Impact of Tsunami on Heterogeneous Economic Sectors: The Case of Sri Lanka

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Abstract Although natural disasters can cause enormous destruction to a country's economy, there remains an unsettled debate on whether disasters bring similarly large negative impacts throughout heterogeneous sectors of an economy. The literature indicates that the consequences for the economy differ according to the magnitude of the disaster, although such findings are inconclusive when other variables such as the scope, scale, type of disaster, the type of economy, etc., are taken into account. On the one hand, natural disasters—such as a tsunami—may destroy a large number of human lives and much physical capital including R&D facilities and therefore have a negative impact on an economy's growth rate. On the other hand, such disasters may have a positive effect through rebuilding a superior infrastructure and the use of more advanced technology. In this paper, we explore whether the 2004 tsunami caused, in the three major sectors of Sri Lanka's economy—agriculture, industry and services—a similar negative impact in both the short and long run. We employed panel fixed effect, difference-in-difference (DID) and panel vector auto regression (exogenous) (PVARX) estimation methods. The results suggest that the effect on each economic sector differed widely. Although the impact was highly negative on all three economic sectors in the first year following the tsunami, the impact on the agricultural sector was comparatively greater and the recovery process was longer than the other sectors. Moreover, the results suggest that industrial and services sectors have actually experienced positive impacts over the long term as indicated by the increase in demand for reconstruction and "building back better" infrastructure after the disaster as well as the considerable inflow of aid and grants that were received for advancement of the industrial and services sectors.

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1 Introduction

At a time when the global climate change is becoming more pronounced, the frequency and magnitude of natural disasters will also continue to rise and prove to be a major impediment against sustainable development (see, for example, Zhang & Managi, 2020). Hence, for production processes, there needs to be far greater attention to pre- and post-disaster mitigation and management strategies. During the period from 1998 to 2017, disaster hit countries recorded direct economic losses of US$2908 Billion, of which climate-related disasters accounted for US$2245 Billion or 77% of the total. Based on this, many international organizations including the IMF, the World Bank and many research organizations, such as the Centre for Research on the Epidemiology of Disasters (CRED) highlighted that beginning from the early part of this century, exogenous shocks such as disasters could have a substantial negative impact on the growth, macroeconomic stability, debt sustainability and poverty of less developed countries. UNISDR (2015) has emphasized that "low-income countries are predominantly vulnerable to natural disasters compared to the developed countries and further, agriculture dependent countries are likely to suffer higher negative impacts than non-agricultural countries." Following these international research initiatives, a number of scholars have continued to explore the nexus between natural disasters and economic growth more deeply and in specific ways.

The 2004 tsunami proved to be the largest global disaster in recent history as it resulted in a death toll of about 282,000 and caused extensive damage in dozens of countries. According to Abbott (2004) as cited by Athukorala and Resosudarmo (2005), the previous deadliest tsunamis were the following (estimated death tolls are in parentheses): Indonesia, 27 August 1883 (36,000); Portugal, 1 November 1755 (30,000); Japan, 15 June 1896 (27,000); Japan, 21 May 1792 (14,000); and Japan, 27 March 1933 (3000). After the damage to Sri Lanka was assessed, the numbers recorded were 35,000 deaths, 500,000 made homeless and some 100,000 houses damaged (Brunet et al., 2008). Without doubt then, it was the biggest natural disaster to strike Sri Lanka. As per the past literature, the economic consequences of a disaster will likely differ according to the magnitude of the disaster (Emanuel, 2011; Keerthiratne & Tol, 2017; Klomp & Valckx, 2014; Zhou & Zhang 2021). However, the literature is inconclusive due to the variations in the scope and scale of disasters, the type of disaster, the type of economy (developed or underdeveloped), and area affected (national or regional) (Easterly & Kraay, 2000; McDermott et al., 2014; Noy & Nualsri, 2011). Natural disasters such as tsunamis may destroy a large amount of human and physical capital as well as R&D facilities and therefore, have a negative impact on the growth rate (Jacoby & Skoufias, 1997; Klomp & Valckx, 2014). On the other hand, replacing the existing technology with more advanced technology may have a positive impact on growth (Hallegatte & Dumas, 2009; Popp, 2006). Hence, investigating the impact of the tsunami on different economic sectors is important due to the severe disruption caused by major disasters to developing economies.

Accordingly, there is an unsettled debate on whether disasters bring similar and large negative impacts throughout the heterogeneous sectors of an economy. The literature indicates that the economic response differs according to the magnitude of a disaster although such findings are inconclusive when other variables such as the scope, scale, type of disaster, the type of economy, etc., are taken into account. Natural disasters—such as a tsunami—may largely have a negative impact on an economy's growth rate, whereas in some instances such disasters may have a positive effect through the rebuilding of destroyed assets with superior and more advanced technology.

The literature on this field is mainly based on endogenous and neo-classical growth theories. After the seminal paper by Albala-Bertrand (1993), many researchers subsequently looked into the impact of disasters on long-term growth. Some predicted that the destruction of capital would drive countries temporarily away from a balanced growth path (Jovel, 1989; Krimgold, 1974; Noy, 2009). Others predicted that even higher growth rates would be experienced after a disaster event (Cavallo et al., 2013; Hallegatte & Dumas, 2009; Loayza et al., 2012; Tol & Leek, 1999). Hallegatte and Dumas (2009) investigated the positive impact of disasters that was achieved through the improvement of existing capital stock. However, the most recent research suggests that whether a natural disaster has a negative or positive effect on economic growth depends on different factors, and ultimately it has to be determined by empirical research (Cavallo et al., 2013; Klomp et al., 2009; Loayza et al., 2012).

Loayza et al. (2012) carried out one of the first studies that emphasized the need to investigate disaggregated economic sectors by going beyond the averaged national economic growth figures. Mohan et al. (2018) examined the different national accounting components of the Gross Domestic Product (GDP) of countries experiencing large natural disasters, especially, hurricane destruction. They concluded that the response of diverse components underlying the GDP is heterogeneous among different sectors. Thus, exploring the impact of disasters was likely to be more complex when it entailed going beyond aggregated sectors. These new findings in the literature on the effects of disasters on economic growth, which go beyond the aggregated disaster impact on aggregated economic growth, have yet to be corroborated but new studies are still rare.

The current study therefore, goes beyond aggregated economic sectors that include agricultural, industrial and services sectors using Sri Lankan provincial level data. Moreover, the study looks into the time specific disaster-economic growth nexus in order to understand the catching up process that follows the destruction wreaked by disasters. Hence, this study is a complex and comprehensive effort to add knowledge to current literature on the disaster-economic growth nexus. In doing so, the focus is on the literature on agriculture dependent small and developing economies that are highly vulnerable to different disasters.

The remainder of the paper is organized as follows. Section 2 presents the methodology and Sect. 3 presents the results followed by a discussion. Section 4 concludes the study with policy recommendations.

2 Data and Methods

The study employs Sri Lankan provincial administrative level data (Sri Lanka constitutes of 9 administrative provinces) in order to capture the impact of different disasters on different economic sectors while taking into account the heterogeneous environment of the country. Hence, data on both GDP and on different disasters is employed. Following the system of National Accounts (2008), GDP has been disaggregated under three main components of the economy—agriculture, industry and services. The data span is from 1997 to 2018. Depending on the analysis and the context, the time span and number of provinces used were adjusted. Inflation-adjusted constant GDP is used throughout the analysis.

The study employs the disaster index, particularly tsunami index in order to capture the impact of 2004 tsunami. Following Fomby et al. (2013) and Keerthiratne and Tol (2017), the population affected from tsunami was employed for the construction of the index. The level of severity is measured using populations affected in each province (i) and in particular, the change in severity over time (yearly) (t). This index is formed normalizing the total population of the previous year in each province. The data was collected from the *Disinventa*r database which is managed by the Disaster Management Center of Sri Lanka.

Difference-In-Difference method (DID)

To investigate the deeper effects of tsunamis, the DID methodology has been employed in a number of previous studies on disaster impacts (Matsuki & Managi, 2016; Rajapaksa et al., 2016). The econometric model employed is as follows:

$$y_{it} = \beta_0 + \beta_1 Damaged_i + \beta_2 After_t + \beta_3 Damaged_i \times After_t + \beta_4 Control_i + \varepsilon_{it} \quad (1)$$

where y_{it} is the log of GDP for different economic sector variables (agriculture, industry and services). $Damaged_i$ is a dummy equal to one if a province is situated in a devastated area, $After_t$ is a dummy equal to one if t is 2005 or 2006; $Control_i$ is selected as a control variable and ε_{it} is the error term.

Time series tests: vector auto regression analysis

To capture the time specific impact on disaster variables on the agriculture sector the panel vector auto regression framework is employed as it facilitates the exploration of external shocks on the economy. The reduced form of the panel vector auto regression model with exogenous shock, (P)VARX takes the form of the following equation:

$$y_t = \Psi_i + \Sigma_{j=1}^{p} \beta_i y_{t-j} \Sigma_{k=0}^{s} \pi_k x_{t-k} + \varepsilon_t \quad (2)$$

where y represents the vector of endogenous variables, namely GDP for agriculture, industry and services; x is the exogenous variable that forms the basis of the tsunami index t stands for time and ε stands for error term. When the panel structure of the data and the panel fixed effect methodology are taken into account, the equation can be written as:

$$y_{i,t} = \Psi_i + \Sigma_{j=1}^{p} \beta_i y_{i,t-j} \Sigma_{k=0}^{s} \pi_k x_{i,t-k} + \varepsilon_{i,t} \tag{3}$$

where i is the provincial index and Ψ_i captures the fixed effect for each country. This equation can be written in the following multiplier form:

$$y_{i,t} = \Omega(L)^{-1}\Phi(L)x_{i,t} + \Omega(L)^{-1}\sigma_{i,t} \tag{4}$$

where L stands for the lag operator and the average reaction of the tsunami shock is captured by $(L)^{-1}\Phi(L)$. The lag structure is an important aspect of this kind of analysis. Both AIC and BIC criteria are employed to select preferable lags. An important assumption of the PVARX technique is that the endogenous variables included in model (x) must be stationary. Hence, order of integration of the variables is an important part of the estimation. For that purpose, both the Levin, Lin and Chu (LLC) unit root test (which assumes that the individual time series in the panel is cross-sectional and independently distributed) and the Pesaran and Shin (CIPS) panel unit root test—which assumes cross sectional dependence as well as serially correlated errors—are employed. Both of these tests were suggested and used by previous studies on this same topic (e.g. Mohan et al., 2018).

3 Results and Discussion

Following the tsunami of 26 December 2004, the greatest impact was felt in the year 2005. The tsunami's impact on different economic sectors is compared over the years 2005–2007. As can be seen in Table 1, in 2005 there was around a 0.7% decline in growth in both the agricultural and industrial sectors. The impact on the services sector was also negative, but it was smaller. However, in 2006, only the agricultural sector showed a negative impact while both the industrial and services sectors grew significantly. This growth continued through the year 2007 although the impact on agriculture continued to be negative. Though these results are indicative, they help to confirm that the agriculture sector is the most highly impacted sector from disasters while the industry and services sectors have shown the capacity to grow after large scale disasters, as many previous studies have shown.

These results are in line with the previous analysis. Interactions with the year dummies for 2005 and 2006 are negative and significant for the agriculture sector while the interaction term for the year 2007 dummy is not significant but with a positive sign. The industry and services sectors show a negative impact only in the first year and thereafter it is positive.

In Table 2, the outcomes from the basic model are set out and include *damaged, after* and the key DID variable—Damaged**after* interaction. The DID variable is negative and significant for agriculture, confirming the results of the previous

Table 1 Impact of the 2004 Tsunami on different economic sectors 2005–2007

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables	Agri	Industry	Services	Agri	Industry	Services	Agri	Industry	Services
Tsunami_2005	−0.00731**	−0.00760**	−0.00148						
	(0.00257)	(0.00256)	(0.00172)						
Tsunami_2006				−0.0112*	0.0124*	0.00671**			
				(0.00455)	(0.00480)	(0.00218)			
Tsunami_2007							−0.00316	0.00460*	0.00295*
							(0.00203)	(0.00180)	(0.00122)
Log_density	0.118	−0.0247	−0.0405	0.141	−0.0233	−0.0344	−0.294	0.0857	0.0328
	(0.111)	(0.0686)	(0.0437)	(0.0988)	(0.0165)	(0.0228)	(0.330)	(0.0585)	(0.0607)
Constant	−0.483	0.427	0.478	−0.542	0.343**	0.411**	1.934	−0.300	0.00272
	(0.624)	(0.381)	(0.244)	(0.556)	(0.0887)	(0.133)	(1.838)	(0.321)	(0.341)
R-squared	0.116	0.135	0.059	0.290	0.395	0.583	0.238	0.301	0.447
Number of pcode	5	5	5	5	5	5	5	5	5

Robust standard errors in parentheses, Tsunami refers tsunami index, pcode refers to number of provinces affected by tsunami, $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0$

Table 2 DID analysis for the 2004 tsunami with "*damage*after*" interaction

	(1)	(2)	(3)
Variables	Agri	Industry	Services
Damaged	0.00140	0.365	0.113
	(0.239)	(0.417)	(0.321)
After	−0.299***	−0.559***	−0.537***
	(0.0594)	(0.107)	(0.0315)
Dam*after	−0.190**	0.515**	0.386
	(0.0936)	(0.249)	(0.274)
Log_density	0.222***	0.784***	0.722***
	(0.0841)	(0.149)	(0.116)
Constant	9.684***	6.690***	7.961***
	(0.475)	(1.022)	(0.781)
Observations	162	162	162
Number of pcode	9	9	9

Robust standard errors in parentheses, pcode refers to number of provinces, ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

analysis. However, for industry it is positive and significant while for services the sign is positive, but not significant. Table 3 reports the estimated coefficient when year dummies are employed instead of the "*after*" dummy. The interaction of the area dummy and the year dummy of 2005, 2006 and 2007 signify recovery from the tsunami, indicating the nature of the impact of major disasters on developing economies.

The impact on differently affected provinces is set out in Table 4. As described earlier, the tsunami impacted the coastal areas of Sri Lanka in the southern, western and eastern seaboard causing considerably more damage than in other areas. In

Table 3 DID analysis for the 2004 Tsunami with "*damage* year*" interaction

Dependent variable	Independent Variable	Coefficient	S.E
Log (Agri)	Damage*2005	−0.203***	(0.0832)
	Damage*2006	−0.257***	(0.0580)
	Damage*2007	0.0867	(0.153)
Log (Industry)	Damage*2005	−0472***	(0.164)
	Damage*2006	0.836***	(0.135)
	Damage*2007	0.659***	(0.180)
Log (Service)	Damage*2005	−0.367***	(0.107)
	Damage*2006	0.600	(0.112)
	Damage*2007	0.530	(0.136)

Robust standard errors in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 4 DID analysis for the 2004 Tsunami with "*Province*after*" interaction

Dependent variable	Independent variable	Coefficient	S.E
Agri	East*after	−0.313***	(0.0586)
Industry	East*after	0.0109	(0.093)
Services	East*after	−0.0871	(0.050)
Agri	South*after	−0.0566	(0.078)
Industry	South*after	0.274***	(0.012)
Services	South*after	−0.0598	(0.088)
Agri	West*after	−0.211***	(0.069)
Industry	West*after	0.356***	(0.104)
Services	West*after	0.673***	(0.147)

Robust standard errors in parentheses, ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

this analysis, provincial dummies were employed (south, east and west) instead of a year dummy. The agriculture sector in all three provinces shows a negative sign while in the eastern and western provinces, significant damage is indicated. For the southern province, the interaction did not show a significant impact. These negative impacts on the agriculture sector should be mainly attributed to damage to the fisheries sector, which contributes around 10% to the agricultural GDP and accounts for a considerably higher share in the Eastern and Western provinces of the country. Interestingly, dummy interactions for the industrial and services sectors in the Western province are highly significant and positive implying an increase in GDP for both these sectors of the Western province as a result of the tsunami. Being the capital province—which includes Sri Lanka's capital city—the Western province is the most industrialized as well as constituting the hub of the country's services sector. These results indicate the increase in demand for reconstruction and "building back better" infrastructure after disasters as well as considerable aid and grants being received for advancement of the industrial and services sectors. Moreover, the services sector generates more services after a catastrophic event and also helps to increase the GDP of the sector.

Time series PVARX analysis results

An important assumption of the PVARX technique is that the endogenous variables included in model (x) must be stationary. Hence, the order of integration of variables is an important part of the estimation. For that purpose, both the Levin, Lin and Chu (LLC) unit root test (which assumes that the individual time series in the panel is cross-sectional and independently distributed) and the Pesaran and Shin (CIPS) panel unit root test—which assumes cross sectional dependence as well as serially correlated errors—are employed.

Further, the LLC test assumes that the coefficient of the autoregressive term is homogeneous across all panels (i) and examines the null hypothesis of $H_0{:}\varphi = 0$, against the alternative $H_1{:}\varphi < 0H_1 : i < 0$. The results of LLC and CIPS are set out in Table 5.

Both tests show that all variables are not stationary at the same time when the levels are tested. However, after differencing all variables become stationary, indicating that these variables are integrated to the order of one, i.e., I (1). With the intention of making estimated coefficients comparable across all GDP components, the first difference of all variables is used for the analysis. BIC criteria are employed to select preferable lags.

Results of the dynamic responses of different economic sectors to the tsunami shocks are presented in Fig. 1. Considering the limitations of small datasets, the

Table 5 LLC and CIPS test results

Variables	LLC			CIPS test		
	Test-Stat	*p*-Value		Test stat	*p*-Value	
Ln (Agri)	3.741	0.000	I(0)	2.967	2.34	I(0)
Ln (Industry)	0.654	0.743	I(1)	1.643	2.34	I(1)
Ln (Services)	1.890	0.293	I(0)	1.745	2.34	I(I)
dln (Agri)	5.827	0.000	I(1)	4.734	2.34	I(1)
dln (Industry)	2.934	0.001	I(1)	4.371	2.34	I(1)
dln (Services)	13.395	0.000	I(1)	3.529	2.34	I(1)

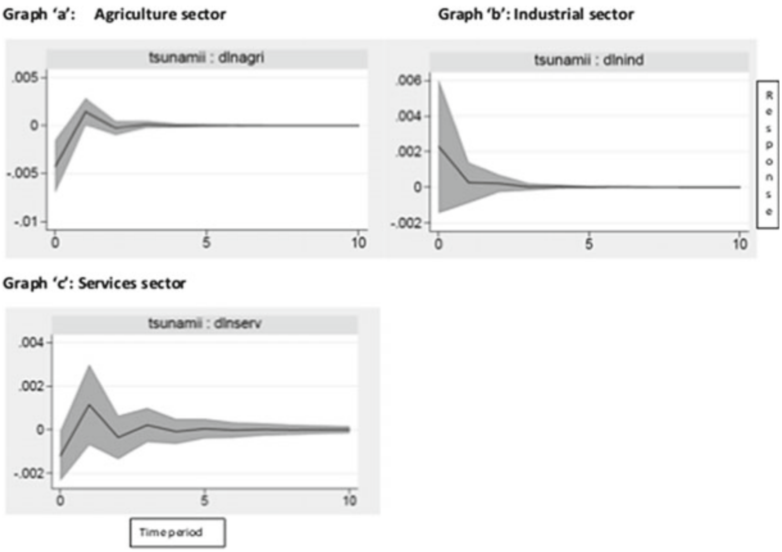

Fig. 1 Impulse responses of different economic sectors for tsunami shock. Mean responses of the different economic sectors' growth to the tsunami index (x axis represents the time period while the y axis represents the response in the graph)

whole dataset is employed, which includes data from 1997 to 2018. Hence, it is acknowledged that the strength of response by different sectors can have an averaging bias due to averaging the data that covers a longer period. Thus, the pattern of the graphs indicates the behavior of the growth of different economic sectors of a developing economy in relation to a sudden impulse in the form of a major natural disaster. This is in line with the findings of the previous literature (Fomby, 2013; Raddatz, 2009; Mohan et al., 2018).

As indicated by the dynamic multiplier effect presented in Graph 'a' in Fig. 1 the instantaneous effect of a tsunami shock was first significantly negative for the agriculture sector but subsequently it stabilized after about three years. These results are consistent with this study's previous analysis, including the DID analysis that indicated that the agriculture sector experienced two years of significant negative effects although in the long run, the effect became insignificant. As per Graph 'b' in Fig. 1, the instantaneous effect of the tsunami shock on the industrial sector was positive but not significant. However, the pattern itself gives an insight into the industrial growth after such a devastating event. The previous results as well as the past literature (Noy, 2009; Loayza et al., 2012) support this conclusion. A possible reason for this behavior is that, after a disaster, governments typically take action to immediately repair damaged infrastructure. As well, new machinery and technology are likely to be purchased by governments—which may be funded by foreign aid—and this can also improve this sector's growth. As shown in Graph 'c' the immediate impact on the services sector was negative and significant although it became positive over time with some fluctuations. With a very high magnitude disaster, the extensive destruction of human capital and infrastructure of the sector produces an immediate slowdown in that sector's growth. However, there is likely to be an overall improvement in the country's economy from the generation of increased services as well as infrastructure rehabilitation, which in turn produce a positive impact on the services sector.

4 Conclusions

Theoretical and empirical results in the literature on the impact of natural disasters on economic growth are rather ambiguous. This is mainly because the economy as a whole and its major sectors are too broad to indicate clearly the impacts of different disasters. Moreover, no uniform impact is indicated by studies of various economic sub-sectors. This study's major finding is that the agriculture sector suffers most from disasters while the impact on industry and the services sectors is positive when considering longer term impacts. The negative impact on the agriculture sector prevails over a longer period compared to the other two economic sectors while the negative impact on the overall growth is visible a year after the occurrence of the disaster. Both DID analysis and VARX analysis of the tsunami event also confirm that after an extreme catastrophic disaster, the agriculture sector is the most vulnerable as well as being the sector that suffers most over an extended period of time when compared to the other sectors.

Much of the literature on the impact of disasters on such matters as crop production and food security, also notes the presence of the same vulnerability in the entire agriculture sector (Auffhammer et al., 2012; Jawid & Khadjavi, 2019; Knox et al., 2012; Morton, 2007; Nguyen & Nguyen, 2020; Schroth et al., 2009). As Knox et al. (2012) point out, in Africa and South Asia the major grain sectors are projected to suffer mean yield losses of 8% by 2050 due to disaster events.

This study is subject to a number of limitations. The investigation is based on aggregated data in respect of different economic sectors. However, not all subsectors of the different economic sectors are equally vulnerable to disasters. The data set that covers a 20-year time span reveals a number of these limitations. As well, in terms of analysing the factors affecting the economic growth of the broader economic sectors, it is impossible to incorporate all of the relevant predictors to explain the outcome variables—as is noted in the literature (Neter et al., 1996). Further, it was not possible to use some of the variables utilized by many previous studies (e.g. Loayza et al., 2012; McDermott et al., 2015) as this study focused on the provinces within a single country.

In respect of policy implications, this study indicates that policy makers should pay more attention to implementing climate and disaster related adaptation practices for the agriculture sector. However, these practices should be tailor-made to suit specific agricultural sub categories, as common adaptation practices applied to different agricultural sub-sectors could well lead to more harm than benefits. While district level and provincial level programs to popularize planned adaptation practices are crucial, farmer level and plantation level awareness of climate change issues can be seen as necessary to increase the adoption rate of adaptation practices.

In relation to the other sectors, line ministries should be aware of the benefits that can be derived from disasters as a result of the high demand that occurs for various services in emergency situations. Therefore, policies should be formulated to enhance the efficiency and productivity of those sectors. It will help to deliver a higher level of service and greater output even under limited capacities. This should apply not only to ministries and departments involved in disaster management, but to all entities engaged in production processes and the provision of services. All these industrial/commercial units should incorporate effective disaster management policies in their mandates and should train their employees to deal with disaster situations in a more effective way. Further, the referred literature also emphasizes the importance of proper planning for the management of natural capital. In particular, pre- and post-disaster management policies should be designed and implemented not only to deal with large disasters but also to cope with the more frequent small-to-medium level disasters.

References

Albala-Bertrand, J. M. (1993). Natural disaster situations and growth: A macroeconomic model for sudden disaster impacts. *World Development, 21*(9), 1417–1434.

Athukorala, P. C., & Resosudarmo, B. P. (2005). The Indian Ocean tsunami: Economic impact, disaster management, and lessons. *Asian Economic Papers, 4*(1), 1–39.

Auffhammer, M., Ramanathan, V., & Vincent, J. R. (2012). Climate change, the monsoon, and rice yield in India. *Climatic Change, 111*(2), 411–424.

Brunet, A., Orr, S. P., Tremblay, J., Robertson, K., Nader, K., & Pitman, R. K. (2008). Effect of post-retrieval propranolol on psychophysiologic responding during subsequent script-driven traumatic imagery in post-traumatic stress disorder. *Journal of Psychiatric Research, 42*(6), 503–506.

Cavallo, E., Galiani, S., Noy, I., & Pantano, J. (2013). Catastrophic natural disasters and economic growth. *Review of Economics and Statistics, 95*(5), 1549–1561.

Dell, M., Jones, B. F., & Olken, B. A. (2014). What do we learn from the weather? The new climate-economy literature. *Journal of Economic Literature, 52*(3), 740–798.

Easterly, W., & Kraay, A. C. (2000). Small states, small problems? Income, growth, and volatility in small states. *World Development, 28* (11), 2013–2027.

Emanuel, K. (2011). Global warming effects on U.S. hurricane damage. Weather Climate and Society. https://doi.org/10.1175/WCAS-D-11-00007.1

Fomby, T., Ikeda, Y., & Loayza, N. (2013). The growth aftermath of natural disasters. *Journal of applied econometrics, 28*(3), 412–434.

Hallegatte, S., & Dumas, P. (2009). Can natural disasters have positive consequences? Investigating the role of embodied technical change. *Ecological Economics, 68*(3), 777–786.

Jacoby, H. G., & Skoufias, E. (1997). Risk, financial markets, and human capital in a developing country. *Review of Economic Studies, 64*(1), 311–335.

Jawid, A., & Khadjavi, M. (2019). Adaptation to climate change in Afghanistan: Evidence on the impact of external interventions. *Economic Analysis and Policy, 64*, 64–82.

Jovel, J. R. (1989). *Natural disasters and their economic and social impact*. CEPAL review.

Keerthiratne, S., & Tol, R. S. (2017). Impact of natural disasters on financial development. *Economics of Disasters and Climate Change, 1*(1), 33–54.

Klomp, J., & Valckx, K. (2014). *Natural disasters and economic growth: A meta-analysis*. Global.

Knox, J., Hess, T., Daccache, A., & Wheeler, T. (2012). Climate change impacts on crop productivity in Africa and South Asia. *Environmental Research Letters, 7*(3), 034032.

Krimgold, F. (1974). *Pre-disaster planning: The role of international aid for pre-disaster planning in developing countries.* . Avdelingen fdr Arkitektur.

Loayza, N. V., Olaberria, E., Rigolini, J., & Christiaensen, L. (2012). Natural disasters and growth: Going beyond the averages. *World Development, 40*(7), 1317–1336.

Matsuki, Y., & Managi, S. (2016). The impact of natural disasters on manufacturing: Plant-level analysis for the great Hanshin-Awaji earthquake. *The Singapore Economic Review, 61*(01), 1640010.

McDermott, T. K., Barry, F., & Tol, R. S. (2014). Disasters and development: Natural disasters, credit constraints, and economic growth. *Oxford Economic Papers, 66*(3), 750–773.

Mohan, P. S., Ouattara, B., & Strobl, E. (2018). Decomposing the macroeconomic effects of natural disasters: A national income accounting perspective. *Ecological Economics, 146*, 1–9.

Morton, J. F. (2007). The impact of climate change on smallholder and subsistence agriculture. *Proceedings of the National Academy of Sciences, 104*(50), 19680–19685.

Neter, J., Kutner, M. H., Nachtsheim, C. J., & Wasserman, W. (1996). *Applied linear statistical models*. Irwin.

Nguyen, G., & Nguyen, T. T. (2020). Exposure to weather shocks: A comparison between self-reported record and extreme weather data. *Economic Analysis and Policy, 65*, 117–138.

Noy, I. (2009). The macroeconomic consequences of disasters. *Journal of Development Economics, 88*(2), 221–231.

Noy, I., & Nualsri, A. (2011). Fiscal storms: Public spending and revenues in the aftermath of natural disasters. *Environment and Development Economics, 16*, 113–128.

Popp, A. (2006). The effects of natural disasters on long run growth. *Major Themes in Economics, 8*(1), 61–82.

Raddatz, C. (2009). *The wrath of god: Macroeconomic costs of natural disasters.* The World Bank.

Rajapaksa, D., Wilson, C., Managi, S., Hoang, V., & Lee, B. (2016). Flood risk information, actual floods and property values: A quasi-experimental analysis. *Economic Record, 92*, 52–67.

Schroth, G., Laderach, P., Dempewolf, J., Philpott, S., Haggar, J., Eakin, H., Castillejos, T., Moreno, J. G., Pinto, L. S., Hernandez, R., & Eitzinger, A. (2009). Towards a climate change adaptation strategy for coffee communities and ecosystems in the Sierra Madre de Chiapas, Mexico. *Mitigation and Adaptation Strategies for Global Change, 14*(7), 605–625.

Tol, R. S., & Leek, F. P. (1999). Economic analysis of natural disasters. *Climate, Change and Risk, 1*(1), 308–327.

UNISDR. (2015). *Global assessment report on disaster risk reduction: Making development sustainable: The future of disaster risk management*. United Nations International Strategy for Disaster Reduction, United Nations. International Strategy.

Zhang, D., & Managi, S. (2020). Financial development, natural disasters, and economics of the Pacific small island states. *Economic Analysis and Policy, 66*, 168–181.

Zhou, Z., & Zhang, L. (2021). Destructive destruction or creative destruction? Unravelling the effects of tropical cyclones on economic growth. *Economic Analysis and Policy, 70*, 380–393.