of Finance, Japan,* 12(1), 47–68, March.

Neumayer, Eric, and Fabian Barthel. 2011. Normalizing economic loss from natural disasters: A global analysis. *Global Environmental Change* 21: 13–24. http://dx/doi/org/10.1016/j.gloenvcha.2010.10.004.

Nickell, S. (1981). Biases in dynamic panel models with fixed effects. *Econometrica*. https://doi.org/10.2307/1911408.

Noy, Ilan. 2009. The macroeconomic consequences of disaster. *Journal of Development Economics* 88: 221–231. http://dx.doi.org/10.1016/j.jdeveco.2008.02.005.

OECD Development Centre. 2006. *Natural Disaster and Vulnerability,* by Dayton-Johnson, Jeff. Policy Brief No.29. Paris: OECD.

Panwar, Vikrant, and Subir Sen. 2019. Economic impact of natural disasters: An empirical re-examination. *Margin: The Journal of Applied Economic Research* 13(1): 109–139. http://dx.doi.org/10.1177/0973801018800087.

Rahman, Muhammad Habibur. 2018. Earthquakes don’t kill, built environment does: Evidence from cross-country data. *Economic Modelling* 70: 458–468. https://doi.org/10.1016/j.econmod.2017.08.027.

Rahman, Muhammad Habibur, and Nejat Anbarci, Prasad Sankar Bhattacharya, and Mehmet Ali Ulubaşoğlu. 2017. Can extreme rainfall trigger democratic change?

The role of flood-induced corruption. *Public Choice* 171(3–4): 331–58. https://dx.doi.org/10.1007/s11127-017-0440-1.

Sawada, Yasuyuki, and Yoshito Takasaki. 2017. Natural disaster, poverty, and development: An introduction. *World Development* 94: 2–15. http://dx.doi.org/10.1016/j.worlddev.2016.12.035.

Schumacher, Ingmar, and Eric Strobl. 2011. Economic development and losses due to natural disasters: The role of hazard exposure. *Ecological Economics* 72: 97–105. http://dx.doi.org/10.1016/j.ecolecon.2011.09.002.

Shoji, Masahiro. 2010. Does contingent repayment in microfinance help the poor during natural disasters? *The Journal of Development Studies* 46(2): 191–210. https://doi.org/10.1080/00220380902952381.

Spence, Robin. 2004. Risk and regulation: Can improved government action reduce the impacts of natural disasters? *Building Research & Information* 32(5): 391–402. https://doi.org/10.1080/0961321042000221043.

Taghizadeh-Hesary, Farhad, and Naoyuki Yoshino. 2019. The way to induce private participation in green finance and investment. *Finance Research Letters* 31: 98–131.

Toya, H., and M. Skidmore. (2007). Economic development and the impacts of natural disasters. *Economics Letters*, 94(1), 20–25. https://dx.doi.org/10.1016/j.econlet.2006.06.020.

UNISDR. 2019. Sendai Framework for Disaster Risk Reduction. https://www.unisdr.org/we/coordinate/sendai-framework (accessed 15 April 2019).

Univrsité Catholique de Louvain (UCL) and Center for Research on the Epidemiology of Disasters (CRED). 2018. Annual Disaster Statistical Review 2017. https://www.cred.be/annual-disaster-statistical-review-2017.

World Bank. 2019. World Bank Open Data. https://data.worldbank.org (accessed 15 April 2019).

Worldwide Governance Indicators. 2019. Worldwide Governance Indicators Data Overview. https://datacatalog.worldbank.org/dataset/worldwide-governance-indicators (accessed 17 July 2019).

Yamamura, Eiji. 2014. Impact of natural disaster on public sector corruption. *Public Choice* 161(3/4): 385–405. https://dx.doi.org/ 10.1007/s11127-014-0154-6.

Yoshino, N. 2010. "Financing Transport Infrastructure Investment." In *Southeast Asian Economic Outlook 2010*, edited by OECD. Paris: OECD Publishing.

———. 2012. Global imbalances and the development of capital flows among Asian countries. *OECD Journal: Financial Market Trends* 2012(1): 81–112.

Yoshino N., V. Pontines. 2015. The Highway Effect on Public Finance: Case of the STAR Highway in the Philippines. ADBI Working Paper 549. Tokyo: Asian Development Bank Institute.

Yoshino N., and Taghizadeh-Hesary, F. (2019). Optimal credit guarantee ratio for small and medium-sized enterprises' financing: Evidence from Asia. *Economic Analysis and Policy*. 62: 342–356. DOI: 10.1016/j.eap.2018.09.011.

Yoshino, N., F. Taghizadeh–Hesary, and M. Nakahigashi. 2019. "Modelling the Social Funding and Spill-Over Tax for Addressing the Green Energy Financing Gap." *Economic Modelling* 77: 34–41. https://doi.org/10.1016/j.econmod.2018.11.018.