Coping with Disasters Due to Natural Hazards: Evidence from the Philippines[1]

Majah-Leah Ravago*
Dennis Mapa*
Jun Carlo Sunglao*
James Roumasset**
*University of the Philippines and **University of Hawaii*

Abstract

We explored how local governments respond to disasters due to natural hazards to determine the mix of risk management and coping strategies (ex ante and ex post) they employ to improve welfare. We focused on disasters caused by hydro-meteorological hazards that occur with high frequency and high probability. Using data from a novel survey that we conducted on disaster risk management practices of local government units (LGUs) in the Philippines, we developed indices of the various risk management and coping strategies of LGUs to explain what aids their recovery from disasters.

The most prominent strategies are risk-coping activities, especially cleanup operations and receiving relief from others. Among ex ante activities, employing long-term precautionary measures improve recovery. These include building resilient housing units; investing in stronger public facilities; building dams, dikes, and embankments; upgrading power and water lines; maintaining roads; identifying relocation areas; and rezoning and land-use regulations. In contrast, interruption of lifeline services such as water and electricity contributes adversely to recovery. Evidence also shows that LGUs' characteristics matter. An LGU with higher local revenues has higher chances of recovery. On the other hand, being located in a province where dynasty share is high contributes negatively to an LGU's recovery. The combination of these ex ante and ex post risk management strategies informs policies on where to put priority and investments in disaster risk management.

Keywords: *Disaster, shock, coping, risk management, local government*

JEL Codes: Q54, D81, I38,

[1] This research was funded by the University of the Philippines System's Balik-PhD Program under the Office of the Vice President for Academic Affairs (OVPAA). The authors are grateful for the excellent research assistance of Angelie Grace Aycardo, Rica Santos, and May Kathleen Montenegro. Any errors of commission or omission are the sole responsibility of the authors.

1. Introduction

The Philippines routinely experiences severe disaster events, including El Niño, La Niña, earthquakes, and typhoons. The natural hazards, which raise the country's disaster risk profile, are inevitable because of the Philippines' geographical location. Over the past decade, these disasters have increasingly become more severe and frequent, adversely affecting the exposed population, more so its poorer segment. The World Risk Report consistently ranks the Philippines third in terms of geographical exposure toward natural hazards. People still vividly recall the shocking damages in the wake of typhoons *Haiyan* (local name *Yolanda*) in 2013, and *Ketsana* (local name *Ondoy*) and *Parma* (local name *Pepeng*) in 2009. Given the prominence of natural disasters, promoting public welfare requires sound risk management as well as economic policies.

How can public policy be designed to balance the available ex ante and ex post controls to maximize expected economic welfare? What public interventions mediate in the adoption of risk management strategies? How effective are such public interventions in mitigating the adverse effects of these shocks on the welfare of the constituents of the LGUs? Our objective is to investigate the economic dynamics of disaster risk management at the local level. Studies show that disasters due to natural hazards adversely impact different aspects of an economy, from long-run growth rates to natural-resource prices (see Cavallo and Noy 2011; Cavallo et al. 2013; Skidmore and Toya 2002; Prestemon and Holmes 2002). However, focusing on the local level is critical because this is where the distributional impacts of both disasters and disaster policies can be effectively assessed. Collecting data from LGUs allow us to evaluate the potential return on various investments in risk management strategies undertaken by local governments.

Our study focused on disasters due to hydro-meteorological hazards (i.e., strong winds and rain, flood, landslides, and big waves).[2] Our contribution to the literature is the development of a survey instrument that collects primary data from local government units in the Philippines that aids in understanding how ex-ante and ex-post risk management strategies can aid in faster recovery of local government units.

In the next two sections, we review the Philippines' vulnerability to disasters due to natural hazards and discuss related literature. Section 4 presents our survey of LGUs in the Philippines and the stylized facts on their disaster risk management practices. Section 5 discusses our empirical analysis. Using the data from our survey, we developed indices of various risk management and coping strategies of LGUs. We then use these indices in our logit model regression to explain what aids in their recovery from disasters caused by natural events. The last section provides conclusions and policy implications.

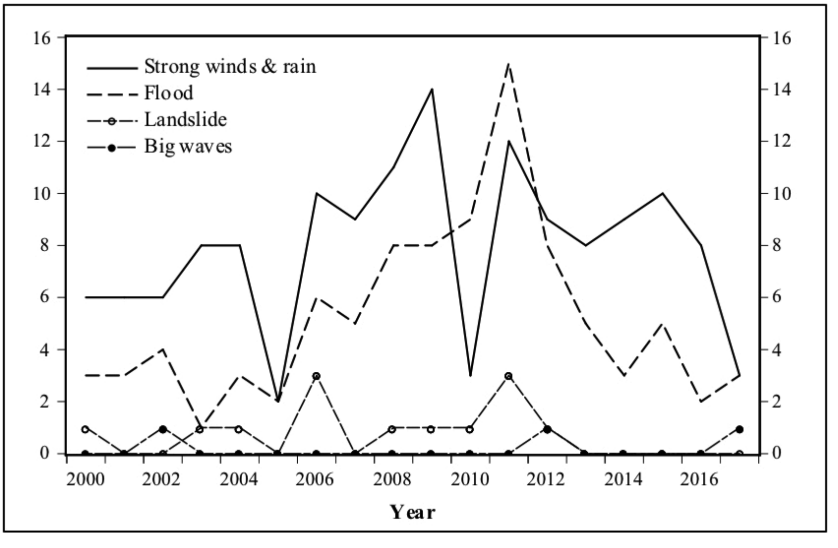
[2] While our survey covered eight shocks caused by natural hazards, including drought and geological-related hazards, the difference in frequency of occurrence, probabilities, and political economy responses (Vorhies 2012; Charveriat 2000) warranted a separate analysis of disasters due to hydro-meteorological hazards from those due to geological hazards.

2. The Philippines' Vulnerability to Disasters

It is important to distinguish natural hazards versus disasters. Naturally occurring events only reach disaster status when they overwhelm local response capacity and cause great damage and human suffering. The Centre for Research on the Epidemiology of Disasters (CRED) maintains the Emergency Events Database (EM-DAT), which is the largest database of natural disasters at the country level. For a natural hazard to be counted as a disaster by CRED, the following criteria must be satisfied: 10 or more people were killed, 100 or more people were injured or suffered losses, a state of emergency has been declared, and a call for international assistance has been issued.

Figure 1 presents the year-on-year occurrence of disasters in the Philippines from 2000 to 2017 based on CRED's definition of disasters due to hydro-meteorological hazards. An upward trend is observed from 2005 to 2011, and in 2013 due to typhoon *Haiyan* (*Yolanda*). An average of 20 typhoons (strong winds and rains) annually pass through the Philippines; 14 reached disaster status in 2009. Disastrous flooding has also increased, registering the highest incidence of 15 floods in 2011.

Figure 1. Incidence of disasters due to hydro-meteorological hazards, 2000-2017.



Note: *Hydro-meteorological hazards: Strong winds and rain, flood, landslide, and big waves

Sources of basic data:

(1) EM-DAT: The Emergency Events Database - Universite catholique de Louvain (UCL) - CRED, D. Guha-Sapir, Brussels, Belgium (www.emdat.be) accessed on 20 Feb 2018

(2) National Centers for Environmental Information – National Oceanic and Atmospheric Administration (NOAA) - Boulder, CO USA (www.ngdc.noaa.gov) accessed on 20 Feb 2018

When local response capacity is limited, natural hazards can easily elevate into disasters and take a toll on the economy. Table 1 shows the total value of damages and losses from disasters due to flood, strong winds and rains, landslides, and big waves from 2000 to 2017. Not surprisingly, the more severe the disaster is, the higher is the value of damages and losses. The costliest disaster since 2000 had been due to typhoon *Haiyan* (*Yolanda*), where economic damages and losses reached about USD 12 billion. This experience demonstrates that gains from various economic reforms undertaken over the years can be negated by a single disaster.

Table 1. Total value of damage and loss to the economy due to hydro-meteorological hazards.*

Year	No. of occurrences	Total deaths	Injured	Affected	Homeless	Total affected	Total damage ('000 USD)
2000	10	736	393	6,230,269	125,250	6,355,912	87,544.00
2001	9	630	480	3,441,257	100,000	3,541,737	107,061.00
2002	11	305	136	1,134,628	3,000	1,137,761	15,376.00
2003	10	350	75	604,471	83,203	687,749	42,302.00
2004	12	1,918	1,321	3,252,957	8,700	3,262,978	138,867.00
2005	4	39	-	213,057	-	213,057	2,515.00
2006	19	2,984	2,703	8,566,265	-	8,568,968	347,281.00
2007	14	129	24	2,009,032	-	2,009,056	16,815.00
2008	20	959	1,015	8,404,236	54,645	8,459,896	481,202.00
2009	23	1,307	898	13,303,957	100	13,304,955	962,017.00
2010	13	376	157	5,443,250	-	5,443,407	335,087.00
2011	30	1,933	6,500	11,681,893	-	11,688,393	730,025.00
2012	19	2,271	2,756	12,136,613	35,762	12,175,131	993,467.00
2013	13	7,520	28,917	22,415,992	-	22,444,909	12,371,351.00
2014	12	331	2,269	13,211,844	-	13,214,113	1,062,899.00
2015	15	201	131	3,834,083	3,300	3,837,514	1,881,567.00
2016	10	79	2	5,534,608	-	5,534,610	180,074.00
2017	7	67	12	1,848,350	-	1,848,360	10,100.00

Notes: *Hydro-meteorological hazards: strong winds & rain, flood, landslide, and big waves

Sources of basic data:

(1) EM-DAT: The Emergency Events Database - Universite catholique de Louvain (UCL) - CRED, D. Guha-Sapir, Brussels, Belgium (www.emdat.be) accessed on 20 Feb 2018

(2) National Centers for Environmental Information – National Oceanic and Atmospheric Administration (NOAA) - Boulder, CO USA (www.ngdc.noaa.gov) accessed on 20 Feb 2018

Given the Philippines' vulnerability to disasters, the challenge to the government has been to improve the local response capacity to mitigate damages and losses. By all accounts, disaster risk management in the Philippines still has a long way to go (Santiago et al. 2016; Ravago et al. 2016a). Funds are clearly lagging behind expressed needs for disaster risk management programs, and there is little flexibility in the budget to account for shocks in fiscal spending brought about by natural hazards. LGUs across the country have varying disaster-related demands and revenue-raising capabilities, but these variances are not considered in the allocation of disaster funds, creating an imbalance between local resources and risk exposure. Furthermore, funding is not only inadequate in terms of amount but also underutilized, mostly due to misidentification of needs and bureaucratic inefficiencies, as outlined in a report of the Commission on Audit (2014).

3. Related Literature

An important theme in disaster research is local or regional impact. After all, disasters are localized shocks—that is, every disaster that hits a country can have catastrophic impact in some areas, while other areas can be completely unaffected. Bertinelli and Strobl (2013) and Strobl (2012), employing nightlight satellite imagery, investigated the impact of hurricane strikes on the local economic activity in the Caribbean. Evidence shows that the impact at the local level is more than twice what is shown in the aggregated analysis. Similarly, Rodriguez-Oreggia et al. (2013) found that disasters had significant impact on affected municipalities in Mexico in terms of human development and poverty. Disaggregating by type of event, they found that floods and droughts had more significant adverse effects. The political variables seem to be relevant in explaining the magnitude of the impact of disasters, opening a room for analysis on such issue.

We note that decentralization of post-disaster response may be undermined by damages on local government infrastructure, such as heavy casualties among staff; damage to buildings, equipment, or files used in administration and service provision; and loss of local taxes through lost lives, property, and businesses. These damages not only decrease the local government's capacity, but also increases their dependence on the central government. Sobel and Leeson (2006) argue that these difficulties are due to two things. One, there is incentive for local officials to exaggerate requests, and little incentive to provide accurate information on needs. Two, there are no price signals that can efficiently allocate the provision of mitigation 'goods'.

On the economic recovery following a disaster due to natural hazards, four competing hypotheses are offered in the literature describing the long-term evolution of welfare as represented by the gross domestic product per capita. Hsiang and Jina (2014) provide a schematic illustration of these trajectories, namely: creative destruction, build back better, recovery to trend, and no recovery.

The "creative destruction" hypothesis posits that disasters provide temporary economic stimulation (i.e., innovation) due to higher demand for goods and services as lost and damage capital is being replaced. Skidmore and Toya (2002); Belasen and Polachek (2008); Hsiang (2010); and Deryugina (2011) are some examples that follow this line of analysis. The "build back better" hypothesis argues that disaster adversely impacts growth initially, but the gradual replacement of lost and damage assets result in a positive effect on long-run growth (Cuaresma et al. 2008; Hallegatte and Dumas 2009). The "recovery to trend" hypothesis also conjectures a negative effect on growth but only for a finite period; then economic growth rebounds to an aberrantly high level until income levels converge to the pre-disaster trend (Yang 2008; Strobl 2011). Finally, the "no recovery" hypothesis, which is the pessimistic among the four hypotheses, posits that lost and damaged productive capital is replaced, but there is no rebound effect. Post-disaster output may continue to grow in the long run but it is permanently lower than the pre-disaster trend. Examples of studies along this line include Field et al. (2012) and Anttila-Hughes and Hsiang (2013). Field et al. (2012), however, note that no study thus far has falsified any of the four hypotheses on trajectory of welfare.

4. Survey of Local Government Units

We explored how LGUs in the Philippines respond to disasters due to natural hazards to determine the mix of ex ante and ex post risk management strategies they employ to improve welfare. With officials from the Local Disaster Risk Reduction and Management Offices (LDRRMOs) as respondents, we conducted a survey[3] on disasters due to natural hazards that had struck their respective areas.

The survey used a multi-stage cluster sampling design with a nationally representative sample of 193 municipalities and cities that were randomly drawn from 47 out of the 81 provinces of the Philippines. The sample selection was based on high- and low-risk in terms of weather conditions, population density to account for exposure, and security issues (especially in southern Philippines), resulting in the exclusion of 34 provinces. The bases of risk classification were the calculated risk by the Manila Observatory (2005) for the provincial level and Project NOAH[4] for the municipal level. The survey was done from November 2016 to April 2017 and from September to October 2017.[5]

We obtain information on the profile and characteristics of the LDRRMO officials and their respective LGUs. We also have information on the incidence of shocks, related damages, and state of recovery. The risk management strategies correspond to potential actions taken at the various levels. These strategies include controls or ex ante reduction of exposure, early warning and response, ex post reduction of exposure, and coping strategies.

[3] Our survey instrument modified and augmented the questionnaire of the Philippine Center of Economic Development (PCED) Social Protection Survey (Ravago et al. 2016b).

[4] Project NOAH (Nationwide Operational Assessment of Hazards) is a multidisciplinary research with the goal of helping reduce the impacts of hazards.

[5] The declaration of martial Law in Mindanao affected the schedule of the survey. It was initially announced that the martial law would be lifted on 22 July 2017 but was extended until 31 December 2017. Due to safety concerns, some of the provinces in Mindanao had to be replaced with other provinces of similar characteristics.

The demographic profile of the respondents (LGUs represented mostly by LDRRMO officials) shows that they were 18-60 years old and mostly (72.54%) reached or graduated from college while more than a fourth (26.42%) held postgraduate degrees.

4.1. Stylized Facts from the Survey

The analysis in this paper focuses on four shocks or disasters caused by hydro-meteorological hazards,[6] namely: (1) strong winds and rains, (2) flood due to continuous rains and storms, (3) landslides/mudslides, and (4) big waves, including tsunami and storm surge. The respondents were asked to recall any experience of these shocks starting in January 2009. Table 2 shows the incidence of these shocks, with 189 out of 193 sample municipalities having been affected by at least one of these four hazards. Among the four shocks experienced by the municipalities, the most prevalent shock is due to strong wind and rains, accounting for 87 percent of the incidence of shocks among the sample LGUs.

Table 2. Incidence of shocks due to hydro-meteorological hazards in the sample municipalities of the Philippines starting in 2009.

Shock	Yes (%)	No (%)	Total (%)
Combined hydro-meteorological hazards	189	4	193
	(98)	(2)	(100)
Strong winds and rain	167	26	193
	(87)	(13)	(100)
Flood due to continuous rain, storms	147	46	193
	(76)	(24)	(100)
Landslide/mudslide	46	147	193
	(24)	(76)	(100)
Big waves (including tsunami and storm surge)	31	162	193
	(16)	(84)	(100)

After reporting the shocks that they had experienced, the respondents were asked to qualify these shocks in terms of severity. About 60 percent of them ranked the hydro-meteorological shocks they experienced as "very severe" and "most severe". The respondents were also asked about valuation of damage and loss to infrastructure, economic, social, and cross-sectoral sectors.[7]

As regards recovery, 67 percent of the sample municipalities indicated having completely recovered from the shocks they experienced starting in 2009 (Table 3a). As of 2017, about 79 percent of the 189 sample municipalities reported that

[6] Shocks due to geological hazards would require a different approach in analysis given the low probability and less frequency of occurrence.

[7] Whenever possible, an official written loss and damage report is requested if available.

their recovery had been better than before (Table 3b). Recovery in this context is understood to be in terms of the well-being of the municipalities, using as indicators the number of families affected and the cost of damage and loss. The evolution of recovery (Hsiang and Jina 2014) matters when evaluating the welfare of the municipalities that have experienced shocks.

Table 3a. Incidence of recovery from shocks experienced by the sample municipalities starting in 2009.

Shock	Not at all (%)	Not much, but some (%)	Much, but not completely (%)	Yes, completely (%)	Total (%)
Combined hydro-meteorological hazards	5 (3)	13 (7)	44 (23)	127 (67)	189 (100)

Table 3b. State of recovery of the sample municipalities as of 2017.

Shock	Better than before (%)	Same as before (%)	Worse than before (%)	Don't know (%)	Total (%)
Combined hydro-meteorological hazards	150 (79)	32 (17)	2 (1)	5 (3)	189 (100)

To determine various disaster risk management strategies these municipalities have undertaken to deal with the consequences of the aforementioned disasters, the respondents were asked about risk management activities, ex ante and ex post, that helped them cope with the adverse effects of the shock. These strategies were undertaken at various time frames – before, during, and after the disaster. The ex ante strategies or controls are classified as long-term, medium-term, and short-term precautionary measures. Long-term precautionary measures are activities conducted by the LGUs in less than a year to as long as more than three years. Long-term precautionary measures undertaken, which include building resilient housing, investing in stronger public facilities, building dams, upgrading power lines, road repairs, identifying relocation areas, rezoning, and building drainage. Interestingly, rezoning and land-use regulations were conducted by less than 50 percent of the sample municipalities as of 2017.

The medium-term precautionary measures are activities conducted in anticipation that these hazards will take place soon. The time horizon for these activities are typically one year or shorter. These include cleaning sewers and canals and strengthening embankments. The survey reports that more than 50 percent of the sample municipalities had undertaken medium-term precautionary measures. Receiving timely information is crucial in reducing losses and damages resulting from these hydro-meteorological hazards. About 94 percent of the respondent municipalities received a warning before the disaster occurred and most of them responded to the warnings.

Once these natural hazards are known to occur at a certain time, the sample municipalities conducted short-term precautionary measures in order to minimize exposure and damage. Such activities are implemented typically about a day or so before the shock. They include suspension of classes, issuance of gale warnings, and road closures. The most frequent is suspension of classes; 91 percent of the sample municipalities reported doing this for all hydro-meteorological hazards.

When these hydro-meteorological hazards strike and overwhelm the local capacity, they become a disaster. When this happens, immediate responses—including search and rescue operations, evacuation, and declaration of state of calamity—should be immediately undertaken to reduce the distribution of initial losses. Evacuation was a top immediate response among the respondents, with more than 80 percent of the 189 municipalities issuing warnings and ordering evacuation.

Another immediate response of LGUs had been to declare their area as being under a state of calamity. Doing so made them eligible to avail funds from local and national sources. About 21 percent of the respondents availed of the National Calamity Fund. More LGUs availed of the Quick Response Fund because it is local and relatively easier to access. Local governments are mandated as per Republic Act 10121 to set aside five percent of their estimated revenue from regular sources for their disaster council. Of this allocation, 30 percent is automatically set aside as Quick Response Fund, which serves as a standby fund for relief and recovery programs when disaster strikes. The remaining 70 percent of the five percent allocation can be used for ex ante precautionary measures.

Extending assistance or relief is also an immediate response. About 94 percent of the 189 municipalities reported that they provided relief to their constituents. About 85 percent reported that they had received assistance from other government agencies, LGUs, and nongovernment organizations (NGOs).

After the initial shock of a disaster had worn off, the LGUs undertook coping strategies for recovery, usually starting with cleanup operations. The cash- and food-for work strategy have gained popularity in the Philippines, with almost half of the sample municipalities offering such programs to speed up recovery among their constituents. In contrast, the facility for loans at the LGU level is yet to develop. Only a handful fully understand that LGUs can actually take out loans.

After the ex post loss reduction strategies, rebuilding and rehabilitation activities were started to fully restore the welfare of the constituents. About 87 percent of the municipalities reported that either water or power services were interrupted during the disaster and they had to fix these as soon as possible. About 77 percent of the sample municipalities also indicated that their public infrastructure broke down during or after the disaster.

Finally, there are cases when a disaster totally wipes out the livelihoods and houses in a village. A housing and relocation program is the most expensive strategy to rebuild a community, often requiring funding from the national government. Only about 23 percent of the sample municipalities put in place a housing program because of a shock.

5. Empirical Analysis

Given the information presented above, we investigated which among the various risk management activities aid the recovery of the municipalities. Natural hazards are exogenous events. Ex ante and ex post risk management activities are mainly undertaken to reduce the potential exposure of the population, infrastructure damages, and expected losses. The ultimate goal is to build resilience.[8]

5.1. Data and the Development of Indices

Our survey defined shock to respondents as an unforeseen adverse event that can lead to a decrease in their welfare. The incidence of shocks and severity are respondents' perceptions based on this definition. Severity in our analysis takes the value of zero when respondents say the shock is "least" or "somewhat severe" and one when shock is "very" or "most severe." To validate that these shocks were indeed severe and can potentially decrease welfare, we ran a correlation between the reported severity and several indicators of typhoon strength, which include storm signal, cyclone scale, intensity, and peak. Table 4a shows that storm signals, as defined by the Philippine Atmospheric, Geophysical and Astronomical Services Administration (PAGASA), the peak is positively correlated with the reported severity. Table 4b shows the test of independence between the perceived severity and each of the four indicators of typhoon strength. Except for cyclone scale, the three pairings resulted in significant and dependent relationships. Hence, the correlation and independence tests validated the respondents' perceived shock and severity according to the standard measure of typhoon strength.

Table 4a. Correlation of severity of shocks due to hydro-meteorological hazards and typhoon variables.

Variable	Type			**Remarks**
Storm signal+	Ordinal	Asymmetric Somer's D 95% CI	0.169 (0.013, 0.317)*	Weak positive linear relationship
Cyclone scale++	Ordinal	Asymmetric Somer's D 95% CI	0.090 (-0.059, 0.234)	Not significant

[8] Ravago et al. 2018a and Ravago et al. 2016a

Intensity (hpA)	Ratio	Point-Biserial Correlation t-stat p-value	0.057 0.785 0.434	Not significant
Peak (kmh)	Ratio	Point-Biserial Correlation t-stat p-value	0.245 3.4502 0.001**	Weak positive linear relationship

Notes: * significant at 5% level; ** significant at 1% level.
(+) Based on PAGASA public storm signal warning
(++) Based on the Australian tropical cyclone intensity scale

Table 4b. Test of independence: combined shocks' severity and typhoon variables.

Variable	Type	Pearson Chi^2 Coefficient	p-value	Remarks
Storm signal+	Ordinal	13.69	0.003**	Dependent
Cyclone scale++	Ordinal	1.44	0.23	Independent
Intensity (hpA)	Ratio	47.18	0.001**	Dependent
Peak (kmh)	Ratio	28.08	0.044*	Dependent

Notes: * significant at 5% level; ** significant at 1% level
(+) Based on PAGASA public storm signal warning
(++) Based on the Australian tropical cyclone intensity scale

Our survey probed deeper, asking about the length of implementation and number of activities or items, such as training, assets, and other information pertaining to a particular type of risk management activities. To capture all this information, we developed indices for all risk management activities, including precautionary measures, response, recovery, rehabilitation, and rebuilding. Overall, we have 19 indices (Ravago et al. 2018b).

The following is an illustration of the computation using Long-Term Precautionary Measure Index (LTPMI) as an example. Equation (1) is the index for each type of hydro-meteorological hazards: Strong winds and rain, floods, landslide and big waves, equation (2) is the unweighted index, and equation (3) is the weighted index, with weights according to the incidence of shocks. In equation 1, some indices have two components: 1) time of implementation; and 2) length of implementation (Ravago et al. 2018b). Whenever these two components are available, we use geometric mean to account for compounding effects over time due to large values. Geometric mean would not be overly influenced by the very large values in a skewed distribution (Spizman & Weinstein, 2008; Kirkwood & Sterne, 2003). While arithmetic mean is convenient, it would be inaccurate in this case.

The LTPMI is simply the weighted average of the type of long-term precautionary measures conducted by a city/municipality before the hydro-meteorological hazard occurred multiplied with its length of implementation. For LTPMI, we only have information on its length of implementation, hence the use of arithmetic mean will suffice.

$$LTPMI_{i,s} = \frac{\sum_{j=1}^{4} LTPM_{ij,s} \times LI_{ij,s}}{8 \times 4} \times 100\% \qquad (1)$$

$$\widetilde{LTPMI}_i = \frac{\sum_{s=1}^{4} LTPMI_{i,s}}{4} \times 100\% \qquad (2)$$

where:

$LTPMI_{i,s}$ ≡ Long-Term Precautionary Measures Index of i^{th} city/municipality for s^{th} type of hydro-meteorological hazard [SHOCK];

$LTPM_{ij,s}$ ≡ Indicator variable for the type of long-term precautionary measure conducted by i^{th} city/municipality for s^{th} hydro-meteorological hazard (1–Yes, 0–No);

LI_{ij} ≡ Ordinal variable for the length of implementation of j^{th} type of long-term precautionary measure conducted by i^{th} city/municipality for s^{th} type of hydro-meteorological hazard ≡ {1-less than 1 year before [SHOCK], 2-1 to 2 years before [SHOCK], 3-2 to 3 years before [SHOCK], 4-more than 3 years before [SHOCK]}; i ≡ city/municipality ≡ 1, 2, 3, …, N;

j ≡ Type of long-term precautionary measure ≡ {1-build resilient housing units, 2-invest in stronger public facilities, 3-build (cement) dams, dikes and river embankments, 4-upgrade power and water lines, 5-major road repairs, 6-identify relocation areas, 7-rezoning and land-use regulations, 8-build drainage};

s ≡ Type of hydro-meteorological hazard [SHOCK] ≡ {1-strong winds & rain, 2-flood, 3-landslide, 4–big waves}.

$\widetilde{LTPMI}_i$≡Unweighted Long-Term Precautionary Measures Index of i^{th} city/municipality;

We used weights according to incidence of shocks experienced. Among the 189 cities/municipalities that experienced the most severe combined hydro-meteorological shocks, the distribution of those affected are the following: strong winds & rain - 167, floods - 20, landslide – 2 and big waves – 0. Hence, the weights of each shock are as follows:

$$w_1 = \frac{167}{189}, w_2 = \frac{20}{189}, w_3 = \frac{2}{189} \text{ and } w_4 = 0$$

where w_1 is the weight for strong winds & rain; w_2 is the weight for floods; w_3 is the weight for landslide; and w_4 is the weight for big waves. This weighting method gives more importance on the preparedness of LGUs on the hazards that many of them experienced, i.e. strong winds and rain.

$$\overline{LTPMI_i} = \left(w_1 LTPMI_{i,1} + w_2 LTPMI_{i,2} + w_3 LTPMI_{i,3} + w_4 LTPMI_{i,4}\right) \times 100\% \tag{3}$$

where $\overline{LTPMI_i} \equiv$ Weighted Long-Term Precautionary Measures Index of i^{th} city/municipality.

The value of the index is between 0 and 1, with 1 being the best measure. A complete list of all these indices is given in Appendix Table A1. The computational details of all indices are in Ravago et al. 2018b.

The initial conditions of an LGU, such as population size and income, matters. The population of about 85 percent of the sample municipalities range from 41,000 to 2 million. In terms of poverty incidence, 22.8 percent were in the fourth and fifth quantiles, indicating that these municipalities/cities had a high poverty incidence. The revenues of the sample municipalities were coming largely from local sources, external source, tax, and internal revenue allotment (IRA). Moreover, about 18 percent of the sample cities had a total income of PhP 400 million and above; about 30 percent of sample municipalities had an income of more than PhP 55 million.

Institutions and the political economy play a role in shaping the economic policies on disaster risk management strategies (Vorhies 2012; Charveriat 2000; Cohen and Werker 2008). We used the dynastic nature of governance (Mendoza et al. 2016; Balisacan and Fuwa 2004) in the Philippines as proxy variable for institutions. Dynasty refers to families who have established political or economic dominance in a province. Table 5 shows data on political dynasties in the sample municipalities. "Dynasty share" is the proportion of elected local officials occupied by dynasties. "Dynasty large" refers to the proportion of elected local officials occupied by the largest dynasty in a province. "Dynasty sum of squares" is the sum of squares of elected local officials occupied by "fat" dynasties. "Fat" dynasties pertain to the presence of "thick" clan ties, possessing more than one surname and province match for that particular year.

Table 5. Profile of dynastic governance and poverty in sample municipalities in the Philippines.

Revenue	Mean	SD	Min	Max
Dynasty share 2013	0.4516	0.0958	0.1667	0.6232
Dynasty largest 2013	0.0217	0.0102	0.0088	0.0617
Dynasty sum of squares 2013	0.0031	0.0018	0.0012	0.0091
Human development index 2009	0.5547	0.0950	0.3530	0.8490
Poverty threshold 2012 (PhP)	18,770.82	1,199.72	15,890.89	21,884.56
Poverty incidence 2012	24.64	13.10	2.55	55.43
Poverty magnitude 2012	65,087.24	43,097.37	5,120.80	185,602.50

Source of basic data: Asian Institute of Management (AIM) Policy Center Political Dynasties Dataset used in Mendoza et al. (2016)

The complete summary statistics for the data used in the analysis is provided in Appendix Table A2.

5.2. Empirical model and results

We consider the perceived "recovery" variable as an indicator of resilience. We use the *logit* model given in equation (4) to determine which among the risk management activities available to LGUs contribute to the probability of full recovery.[9] The left-hand side takes on the value 1 when the respondent experiences full recovery, and 0 otherwise. The *logit* model is represented by:

$$\Pr(Y_i = 1|X, N, \alpha, \beta) = \frac{\exp\,(N_i\alpha + X_i\beta)}{1 + \exp\,(N_i\alpha + X_i\beta)} \qquad (4)$$

where *N* represents the various risk management activities—long-, mid-, and short-term precautionary measures—undertaken by LGUs in anticipation of shocks. The *logit* model takes into account all other ex ante and ex ost risk management activities. We control for initial conditions of the LGUs, denoted by the vector of variables *X*, which include educational attainment of the DRRM officer, LGU's population, poverty index, disaster risk classification, DRRM funding, total local revenues, non-tax revenues, training received and conducted by the DRRM staff, and various assets owned by the DRRM office.

Applying the *logit* model in equation (4), we consider two specifications referred to as Model 1 and Model 2. Model 1 has the complete observation of 189 LGUs and uses the *N* variables from our survey and secondary data in *X*. Model 2 has only 177 LGUs because the additional variables on dynasty representing institutions do not have information for all the LGUs in the sample. Table 6 presents the final model and Appendix A3 the full model.

The results show that severity of disasters matters to the LGU's complete recovery, the more severe the disaster, the lower the likelihood for complete recovery. In Model 2, the probability decreases by about 32 percentage points (marginal effect) as disaster becomes severe, controlling for other factors. We also control for the number of years since the shock occurred. This variable is positive and significant implying a higher likelihood of recovery by 5 percentage points for every year that passed since the shock was experienced. The results also show that cleanup operations and receiving assistance from others are the most prominent risk management activities for LGUs. Carrying out long-term precautionary measures are also significant, albeit one-sided.

---

[9] Ravago and Mapa (2014) and (2015) implement a similar model for the household of the Philippines.

Table 6. Risk management activities that influence recovery (final model).

Dependent variable: full recovery = 1	Model 1		Model 2	
	Coefficient	Marginal Effect	Coefficient	Marginal Effect
Shock severity				
Severity of shock/disaster	-1.818	-0.283	-1.991	-0.322
	(1.168)	(0.177)	(1.183)*	(0.185)*
No. of years since the shock occurred	0.326	0.051	0.329	0.053
	(0.137)**	(0.02)**	(0.14)**	(0.021)**
Indices of ex-ante risk management activities				
Long-Term Precautionary Measures Index	1.380	0.215	1.408	0.228
	(0.878)	(0.129)*	(0.881)	(0.135)*
Warnings Index	-0.877	-0.136	-0.720	-0.116
	(0.712)	(0.108)	(0.725)	(0.116)
Indices of ex-post risk management activities				
Evacuation Order and Center Index	-2.727	-0.424	-2.893	-0.468
	(1.333)**	(0.211)**	(1.473)**	(0.241)*
Interaction of Evacuation Index and Severity	1.852	0.288	1.772	0.286
	(1.572)	(0.248)	(1.675)	(0.274)
Relief Index	-1.982	-0.308	-2.547	-0.412
	(1.843)	(0.277)	(1.892)	(0.292)
Interaction of Relief Index and Severity	-0.166	-0.026	0.085	0.014
	(1.937)	(0.302)	(2.05)	(0.331)
Relief and Assistance from Others Index	1.490	0.232	1.537	0.248
	(1.115)	(0.17)	(1.069)	(0.169)
Cleanup Operations Index	3.043	0.473	3.314	0.536
	(1.033)***	(0.15)***	(1.088)***	(0.16)***

Dependent variable: full recovery = 1	Model 1		Model 2	
	Coefficient	Marginal Effect	Coefficient	Marginal Effect
Employment Index	-2.018	-0.314	-2.252	-0.364
	(1.207)*	(0.182)*	(1.221)*	(0.188)*
Service Interruption Index	-1.488	-0.231	-1.440	-0.233
	(0.837)*	(0.125)*	(0.799)*	(0.123)*
Infrastructure Index	1.065	0.166	1.205	0.195
	(1.218)	(0.187)	(1.178)	(0.187)
Control variables				
Dynasty share 2013			-4.256	-0.688
			(2.108)**	(0.328)**
Log of poverty incidence 2012			0.546	0.088
			(0.296)*	(0.048)*
Education of DRRM officer	0.349	0.054		
	(0.428)	(0.067)		
Poverty Index	0.019	0.003		
	(0.018)	(0.003)		
Log of total local revenues	0.464	0.072	0.404	0.065
	(0.151)***	(0.022)***	(0.13)***	(0.019)***
Number of Observations	189		177	
Log pseudo-likelihood	-89.1346		-86.2342	
p-value	0.0048		0.0134	
McFadden R-square =	0.2547		0.2477	

Notes: Model 1 has the complete observation of 189 LGUs and uses the *N* variables from our survey and secondary data in *X*. Model 2 has only 177 LGUs because the additional variables on dynasty representing institutions do not have information for all the LGUs in the sample.
Robust standard errors are in parentheses. ***significant at 1% level; **significant at 5% level; *significant at 10% level; $^{+}$ one-sided significant

Since the values of all the index variables are between zero and one, we interpret the values at the extreme, that is, either doing all the activities related to the respective indices or doing nothing. We interpret the marginal effect not in terms of the "stated marginal effect value" but by the "stated marginal effect divided by 100." For the LGUs that undertook precautionary measures before the onset of the hydro-meteorological hazards, a one-percentage point effect on the LTPMI increases the estimated probability of full recovery by 0.0023 (0.228/100), controlling for other factors. While a one-percentage point increase in the LTPMI may be small on a cursory examination, however, for an LGU without any LTPMI (value equal to 0) and an LGU with all the LTPMI (value is 1% or 100%), the increase in the estimated probability of recovery of the latter is 23 percentage points, which is large, controlling the other factors.

We similarly interpret the coefficient of the other index variables. For an LGU with an index value for cleanup operations equal to one, the probability of recovery is 54 percentage points relative to an LGU with index value equal to zero. An LGU with an index value equal to one for relief and assistance from others, the probability of recovery is 25 percentage points.

Delays in the restoration of interrupted lifeline services (e.g., water and power) have an adverse effect on the welfare of the LGUs. For an LGU with service interruption index equal to 1 (full-service interruption), the decrease in probability of recovery is 23 percent.

Some risk management activities, such as issuing evacuation order and providing relief assistance, obtained unexpected signs, although insignificant. One plausible explanation is that the disaster experienced may be very severe that even undertaking these activities are not sufficient for recovery. Severity is coded as a nominal (binary) variable.[10] An area experiencing most severe or very severe impact of the disaster decreases the probability of complete recovery by 32 percentage points (marginal effect), relative to an area experiencing somewhat or least severe impact, controlling for other factors. We interacted the activities with the severity variable, but the interaction terms did not come out to be significant.

The characteristics of the LGUs also matter in the likelihood of recovery after a disaster. A one-percentage point increase in the total revenues of an LGU increases recovery by seven percentage points (marginal effect). A one-percentage point increase in dynasty share in the province where the LGU is located decreases the probability of recovery by 0.69 percentage point.

6. Concluding Remarks

Empirical evidence shows that local governments employ various risk management strategies to cope with shocks/disasters and smooth consumption in the process. To lower the risk of loss, empirical data show that the most prominent risk-reducing strategies are the long-term precautionary measures. These include building resilient housing units; investing in stronger public facilities; building dams, dikes, and embankments; upgrading power and water lines; maintaining roads; identifying relocation areas; and rezoning and land-use regulations. Doing cleanup operations is another prominent strategy, and receiving assistance from others also aid toward the recovery of LGUs.

The benefits of disaster risk management are clearly identified, yet there is a clear under-investment in preparedness in both developing and developed countries (Charveriat 2000). One reason is that investments in disaster risk management are largely public goods, which explains why markets are not adequately providing them. Moreover, some political economy issues may also explain why public policies tend to fail at providing adequate levels of disaster

[10] 1 – most or very severe, and 0 – somewhat or least severe

risk reduction. On the supply side, these investments (e.g., land-use planning and construction of disaster-proof infrastructure) are generally long term. Because the benefits are intangible and occur in a period longer than most political mandates, the incentives for decision-makers to invest political power into long-term safety benefits are limited.

Public interventions aim to dampen the risks associated with natural disasters. How do these interventions interact with household strategies to adapt to shocks arising from extreme climatic events? Little is known about such interactions, and the consequences they have on the welfare of the vulnerable sectors of society. Some approaches to disaster risk management relate to reducing vulnerabilities without considering the full range of possible outcomes and their likelihoods. This can only lead to sub-optimal strategies since the benefits of risk reduction are not weighed against the foregone opportunity costs of all possible strategies. Whereas, the standard theory of decision making under uncertainty typically relates to a single decision, given a distribution of outcomes for each value of the decision variable. In contrast, the objective of disaster management is to select a sequential portfolio of management strategies.

Considering that the Philippines aims to establish a well-functioning social protection program, it is imperative to know the magnitude of the effects of natural disasters on various dimensions of welfare and how the macro and micro coping strategies complement or crowd out each other in mitigating the impact of the adverse consequences. Understanding the factors that determine why households choose a particular coping method or combination thereof is critical in formulating effective targeting interventions at both the community and national levels. Advancing a general framework of disaster risk management (see for example Ravago et al. 2018a) and understanding the complex multilevel decision structure is of critical importance.

References

Anttila-Hughes, J., and S. Hsiang. 2013. "Destruction, Disinvestment, and Death: Economic and Human Losses Following Environmental Disaster." SSRN: https://ssrn.com/abstract=2220501 or doi.org/10.2139/ssrn.2220501.

Bureau of Meteorology, Australia. 2018. "Australian tropical cyclone intensity scale," http://www.bom.gov.au/cyclone/about/intensity.shtml

Belasen, A.R., and S.W. Polachek. 2008. "How Hurricanes Affect Wages and Employment in Local Labor Markets." *The American Economic Review* 98(2):49–53.

Balisacan, A., and N. Fuwa. 2004. "Going Beyond Cross-Country Averages: Growth, Inequality and Poverty Reduction in the Philippines." *World Development* 32:1891-1907.

Bertinelli, L., and E. Strobl. 2013. "Quantifying the Local Economic Growth Impact of Hurricane Strikes: an Analysis from Outer Space for the Caribbean." *Journal of Applied Meteorology and Climatology* 52(8):1688–1697.

Cavallo, E., and I. Noy. 2011. "Natural Disasters and the Economy - A Survey." *International Review of Environmental and Resource Economics* 5(1):63-102. http://dx.doi.org/10.1561/101.00000039

Cavallo, E., S. Galiani, I. Noy, and J. Pantano. 2013. "Catastrophic Natural Disasters and Economic Growth." *Review of Economics and Statistics* 95(5):1549-1561.

Charveriat, C. 2000. "Natural disasters in Latin America and the Caribbean: An Overview of Risk", Working Paper 434, Inter-American Development Bank. https://www.unisdr.org/preventionweb/files/2544_ENVNatDisastLACeline.pdf

Cohen, C., and E. D. Werker. 2008. "The Political Economy of 'Natural' Disasters." *Journal of Conflict Resolution* 52(6):795–819. https://doi.org/10.1177/0022002708322157.

Commission on Audit. 2014. *Disaster Management Practices in the Philippines: An Assesment*. https://www.coa.gov.ph/disaster_audit/doc/National.pdf

Cuaresma, J. C., J. Hlouskova, and M. Obersteiner. 2008. "Natural Disasters as Creative Destruction? Evidence from Developing Countries." *Economic Inquiry* 46 (2):214–226.

Deryugina, T. 2011. "The Dynamic Effects of Hurricanes in the US: The Role of Non-Disaster Transfer Payments." Working Papers 1107, Massachusetts Institute of Technology, Center for Energy and Environmental Policy Research. https://dspace.mit.edu/handle/1721.1/66278.

EM-DAT: The Emergency Events Database - Universite catholique de Louvain (UCL) - CRED, D. Guha-Sapir, Brussels, Belgium (www.emdat.be) accessed on 20 Feb 2018

Field, C.B., V. Barros, T.F. Stocker, D. Qin, D.J. Dokken, K.L. Ebi, M.D. Mastrandrea, K.J. Mach, G.-K. Plattner, S.K. Allen, M. Tignor, and P.M. Midgley (eds). 2012. *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation*. Cambridge University Press: New York. https://www.ipcc.ch/pdf/special-reports/srex/SREX_Full_Report.pdf

Hallegatte, S., and P. Dumas. 2009. "Can Natural Disasters have Positive Consequences? Investigating the Role of Embodied Technical Change." *Ecological Economics* 68 (3):777–786.

Hsiang, Solomon M. 2010. "Temperatures and Cyclones Strongly Associated with Economic Production in the Caribbean and Central America." *Proceedings of the National Academy of Sciences* 107 (35):15367–15372.

Hsiang, S., and A. Jina. 2014. "The Causal Effect of Environmental Catastrophe on Long-Run Economic Growth: Evidence from 6,700 Cyclones." *NBER Working Paper No. 20352.* http://www.nber.org/papers/w20352

Kirkwood, B. and J. Sterne. 2003. *Essential Medical Statistics*, Ch 4, 2nd Edition, Wiley-Blackwell

Manila Observatory. 2005. "Mapping Philippine Vulnerability to Environmental Disasters." http://vm.observatory.ph/summary.html accessed in June 2015.

Mendoza, R., E. Beja Jr., V. Venida, and D. Yap. 2016. "Political Dynasties and Poverty: Measurement and Evidence of Linkages in the Philippines." *Oxford Development Studies* 44(2).

National Centers for Environmental Information – National Oceanic and Atmospheric Administration (NOAA) - Boulder, CO USA (www.ngdc.noaa.gov) accessed on 20 Feb 2018

National Disaster Risk Reduction and Management Council (NDRRMC). http://www.gov.ph/2013/11/11/ndrrmc-typhoon-yolanda-report-per-province-november-11-2013/ accessed on 10 Dec 2014.

Prestemon, J., and T. Holmes. 2002. "Timber Price Dynamic Following a Natural Catastrophe." *American Journal of Agricultural Economic*s 82(1):145-160.

PAGASA 2018. https://www1.pagasa.dost.gov.ph/index.php/20-weather

Philippine Statistics Authority. 2012. "Poverty Incidence." https://www.psa.gov.ph/content/poverty-incidence-among-filipinos-registered-216-2015-psa

Ravago, M., and D. Mapa. 2015. "Household Coping and Recovery from Nature's Wrath: Rising from the Ruins of Yolanda." *UPSE Discussion Paper 2015-16.* http://www.econ.upd.edu.ph/dp/index.php/dp/article/view/1486.

Ravago, M., and D. Mapa. 2014. "Eastern Visayas after Yolanda: Evidence from Household Survey." *PCED Policy Note 2014-5*. http://www.pced.gov.ph/wp-content/uploads/2014/11/PN-2014-5-rev-4-111014.pdf.

Ravago, M.V., J. Roumasset, and K. Jandoc. 2018a. "Risk Management and Coping Strategies," in M. Rosegrant and M. Sombilla (eds), *The Future of Philippine Agriculture: Scenarios, Policies, and Investments under Climate Change.* Singapore: Institute of Southeast Asian Studies.

Ravago, M., D. Mapa. J. Sunglao, A. Aycardo. 2018b. "Coping Strategies to Natural Disasters: Micro-Meso-Macro Interactions and Consequences Technical Report on the Survey of Local Government Units DRRM Office."

Ravago, M., J. Roumasset, and K. Jandoc. 2016a. "Risk Management and Coping Strategies: Climate Change and Agriculture in the Philippines." *Philippine Review of Economics* 53(2):64-103.

Ravago, M., S. Quimbo, D. Mapa, A. Kraft, and J. Capuno. 2016b. "Technical Report on Social Protection Survey of the Philippine Center of Economic Development." *UP School of Economics Working Paper 2016-06*. Quezon City, Philippines: UPSE.

Rodriguez-Oreggia E., A. De La Fuente, R. De La Torre, and H.A. Moreno. 2013. "Natural Disasters, Human Development and Poverty at the Municipal level in Mexico." *The Journal of Development Studies* 49 (3):442–455.

Santiago, J.S.S., W.S. Manuela, M.L.L. Tan, S.K. Sañez, and A.Z.U. Tong. 2016. "Of Timelines and Timeliness: Lessons from Typhoon Haiyan in Early Disaster Response." *Disasters* 40:644–667. doi:10.1111/disa.12178.

Skidmore, M. and H. Toya. 2002. "Do Natural Disasters Promote Long-Run Growth?" *Economic Inquiry* 40 (4):664–687.

Skidmore, M., and H. Toya. 2013. "Natural Disaster Impacts and Fiscal Decentralization." *Land Economics* 89(1):101–117.

Sobel, R., and P. Leeson. 2006. "Government's Response to Hurricane Katrina: A Public Choice Analysis." *Public Choice* 127(1-2):55–73.

Spizman, L. and M.A. Weinstein. 2008. "A Note on Utilizing the Geometric Mean: When, Why and How the Forensic Economist Should Employ the Geometric Mean.*Journal of Legal Economics*, 15(1): pp. 43-55.

Strobl, E. 2011. "The Economic Growth Impact of Hurricanes: Evidence from U.S. Coastal Counties." *Review of Economics and Statistics* 93(2): 575-589.

Strobl, E. 2012. "The Economic Growth Impact of Natural Disasters in Developing Countries: Evidence from Hurricane Strikes in the Central American and Caribbean Regions." *Journal of Development Economics* 97(1):130–141.

Vorhies, F. 2012. "The Economics of Investing in Disaster Risk Reduction." Geneva, Switzerland: UN International Strategy for Disaster Reduction. https://www.preventionweb.net/posthfa/documents/drreconomicsworkingpaperfinal.pdf.

World Risk Report. 2017. Relief Web. https://reliefweb.int/report/world/world-risk-report-2017

Yang, D. 2008. "Coping with Disaster: The Impact of Hurricanes on International Financial Flows, 1970-2002." *Advances in Economic Analysis & Policy* 8(1):1903–1903.

Table A1. Indices of risk management activities.

No.	Index	Description
1	**Long-Term Precautionary Measures Index (LTPMI)**	Product of type of long-term precautionary measures conducted by a city/ municipality before the shock occurred and its length of implementation
2	**Mid-term Precautionary Measures Index (MTPMI)**	Product of type of mid-term precautionary measures conducted by a city/ municipality before the shock occurred and its frequency of implementation
3	**Short-Term Precautionary Measures Index (STPMI)**	Two components: (1) unweighted average of product of type of short-term precautionary measures conducted by a city/ municipality before the shock occurred and time of implementation and (2) unweighted average of product of type of short-term precautionary measures conducted by a city/ municipality before the shock occurred and its length of implementation
4	**Warning Index (WI)**	Three indices: (1) Source of Warnings Index (SWI), (2) Preparatory Checks Index (PCI), and (3) Warning Issued Index (WII)
5	**Evacuation Index (EI)**	Three indices: (1) Evacuation Order Index (EOI), (2) Evacuation Center Index (ECI), and (3) Evacuation Center Facilities Index (ECFI)
6	**Search and Rescue Index (SRI)**	Product of the indicator variable if the city/ municipality conducted search & rescue and the ordinal variable for number of people rescued
7	**Shock Effects to Constituents Index (SECI)**	Product of the indicator variable if the shock resulted in death, illness, or injury of the constituents and the types of effects
8	**Quick Response Fund Index (QRFI)**	Two indices: (1) Quick Response Fund Uses Index (QRFUI) and (2) Quick Response Fund Monetary Assistance Index (QRF-MAI)
9	**National Disaster Fund Index (NDFI)**	Two indices: (1) National Disaster Fund Sources & Uses Index (NDFSUI) and (2) National Disaster Fund Monetary Assistance Index (NDF-MAI)
10	**Relief Index (RI)**	Two indices: (1) Relief Assistance Index (RAI) and (2) Relief Goods Index (RGI)

No.	Index	Description
11	**Cleanup Operations Index (COI)**	Two components: (1) product of the indicator variable if the city/ municipality has undertaken cleanup operations and when it started and (2) product of the indicator variable if the city/ municipality has undertaken cleanup operations and duration
12	**Employment Index (EI)**	Product of two components: (1) product of the indicator variable if the city/ municipality has a cash-for-work program for the shock and the daily wage rate and (2) product of the indicator variable if the city/ municipality has a food-for-work program for the shock and the value of food for a day's work
13	**Response & Assistance from Others Index (RAOI)**	Two indices: (1) Response from Others Index (ROI) and (2) Assistance from Others Index (AOI)
14	**Service Interruption Index (SII)**	Product of the indicator variable if the city/ municipality had any service interruption during the shock and the types of service interruption
15	**Type of Service Interruption Index (TSII)**	Three indices: (1) Water Supply Interruption Index (WSII), (2) Telecommunication Interruption Index (TII), and (3) Electricity Interruption Index (EII)
16	**Infrastructure Index (II)**	Two indices: (1) Infrastructure Breakdown Index (IBI) and (2) Infrastructure Repair Index (IRI)
17	**Housing Program Index (HPI)**	Product of the indicator variable if the city/ municipality has any housing programs in response to the shock and when it was started
18	**Trainings Index (TI)**	Two indices: (1) Training Given Index (TGI) and (2) Training Received Index (TRI)
19	**Assets Index (AI)**	Seven indices: (1) Asset Vehicle Index (AVI), (2) Asset Emergency Shelter Index (AESI), (3) Asset Facilities and Resources Index (AFRI), (4) Asset Search and Rescue Index (ASRI), (5) Asset Information Index (AII), (6) Asset Relief Goods Index (ARGI), and (7) Asset Medical Supplies Index (AMSI)

Note: See Ravago et al. 2018b for the details of the computation of these indices.

Table A2. Summary statistics

Explanatory variable	Obs	Mean	Min	Max
Recovery				
Full Recovery from [SHOCK]	189	0.672	0	1
Shock severity				
Severity of [SHOCK]	189	0.614	0	1
Time of [SHOCK]	189	2.940	0.25	7.833
Indices of ex ante risk management activities				
Long-Term Precautionary Measures Index	193	0.231	0	0.997
Mid-term Precautionary Measures Index	193	0.367	0	1
Short-Term Precautionary Measures Index	193	0.348	0	0.903
Warnings Index	193	0.449	0	1
DRRM Training Index	193	0.334	0	0.913
DRRM Asset Index	193	0.585	0	0.986
Indices of ex post risk management activities				
Evacuation Order and Center Index	193	0.506	0	0.989
Search and Rescue Index	193	0.126	0	0.989
Shock Effects to Constituents Index	193	0.206	0	1
Quick Response Fund Index	193	0.128	0	0.989
National Disaster Fund Index	193	0.043	0	0.989
Relief Index	193	0.545	0	0.952
Relief and Assistance from Others Index	193	0.387	0	0.94
Cleanup Operations Index	193	0.610	0	1
Employment Index	193	0.095	0	0.626
Service Interruption Index	193	0.509	0	1
Types of Service Interruption Index	193	0.097	0	0.631
Infrastructure Index	193	0.256	0	0.67
Housing Program Index	193	0.079	0	1
Control variables				
Dynasty Share 2013	177	0.452	0.167	0.623
Dynasty Largest 2013	177	0.022	0.009	0.062

Explanatory variable	Obs	Mean	Min	Max
Dynasty Sum of Squares 2013	177	0.003	0.001	0.009
Human Development Index 2009	177	0.555	0.353	0.849
Log of Poverty Threshold 2012	177	9.837	9.674	9.994
Log of Poverty Incidence 2012	177	3.016	0.938	4.015
Log of Poverty Magnitude 2012	177	10.790	8.541	12.130
Education of DRRM Officer	193	3.254	2	4
Log of Population	193	11.550	9.409	14.89
Poverty Index	193	20.570	0.28	60.21
Disaster Risk Classification	193	1.482	1	2
Log of DRRM Funding	193	2.474	0.827	5.193
Log of Total Local Revenues	193	4.230	0.296	9.758
Log of Total Non-tax Revenues	193	3.298	-0.849	7.369

Table A3. Risk management activities that influence recovery (full model).

Explanatory variable	Model 1		Model 2	
	Coefficient	Marginal Effect	Coefficient	Marginal Effect
Shock severity				
Severity of [SHOCK]	-1.946	-0.292	-2.480	-0.373
	(1.136)*	(0.167)*	(1.272)*	(0.184)**
Time between [SHOCK]	0.391	0.059	0.446	0.067
	(0.158)**	(0.022)***	(0.176)**	(0.024)***
Indices of ex-ante risk management activities				
Long Term Precautionary Measures Index	1.617	0.243	1.573	0.236
	(0.916)*	(0.131)*	(0.988)	(0.147)
Mid-term Precautionary Measures Index	0.031	0.005	0.507	0.076
	(1.161)	(0.174)	(1.369)	(0.205)
Short Term Precautionary Measures Index	1.076	0.162	1.041	0.156

Explanatory variable	Model 1 Coefficient	Model 1 Marginal Effect	Model 2 Coefficient	Model 2 Marginal Effect
	(1.259)	(0.187)	(1.47)	(0.221)
Warnings Index	-0.873	-0.131	-0.838	-0.126
	(0.77)	(0.113)	(0.9)	(0.133)
DRRM Training Index	0.363	0.055	0.450	0.068
	(1.483)	(0.223)	(1.547)	(0.233)
DRRM Asset Index	0.330	0.050	0.452	0.068
	(0.731)	(0.109)	(0.814)	(0.121)
Indices of ex-post risk management activities				
Evacuation Order and Center Index	-3.043	-0.457	-3.891	-0.585
	(1.502)**	(0.23)**	(1.842)**	(0.277)**
Interaction of Evacuation Index and Severity	1.720	0.258	2.119	0.318
	(1.712)	(0.261)	(1.978)	(0.299)
Search and Rescue Index	-0.741	-0.111	-1.625	-0.244
	(1.015)	(0.152)	(1.162)	(0.175)
Shock Effects to Constituents Index	-0.393	-0.059	-0.175	-0.026
	(0.825)	(0.124)	(0.91)	(0.136)
Quick Response Fund Index	0.503	0.076	0.503	0.076
	(0.884)	(0.134)	(0.919)	(0.139)
National Disaster Fund Index	2.266	0.340	3.021	0.454
	(1.558)	(0.234)	(1.887)	(0.281)
Relief Index	-2.505	-0.376	-3.206	-0.482
	(1.916)	(0.277)	(2.165)	(0.315)
Interaction of Relief Index and Severity	0.298	0.045	0.240	0.036
	(1.926)	(0.288)	(2.241)	(0.336)
Relief and Assistance from Others Index	1.663	0.250	1.755	0.264
	(1.218)	(0.179)	(1.207)	(0.181)
Cleanup Operations Index	2.518	0.378	3.078	0.462
	(1.063)**	(0.156)**	(1.21)**	(0.171)***
Employment Index	-2.241	-0.336	-2.750	-0.413

Explanatory variable	Model 1		Model 2	
	Coefficient	Marginal Effect	Coefficient	Marginal Effect
	(1.456)	(0.216)	(1.506)*	(0.225)*
Service Interruption Index	-0.740	-0.111	-0.933	-0.140
	(1.107)	(0.165)	(1.211)	(0.18)
Types of Service Interruption Index	-1.036	-0.156	-1.313	-0.197
	(1.606)	(0.24)	(1.724)	(0.258)
Infrastructure Index	1.421	0.213	2.484	0.373
	(1.213)	(0.179)	(1.251)	(0.185)
Housing Program Index	-1.147	-0.172	-1.409	-0.212
	(1.017)	(0.154)	(1.139)	(0.171)
Control variables				
Dynasty Share 2013			0.099	0.015
			(4.136)	(0.621)
Dynasty Largest 2013			15.800	2.374
			(44.11)	(6.619)
Dynasty Sum of Squares 2013			-393.300	-59.090
			(329.6)	(48.73)
Human Development Index 2009			4.006	0.602
			(4.512)	(0.688)
Log of Poverty Threshold 2012			4.190	0.630
			(4.581)	(0.693)
Log of Poverty Incidence 2012			1.797	0.270
			(0.897)**	(0.135)**
Log of Poverty Magnitude 2012			-0.638	-0.096
			(0.6)	(0.089)
Education of DRRM Officer	0.405	0.061	0.158	0.024
	(0.45)	(0.068)	(0.468)	(0.071)
Log of Population	-0.292	-0.044	0.325	0.049
	(0.736)	(0.11)	(0.813)	(0.123)
Poverty Index	0.022	0.003	-0.004	-0.001
	(0.020)	(0.003)	(0.026)	(0.004)
Disaster Risk Classification	0.109	0.016	0.111	0.017

Explanatory variable	Model 1		Model 2	
	Coefficient	Marginal Effect	Coefficient	Marginal Effect
	(0.38)	(0.057)	(0.413)	(0.062)
Log of DRRM Funding	-0.104	-0.016	-0.306	-0.046
	(0.648)	-0.097	(0.663)	(0.1)
Log of Total Local Revenues	0.492	0.074	0.604	0.091
	(0.542)	(0.08)	(0.601)	(0.088)
Log of Total Non-tax Revenues	0.229	0.034	-0.097	-0.015
	(0.52)	(0.078)	(0.574)	(0.086)
Number of Observations	189		177	
Log pseudo-likelihood	-86.3959		-80.7903	
p-value	0.0068		0.0039	
McFadden R-square =	0.2776		0.2952	

Notes: Robust standard errors are in parentheses. ***significant at 1% level; **significant at 5% level; *significant at 10% level; $^{+}$ one-sided significant