NATIONAL-TO-LOCAL AID AND RECOVERY FROM EXTREME WEATHER EVENTS

EVIDENCE FROM THE PHILIPPINES

Michael R.M. Abrigo and Arlan Brucal

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National-to-Local Aid and Recovery from Extreme Weather Events Evidence from the Philippines

Michael R.M. Abrigo and Arlan Brucal

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ABSTRACT

We examine the link between extreme weather events and national aid and transfers at the municipal level in the Philippines between 1992 and 2015. Using local-level data of public income and expenditures, local precipitation, poverty incidence, and satellite-based night light luminosity, we find that the national government seems to exhibit strategic behavior by allocating more national aid and transfers during dry spells, in which damage is significantly higher and more prolonged compared to periods of higher-than-usual precipitation. Notwithstanding, the amount of national aid and transfers in these events were very small at about $2 per capita per affected municipality, suggesting that the lack of effectiveness of aid and transfers could be the result of a lack of capacity rather than poor government allocation of public funds.

Keywords: aid and transfers, impact evaluation, natural disasters

JEL codes: H84, O19, Q54

I. INTRODUCTION

Climate change impacts the hydrological cycle causing disruptions in the amount, frequency, and intensity of precipitation ranging from intense droughts to torrential rains. These two extremes in precipitation threaten a number of economic activities and may cause humanitarian crises, for example food insecurity and poverty, particularly in areas reliant on agriculture. Meanwhile, climate change effects are not spread equally. Local conditions can aggravate or mitigate possible threats. Illinois, for instance, has experienced no increase in the frequency of droughts and intense rainfall though increasing amounts of precipitation have been observed in previous years (Dahal, Gautam, and Bhattarai 2018). Meanwhile, certain local areas in the Philippines, mostly in the north, are more often visited by typhoons and hurricanes, while other areas (mostly in the south) experienced more pronounced droughts than others. This heterogeneity in exposure to extreme precipitation among local areas necessitates analyses of impacts at the local level. Surprisingly, most of the studies have been done either in a cross-country setting using aggregate outcome variables or in the context of large damage, which poses some concerns on the generalizability of the results, particularly at the local level.[1]

The recent proliferation of information, potentially due to new media, about climate change and extreme weather events has changed the way people perceive their damage, and, consequently, their responses (Becerra, Cavallo, and Noy 2015). For instance, the 2013 typhoon *Haiyan* in the Philippines generated a significant amount of national and international attention. Along with the increased attention are pledges of aid from private charities, government and nongovernment organizations, multilateral organizations, private companies, and the general public. Quite surprisingly, there was no empirical evidence on how much of these pledges were actually disbursed, when these pledges actually arrived, or how effective they were in influencing the recovery of affected areas. This raises the following questions: How much do aid and intergovernmental transfers really increase in the aftermath of disasters? Are these increases sizable in terms of the damage caused by disasters? Do aid and intergovernmental transfers influence the recovery process of the affected regions? If they do, what are the potential mechanisms by which these funds can influence the affected region's recovery process? Despite the obvious importance of these funds, very few researchers have looked into these questions systematically.[2]

This study aims to contribute to the nascent literature on the link between extreme weather events and intergovernmental transfers. We contribute to the literature in several respects. First, most of the studies have been done in a cross-country setting using aggregate outcome variables. In contrast, extreme weather events typically occur at the local and regional level, which makes it imperative to understand intergovernmental and intragovernmental dynamics in responding to these shocks and how aid and transfers influence these dynamics. To address this issue, we combine data for annual mean precipitation, average radiance obtained from satellite nighttime images as a metric of physical economic activity (see, for example, Li et al. 2013), poverty incidence, and local government finance indicators (e.g., total income, total income from local sources, interlocal transfers, aids and

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[1] Most studies on natural disasters employ Emergency Events Database (EM-DAT) (see, for example, Strömberg [2007]), which defines a disaster as a situation or event that overwhelms local capacity, necessitating a request to the national or international level for external assistance, or is recognized as such by a multilateral agency or by at least two sources, such as national, regional, or international assistance groups and the media. To be in the EM-DAT, at least one of the following criteria should be met: (i) 10 or more people were killed, (ii) 100 or more people are affected, or (iii) a call for international assistance and/or declaration of a state of emergency was made.

[2] An exception is Becerra, Cavallo, and Noy (2014).

extraordinary receipts, among similar others) to examine the link between extreme weather events, intergovernmental transfers, and the recovery process at the local level.

Second, there is no existing data on the disaster-induced aid that actually went to the affected region. Becerra, Cavallo, and Noy (2014) argued that data sources that describe emergency international assistance (e.g., the United Nations Office for the Coordination of Humanitarian Affairs Financial Tracking Service Database [1980–2019]) do not compare their information to disbursements prior to the event, making it difficult to measure the actual change in aid due to extreme weather events. To address this, we use the statement of receipts and expenditures (SRE) from the Bureau of Local Government Finance in the Government of the Philippines' Department of Finance (Government of the Philippines 2009–2018). The SRE provides information on both local or internally generated revenues and external sources of funds, including grants and donations. Our dataset spans from 1992 to 2015, which allows us to track intergovernmental transfers before and after a specific municipality experienced an extreme weather disturbance.[3]

Third, while a few studies looked at the determinants of receiving aid (Becerra, Cavallo, and Noy 2015; Strömberg 2007), to the best of our knowledge, no one has studied the effectiveness of aid in influencing the recovery process of affected areas. We provide insights on this very important issue by using satellite nighttime imagery as a recovery metric and linking the changes in this metric with changes in intergovernmental transfers in the event of extreme precipitation. This approach is appealing in capturing economic activity or economic development in subnational regions of developing countries—particularly where disaggregated data from statistical offices are not available (Bruederle and Hodler 2018). We also used poverty estimates for small areas for the period 2003–2012 from the Philippine Statistics Authority to check for the sensitivity of our analysis to various measures of recovery processes.

We also used detailed local fiscal data from the Government of the Philippines (2009–2018) to determine the magnitude of aid and transfer-induced changes in the subcomponents of public funds (e.g., health, education, infrastructure, etc.) occurring within the sample period. By tracking these changes, we can gain insights on what might be the potential mechanism by which aid can influence the path of recovery in disaster-stricken areas.

The structure of the paper is as follows. First, we review the related literature to provide context for the major issues associated with the link between aid and transfers and disasters in the world and in the Philippines. Next, we discuss the data and introduce some stylized facts on the heterogeneity of precipitation in the Philippines and postdisaster aid and intergovernmental transfer flows in a number of localities. We then explore the effectiveness of these transfers in influencing the patterns of local income and expenditure, as well as economic activity in affected areas. Finally, we conclude with discussion and topics for further research.

II. REVIEW OF RELATED LITERATURE

The succeeding discussion highlights the effects of climate change in aggravating precipitation extremes; thus, creating unprecedented weather events across the world. This is followed by an exploration of postdisaster recovery efforts made by institutions, particularly through governments,

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3 Here, we define extreme weather disturbance as a deviation from the long-run trend in precipitation. More detailed discussion is found in section III.

and kin. Finally, a localized discussion of climate change and disaster recovery efforts will be undertaken using the Philippines as a case study.

A. Climate Change, Weather Shocks, and Precipitation Extremes

Broadly, disasters can be categorized as coming on slowly or rapidly. Global warming and climate change fall under the former, but their effects on temperature lead to a variety of rapid-onset disasters such as storm surges and hurricanes, which are often costly and devastating for communities. Above all, climate change impacts the hydrological cycle, causing disruptions in the amount, frequency, and intensity of precipitation ranging from intense droughts to torrential rains. These two extremes in precipitation threaten agricultural activities and may cause issues in food security throughout the world, especially in areas reliant on agriculture. While this may be the case, climate change effects are not spread equally. Local conditions can aggravate or mitigate possible threats.

1. How Does Climate Change Worsen the Impact of Storms, Droughts, and Flooding?

Typhoons, cyclones, and hurricanes are storms formed through the cycling of moisture and heat during evaporation from oceans. The intensity of these weather events increases as the process takes more repetitions. As heat is a primary component for storm formation, increased temperatures caused by global warming lead to a higher sea surface temperature (SST). Warmer SST increases precipitation; in fact, precipitation tends to increase linearly with increasing SST over tropical monsoon basins (Dado and Takahashi 2017). Intense rainfall is accompanied by frequent flooding, as in the cases of Northern Ghana, Thailand, and the state of Illinois in the United States (US) (Armah et al. 2010, Poapongsakorn and Meethom 2013). Severe floods often result in loss of lives, displacement, and damaged properties and agriculture products. For areas reliant on agriculture, this translates to possible impoverishment, and difficulty recovering. Likewise, droughts have been experienced in India, on the European continent, and in the US state of California (Mall, Attri, and Kumar 2011; Stahl et al. 2016; Wang et al. 2017; Lund et al. 2018) with the same damaging effects as flooding.

Climate change effects do not only result to stronger storms, flooding, and drought but also cause increased climate variability. During the years 2012–2016, California has experienced extreme drought leading to water shortages across agricultural land, cities, and ecosystems amounting to billions of dollars in damages (Lund et al. 2018). This extreme drought, however, was followed by a dramatic switch toward intense rainfall during 2016–2017. This occurrence can be attributed to the North American winter dipole characterized by an extreme surface temperature anomaly in North America and a pronounced "ridge-trough" circulation pattern in the upper atmosphere (Wang et al. 2017).

Similarly, the El Niño–Southern Oscillation highly influences the frequency of droughts and torrential rains across countries near the Pacific and those affected by the monsoons (i.e., South Asia and Southeast Asia). Droughts, for instance, can be exacerbated by El Niño, effectively placing vast areas in a dry spell. There is, however, a different kind of El Niño, characterized by extensive rainfall instead of the usual drought—the Modoki or Dateline El Niño that forms in the central Pacific region near the International Date Line. The Modoki El Niño has been observed in the Philippines in 2004 (Yumul Jr. et al. 2010). Apart from the damaging impacts of precipitation extremes to agriculture, communities can also suffer through poorer health conditions potentially causing around 250,000 additional deaths globally each year in malnutrition, malaria, diarrhea, and heat stress during the years 2030–2050, though having high per capita expenditures in public health could mitigate this, as is the case with the Latin American countries Argentina, Brazil, Chile, Costa Rica, Mexico, Panama, Paraguay, and Uruguay (Nagy et al. 2018). Other potential damage include water shortages, food disruption and

price hikes, and increased pressure on the power grid, particularly in areas with high reliance on hydropower. If compounded, the damage can lead to serious economic consequences at the national level.

2. Gauging the Impacts of Extreme Weather Events

Stronger storms, lengthier droughts, and heavier rains all lead to costlier damage to communities—not only economically, but also socially and psychologically. As global warming continues, frequent erratic weather conditions may possibly occur. Having the means to estimate the severity of droughts and heavy rainfall will be useful especially in crafting national and local policies. Assessing the impact of droughts, for instance, can be done in multiple ways. First, text-based qualitative assessments could be taken as is with the case of using the European Drought Impact Report Inventory, a comprehensive database comprising about 5,000 impact reports from across 33 European countries (Stahl et al. 2016).

Quantitative assessments using the same text-based reports could also be pursued with a logistic regression model, a zero-altered negative binomial regression (hurdle model), or an ensemble regression tree approach (random forest) with each model's results being useful for drought risk management (Bachmair et al. 2017). On the other hand, economic damage from typhoons, hurricanes, and cyclones are modeled using a damage function derived from historical data relating past storms and actual losses; whereas inland flooding can be estimated with the use of remote sensing, such as with the Netherland's Highwater Information System Damage and Casualties Module, utilizing inundation depth and land-use (Ranson, Tarquinio, and Lew 2016). Estimating the economic damage resulting from extreme weather events (EWEs) can be modeled in different ways, from the simplest to the increasingly sophisticated, as with the examples presented above.

Remote sensing in disaster impact assessments has been significantly useful to explain the extent of damage resulting from both slow-onset and rapid-onset EWEs. Using high-resolution optical and thermal imagery and active sensors (such as the synthetic aperture radar) responders can quantify postdisaster damage and monitor recovery efforts (Eguchi et al. 2008). Apart from the imagery and wavelengths captured by satellites, atmospheric remote sensing—using the global navigation satellite systems (GNSS), as with the case of the Hungarian Active GNSS Network—shows the potential of monitoring precipitable water vapor in near-real time. However, atmospheric remote sensing requires an immense amount of spatial data (Rózsa et al. 2012). Similarly, night-light imagery is another way to remotely estimate the impact of disasters and to monitor disaster recovery in communities (Gillespie et al. 2014). Night lights can be measured using either the Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) or the Visible Infrared Imaging Radiometer Suite. Between the two, the latter's day–night band is more powerful, since it collects better imaging data (characterized with greater radiometric accuracy, spatial resolution, and geometric quality) than the DMSP-OLS's lowlight imaging (Elvidge et al. 2013, Jing et al. 2015).

B. Postdisaster Recovery and Rehabilitation Efforts and Financing

Proper rehabilitation efforts after a disaster are a key component needed for vulnerable communities to recover. Broadly, postdisaster efforts can be understood as a three-phase process, with some overlaps from relief to recovery to reconstruction (Ghesquiere and Mahul 2010). What differentiates each phase is the urgency of the funds availability and the time each consumes. Relief (phase 1) has the greatest need for immediately available funding sources, as this phase occurs 1–3 months after the disaster. Meanwhile, recovery (phase 2) funding will come during the 3- to 9-month mark. Finally,

reconstruction (phase 3) is the lengthiest and takes up the bulk of needed postdisaster funding. Survivors endeavor to rebuild their lives to at least their predisaster conditions.

Postdisaster financing can be grouped into noninsurance mechanisms (solidarity, informal risk sharing, and intertemporal risk spreading) or insurance mechanisms (risk pooling and transfer, and alternative risk transfer), with financial actors categorized as micro-scale (households, small and medium-sized enterprises, and farms); meso-scale (financial institutions, multilateral banks, and donor organizations); or macro-scale (governments) (Suarez and Linnerooth-Bayer 2011). The narrative for postdisaster financing (Ghesquiere and Mahul 2010) goes as follows: phase 1 is characterized by donor relief (solidarity across all scales), assistance from kin (micro-scale informal risk sharing), and budget reallocation (macro-scale informal risk sharing). Complementing these are insurance instruments, such as catastrophe bonds (meso-scale or macro-scale alternative risk transfer), parametric insurance (meso-scale risk pooling and transfer), and contingency funds (intertemporal risk spreading across all scales). Phase 2, on the other hand, offers credit lines (micro-scale or macro-scale intertemporal risk spreading) for survivors. Finally, phase 3 offers survivors potential donor assistance for their reconstruction efforts, on top of the credit lines made available to them in phase 2.

C. How Do Developed and Developing Countries Recover Differently from Disasters?

Since developing countries have more access to humanitarian aid and official development aid (micro-scale and macro-scale solidarity, respectively), there tends to be more reliance on ex post instruments (funding that requires no advanced planning); whereas developed countries supplement ex post instruments with substantial ex ante budgeting (funding that requires advanced planning) to soften disaster impacts. For instance, insurance cover between developed and developing countries is at a ratio of 30:1 and postdisaster arrangements in developing countries are described as ad hoc and inefficient (Phaup and Kirschner 2010). Insurance policies, however, need to be guarded from incurring moral hazard, defined as the reduced incentive for insured clients to find risk-reducing measures. It has been observed that developed countries Germany and the US generally have no moral hazard incurred on insured individuals, although there is the presence of adverse risk selection (Hudson et al. 2017). In 2009, the Organisation for Economic Co-operation and Development held a survey on the budgeting practices of 30 member countries. The survey reveals that grants (micro-scale solidarity) are more common than loans (macro-scale intertemporal risk spreading) but national governments also attempt to reduce consumption losses by utilizing insurance pools (macro-scale risk pooling and transfer) (Phaup and Kirschner 2010).

Kinship, mutual arrangements, and remittances are among the closest resources disaster victims can seek (see, for example, Yang 2008). Together with budget reallocations in government, these all fall under the noninsurance mechanism of informal risk sharing. Contrary to formal insurance policies, these instruments rely more on social capital (Aldrich 2010, 2017). On the other hand, humanitarian aid from donors, both in the private sector and through governments and multilateral financial institutions, are within the scope of solidarity noninsurance mechanisms. Both solidarity and informal risk sharing are considered ex post instruments and are largely observed in developing countries. Most people resort first to family and kin for financial and emotional support before seeking formal channels although they seek professionals first for medical care (Versluis 2014). For instance, in the wake of the 2010 Haiti earthquake, 40% of survivors received informal aid (remittances) from family members living abroad. During the 2004 tsunami that hit India, Indonesia, Sri Lanka, Thailand, and 10 more countries, a total of $14.1 million was raised from international sources. Donations came from government (46.1%), the private sector (39%), and others (14.9%), dwarfing relief funds

domestically sourced ($3.6 million) from government and private sector (Jayasuriya and McCawley 2008). While the amount of humanitarian aid has been at the forefront of disaster recovery studies, knowing what the aid accomplishes is an equally important and valid point. However, whether given aid reaches its intended recipients has not been well documented in postdisaster recovery efforts (Becerra, Cavallo, and Noy 2015). Meanwhile, larger social capital has also been observed to positively impact reconstruction efforts. In the People's Republic of China, as rural communities in Wenchuan County in Sichuan Province began to reconstruct houses, larger social network ties were observed to increase the amount of government aid received—because network members tend to assist each other in applying for and obtaining humanitarian aid (Wei and Han 2018). Most postdisaster recovery efforts are focused on the physical reconstruction of community assets but fail to fully address rehabilitation efforts on weakened employment, mental health, and social networks within postdisaster areas, often with the local community not being approached for their relevant inputs (Alipour et al. 2015). This failure to incorporate the insights and experiences of the local community can be traced to a top-down paternalistic approach to rehabilitation.

D. Disaster Response Preparedness and Structure in the Philippines

With the tropical and maritime climate in the Philippines, rainfall becomes a significant driver of climate variability. Seasonal rainfall in the Philippines is influenced by large-scale systems, such as with the monsoons, typhoons, EWEs, and the El Niño–Southern Oscillation. Typhoons, for instance, play a key role in bringing torrential rains in the Philippines: 40% of rainfall in Luzon comes from typhoons (Bagtasa 2017). Around 19–20 typhoons enter the Philippine area of responsibility and about 7–9 make landfall (Cruz et al. 2016). Numerous typhoons bringing torrential rains into the country lead to frequent flooding, landslide occurrence, and multiple damage to property and living. In the case of Davao Oriental, for instance, 15.3% of barangays have been identified as having a high and a very high risk of flooding in the years 2030, 2050, and 2100 (Cabrera and Lee 2018); descriptions that are parallel to the Philippines being the top country at risk from climate change effects (Kreft, Eckstein, and Melchior 2015).

In 2010, Republic Act 10121, or the Philippine Disaster Risk Reduction and Management Act, created the National Disaster Risk Reduction Management Council, which serves as the Philippines primary agency for disaster-related activities. In the Philippines, disaster response activities have been done through a Comprehensive Rehabilitation and Recovery Plan headed by an ad hoc body, as has been the case during the postdisaster recovery from Typhoon Pablo (*Bopha*) and Typhoon Yolanda (*Haiyan*). This setup makes crucial rehabilitation efforts heavily dependent on the coordination capabilities of the ad hoc body (Villacin 2017).

Despite being ranked as the country most vulnerable to climate change (Institute for Economics and Peace 2019), the Philippines has yet to have its own departmental level agency of government, albeit a bill creating the Department of Disaster Resilience and Emergency Management has already been filed in the Senate (S. No. 1735 2018)(Government of the Philippines 2018). Should this department be established, three attached agencies would accompany it: the Bureau of Disaster Resilience, the Bureau of Disaster Preparation and Response, and the Bureau of Knowledge Management and Dissemination. These attempts toward a better institutional framework for disaster response are in accordance with the country's participation as a signatory to the Hyogo Framework of Action and the Sendai Framework—both global attempts to substantially reduce disaster losses using disaster risk management. Republic Act 10121, however, has been characterized as having weak grounding and implementation, citing the lack of a high-level institutional leadership that can vertically and horizontally pursue disaster risk reduction and management initiatives (Domingo 2017).

Consistent with the behavior of developing countries, the Philippines relies more on ex post instruments that ultimately exert pressure on limited fiscal resources, although the Philippine government has made attempts to integrate more ex ante policies, such as with the World Bank $500 million catastrophe drawdown option (Villacin 2017).

III. EMPIRICAL STRATEGY

A. Data

To examine the link between disaster occurrence and the influence of intergovernmental transfers in the recovery process of affected areas, we combined municipal- and city-level data of annual mean precipitation, small area poverty estimates, and local government finance indicators (e.g., total income, total income from local sources, interlocal transfers, aids and extraordinary receipts, and others). Gridded annual precipitation estimates for 1990–2015 by the University of East Anglia Climatic Research Unit (Harris et al. 2014), and DMSP-OLS night-light composites (see, for example, Small et al. 2005, Small and Elvidge 2013) for the period 1992–2013 were downloaded for cities and municipalities from the AidData geodatabase of the William and Mary's Global Research Institute (Goodman, Benyishay, and Runfola 2017).[4] Estimates of small area headcount poverty rates for cities and municipalities covering the years 2003, 2006, 2009, and 2012 were collated from the Philippine Statistics Authority database (National Statistical Coordination Board 2009, 2013; Philippine Statistics Authority 2016). The different municipal-/city-level databases were matched using the 2018 Philippine Standard Geographic Code (Philippine Statistics Authority 2018).

Figure 1 presents the standardized deviation of rainfall from its long-run trend in the Philippines for the period 1990–2015. Most of the observations have means within the (−2, 2) band, with negative values suggesting low levels of rainfall from the normal trend, and positive values reflecting high levels from the normal trend. We observe the occurrence of extreme precipitation patterns after 2000, although there is a substantial amount of abnormally low levels of rainfall in the early 1990s. These events coincide with the El Niño phenomenon during 1992–1993, wherein drought damage set back the Philippine agriculture sector by 4.1 billion Philippine peso (₱) ($78.2 million).[5] In total, the dry spell during 1997–1998 brought damage to agriculture amounting to ₱8.46 billion ($161.37 million) and affected 16 regions (GMA News Online 2007).

Local government finance data was sourced from the SRE report by municipality from 1992 to 2017 downloadable from the Government of the Philippines (2009–2018). The SRE provides key local government finance data, including locally sourced income, external sources and expenditures, and other local government unit (LGU) financial statistics. For our purpose, we use per capita aid and other extraordinary transfers (in constant 2000 PHP) as our key metric to represent aid and transfers in our analysis.

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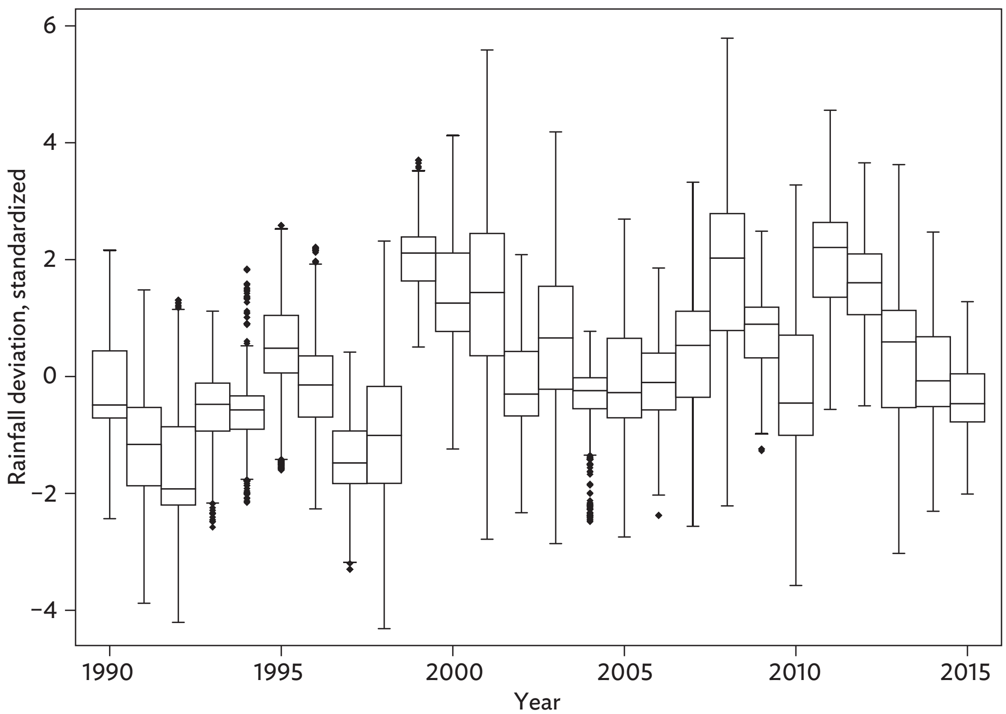
[4] The AidData geodatabase summarizes data drawn from Government of the United States. 1992–2013. "DMSP-OLS Nighttime Lights Composites, Version 4." Boulder: National Oceanic & Atmospheric Administration, National Center for Environmental Information (ngdc.noaa.gov/eog/dmsp/downloadV4composites.html) and Global Research Institute. 1901–2001. "Yearly Precipitation – CRUTS." Williamsburg, VA: The College of William and Mary (https://www.aiddata.org/ for details). The precipitation data are originally available in 0.5°x0.5° spatial resolution, while the DMSP-OLS nightlight luminosity are available in 1km x 1km spatial resolution.

[5] $1 = ₱52.41 (as of 22 May 2019).

Figure 1: Standardized Rainfall Deviation from the Long-Run Trend in the Philippines, 1990–2015



Source: Harris, I., Philip D. Jones, Timothy John Osborn, and David H. Lister. 2014. "Updated High-Resolution Grids of Monthly Climatic Observations–the CRU TS3.10 Dataset." *International Journal of Climatology* 34 (3): 623–42. https://www.aiddata.org/ (accessed 3 October 2018).

Table 1 shows the average per capita aid and transfers at varying levels of rainfall for the period 1992–2015. We observe that areas experiencing a low amount of rainfall (that is, within −2 to −1 standardized deviation from the long-run mean precipitation) receive the highest amount of aid, followed by those that experience high amounts of rainfall. Quite surprisingly, those that experienced extreme precipitation levels received the lowest amount of aid and transfers. This suggests that perhaps the process of national aid and transfer provision to local levels is driven by factors other than the occurrence of extreme weather shocks. More importantly, we also find that the national transfers are quite small, with the highest at about $2 per capita. This observation is consistent with that of Becerra, Cavallo, and Noy (2014) who found that postdisaster aid surges across countries are typically small in relation to the overall damage caused by the disasters.

Table 1: Philippine Aid Transfer Receipt and Rainfall, 1992–2015

Rainfall Deviation	Mean Per Capita Aid and Extraordinary Transfers (Constant PHP)		Share Receiving National Aid (%)
	All Municipalities	Recipients Only	
Extremely low	9.1	59.1	15.4
Low	19.7	97.0	20.3
Normal	14.5	61.6	23.5
High	19.1	77.0	24.8
Extremely high	11.7	51.5	22.7
All municipalities	15.3	66.6	22.9

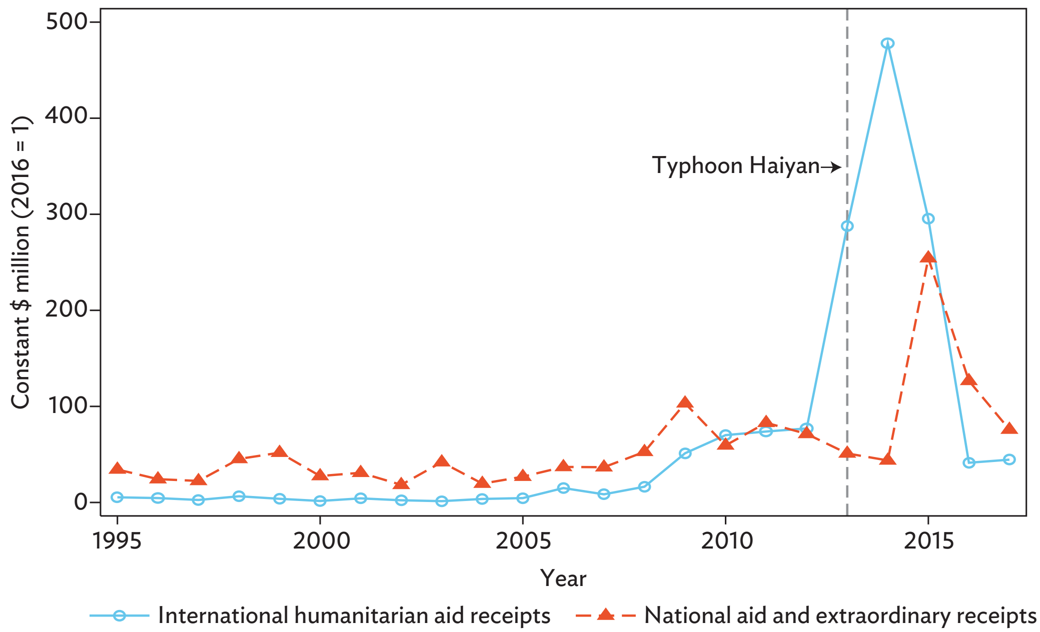
Notes: National aid transfer receipt are in 2000 prices. Extremely low = <−2 standardized deviation (SD) from the long-run trend of precipitation; Low = −2≤ to <−1 SD; Normal = −1 to +1 SD; High = +1< to ≤+2 SD; and Extremely high = >+2 SD. PHP = Philippine peso.
Sources: National aid transfer receipt data from Government of the Philippines (2009–2018); Rainfall data from Government of the United States (1992–2013).

Even with the significantly low amount of national aid and transfers to local communities, the Philippine government has consistently overshadowed and outpaced other countries in terms of providing aid funds to disaster stricken localities.[6] Since 1995, national aid and transfers stood higher by about $30 million from 1995 to 2009 compared to international humanitarian assistance (Figure 2). It was during the aftermath of typhoon *Haiyan* during 2013–2014 when international humanitarian aid received by the Philippines significantly overwhelmed nationally funded aid disbursements, higher by $335 million on the average. In 2015, about 2 years after the disaster, national aid and transfers to local government increased by 256% from its predisaster period, eclipsing international humanitarian aid at $254 million.

We also examined the historical trend of national aid and transfers, the number of affected people during events of abnormal precipitation levels, and the amount of rainfall as measured by the deviation from the normal long-run trend. Note that due to infrequent occurrences, the trend is only applicable to the top 99th percentile of the observations. As shown in Figure 3, we see a very weak but positive correlation between aid inflows and the number of affected people. Meanwhile, there was a relatively stronger positive correlation between aid inflows and disturbances in the amount of rainfall received by the affected locality. The strong positive correlation is particularly observed in dry spells in the early and late 1990s, but the relationship becomes weaker thereafter, primarily due to less frequent occurrences. A correlation matrix is presented in Table 2.

[6] National aid will be able to capture the contribution from international aid, to the extent that this is coursed through the national government.

Figure 2: National Aid Transfers and International Humanitarian Aid to the Philippines



USD = United States dollars.
Sources: National aid transfer receipt data from Government of the Philippines (2009–2018); Rainfall data from Government of the United States (1992–2013).

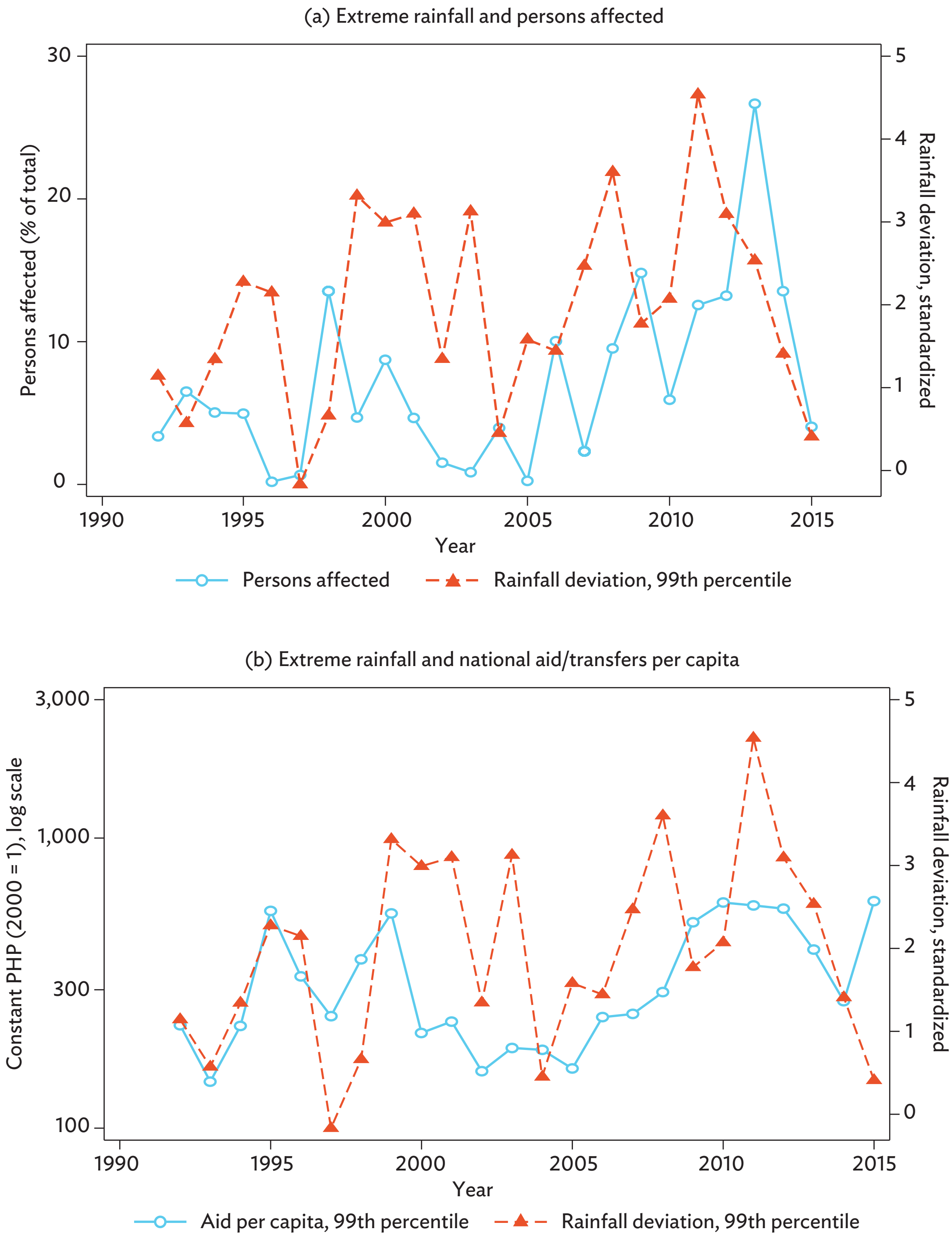
Table 2: Raw Correlations in Extreme Rainfall, Persons Affected, and National Aid Transfers

	Rainfall deviation	Persons affected (%)	Per capita national aid
Rainfall deviation	1.00	–	–
Persons affected (%)	0.23	1.00	–
Per capita national aid	0.33	0.41	1.00

Note: Rainfall deviation and per capita national aid are for the top 99th percentile of the observations.
Source: Authors' calculation based on national aid transfer receipt data from Government of the Philippines (2009–2018). Rainfall data from Government of the United States (1992–2013).

Overall, the stylized facts presented above clearly provide some significant regularities. First, the Philippines is characterized by both extreme weather disturbances: dry spells and higher-than-normal precipitations and the trend changed over the sample period. Second, the amount of national aid and transfers to localities appears to be almost negligible and driven by a number of factors apart from weather disturbances. Third, the national government had been the major source of aid and transfers historically, except when typhoon *Haiyan* devastated some communities in the country.

Figure 3: Historical Trend in Extreme Rainfall, Persons Affected, and National Aid and Transfers



log scale = logarithmic scale, PHP = Philippine peso.
Source: Authors' calculation based on national aid transfer receipt data from Government of the Philippines (2009–2018). Rainfall data from Government of the United States (1992–2013).

B. Estimation Approach

To analyze the impact of aid and transfer inflows into a locality's recovery process in the event of extreme precipitation, we estimate impulse response functions (IRF), which may be depicted as

$$\theta_{t,s,d_i} = E(y_{t+s}|v_t = d_i; X_t) - E(y_{t+s}|v_t = 0; X_t) \tag{1}$$

In the above equation, the impulse response θ_{t,s,d_i} for period $t+s$ and experimental shock d_i is presented as the difference of two forecasts using the information set available up to period t, captured by X_t, and two states of the world, that is, with the experimental shock $v_t = d_i$ and $v_t = 0$ (see, for example, Hamilton 1994; Koop, Pesaran, and Potter 1996). $E(\cdot\,|\,\cdot)$ is the conditional expectation operator.

Following Jorda's (2005) "local projection" technique, the IRF may be calculated by a series of regressions of y_{t+s} on $X_t = \{1, y_t, y_{t-1}, \dots, y_{t-k}, z_t, z_{t-1}, \dots, z_{t-j}\}$, where y_{t+s} is the outcome of interest at period $t+s$, and z_t is a vector of other endogenous or exogenous control variables, with $s, k, j \geq 0$. The regression coefficients on y_t and z_t, respectively, are the responses of y at period $t+s$ for a unit shock on y and z in period t, with the normalization that the impulse response of y on itself equals unity at $s = 0$.

We implement this using our data by running series of regressions of the form

$$\begin{aligned} y_{it+s} = {} & \alpha + \sum_{l=0}^{5} \beta_{l,s}\,\mathrm{RAINFALL}_{i,t-l} + \sum_{l=0}^{5} \gamma_{l,s}\,\mathrm{AID}_{i,t-l} + \sum_{l=0}^{5} \emptyset_{l,s}\,\mathrm{IRA}_{i,t-l} \\ & + \sum_{l=0}^{5} \delta_{l,s}^{AID}\,\mathrm{RAINFALL}_{i,t-l} \cdot \mathrm{AID}_{i,t-l} + \sum_{l=0}^{5} \delta_{l,s}^{IRA}\,\mathrm{RAINFALL}_{i,t-l} \cdot \mathrm{IRA}_{i,t-l} \\ & + \sum_{k=0}^{3} \sigma_{k,s}\,\mathrm{CONTROL}_{it-k} + \lambda_t + m_i + \varepsilon_{it+s} \end{aligned} \tag{2}$$

for forecast horizon $s = 0,1, \dots ,5$. In the above empirical model, y_{it+s} is a vector of outcome variables for municipality i at year $t+s$, which includes per capita income from local sources, per capita local government expenditure, poverty incidence, and the amount of night-lights as proxy for physical economic activity at the local level; RAINFALL is a vector of dummy variables representing different levels of rainfall as defined in Table 1 with normal rainfall, that is, between −1 to +1 standard deviation rainfall, being the base category; AID is per capita aid and extraordinary transfers received by the municipality; IRA is the internal revenue allotment; CONTROL is a vector of control variables (city dummy, population density, and income from local source); λ_t and m_i are year fixed effects and municipality fixed effects, respectively; and ε_{it} is the idiosyncratic error term.[7]

[7] The internal revenue allotment (IRA) is the LGU's share of revenues from the Government of the Philippines. Provinces, independent cities, component cities, municipalities, and barangays (the lowest political unit) each gets a separate allotment.

We are interested in the estimated coefficients $\widehat{\gamma_{0,s}} + \widehat{\delta_{0,s}^{AID}}$ and $\widehat{\emptyset_{0,s}} + \widehat{\delta_{0,s}^{IRA}}$, which represent Jorda's (2005) "local projection" response of our outcome variables on a unit shock of disaster aid and national-to-local intergovernment transfers, respectively, conditional on the rainfall shock that a locality experienced at period t. We are also interested in the estimated coefficients $\widehat{\beta_{0,s}}$, which capture the average response of localities on rainfall shocks after controlling for other factors in our model.

Even if the underlying true IRF is nonlinear, the coefficient estimates $\widehat{\gamma_{0,s}} + \widehat{\delta_{0,s}^{AID}}$, $\widehat{\emptyset_{0,s}} + \widehat{\delta_{0,s}^{IRA}}$, and $\widehat{\beta_{0,s}}$ capture the least squares linear predictor of current and future changes in outcomes y_{t+s} of an average municipality based on the history of rainfall, aid flows, intergovernmental transfers, and controls. It is important to note that the consistency of our estimated coefficients rely on the conditional independence of aid flows, intergovernmental transfers, and rainfall, respectively, at period t and the model residuals at $t + s$ once the history of aid flows, intergovernmental transfers, rainfall, and other control variables up to period t and the time fixed effects and locality fixed effects are taken into account.

IV. RESULTS

A. What Determines Transfers from the National Government?

Before we determine how effective national aid and transfers are in influencing the recovery process of disaster-stricken areas, it is important to first identify the determinants of internal revenue allotment and national aid and extraordinary transfers. To do this, we run a simple regression of log-transformed IRA and aid and transfers on the dummies of precipitation levels, along with other potentially significant explanatory variables (i.e., city dummies, population density, and income from local sources).

Results of the regressions are summarized in Table 3. Columns (1) and (5) include the city dummy only; columns (2) and (6) add other municipality- and time-specific time-varying variables, such as population density and income from local sources; columns (3) and (7) add the precipitation-level dummies; and columns (4) and (8) add the lagged precipitation-level dummies. For each run with precipitation dummies, a joint F-test is conducted to check whether the related regression coefficients are all statistically indistinguishable from zero. Here, we find that all location-specific variables are important in determining internal revenue allotment, which is expected, considering that the allotment, by law, is largely based upon a number of local attributes (e.g., whether it is a city or municipality, land area, and population).[8] We do not find any strong evidence to suggest that the amount of rainfall has a significant effect on the amount of IRA a locality will receive. In contrast, whether a locality is a city or not does not have a strong effect on the amount of national aid and transfers a locality will receive. More importantly, occurrence of extreme rainfall (i.e., drought or torrential rain) is strongly associated with national aid and transfer inflows. Joint significance tests reveal that the amount of rainfall a locality experiences even after 4 years of occurrence has a strong statistical link to the contemporaneous amount of national aid a locality receives.

[8] Section 284 of the Local Government Code of the Philippines (RA 7160) sets up the formula for the distribution of the allotment.

Table 3: Raw Correlations in Extreme Rainfall, Persons Affected, and National Aid Transfers

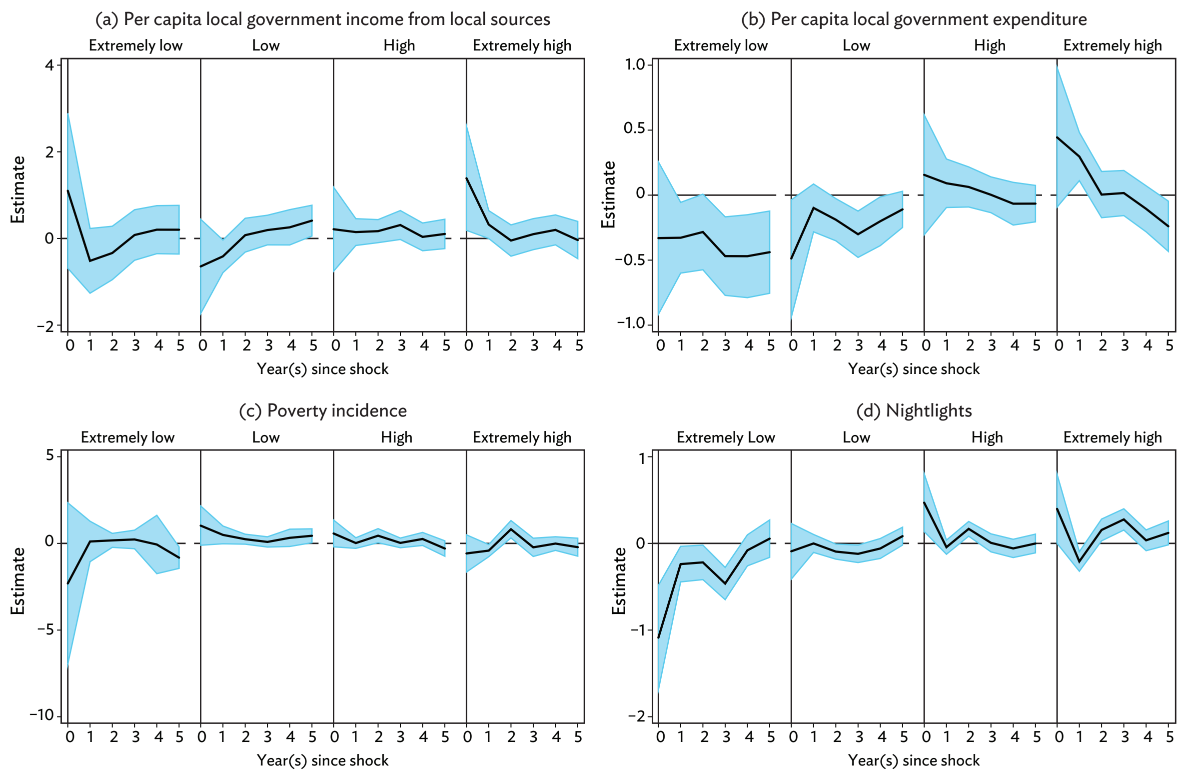
	National Aid per Capita, Log				Internal Revenue Allotment per Capita, Log			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
City (= 1)	0.082	0.013	0.015	0.037	0.821***	0.737***	0.742***	0.76***
	(0.098)	(0.119)	(0.121)	(0.121)	(0.032)	(0.027)	(0.027)	(0.031)
Population density, log		−0.38**	−0.383**	−0.439**		−0.834***	−0.825***	−0.8***
		(0.166)	(0.167)	(0.177)		(0.040)	(0.042)	(0.045)
Locally generated income, log		0.278***	0.269***	0.3***		0.284***	0.273***	0.216***
		(0.083)	(0.086)	(0.096)		(0.022)	(0.019)	(0.019)
Constant	0.631***	−2.031	−1.856	−2.316	5.558***	6.033***	6.168***	7.097***
	(0.035)	(1.457)	(1.493)	(1.670)	(0.018)	(0.369)	(0.335)	(0.345)
F-test, $\tau(0)=0$			2.896**	2.061*			0.809	0.452
F-test, $\tau(1)=0$				1.858				1.276
F-test, $\tau(2)=0$				2.893**				2.468**
F-test, $\tau(3)=0$				4.922***				0.763
F-test, $\tau(4)=0$				4.226***				3.290***
F-test, $\tau(5)=0$				0.718				1.886
Adjusted R-squared	0.016	0.018	0.018	0.020	0.683	0.698	0.697	0.644
Observations	38,040	32,453	31,769	28,436	38,042	32,454	31,770	28,437

log = logarithm.
Notes: Each column represents a separate regression. Unless otherwise stated, all variables are in natural logarithms. Observations with zeros (more than 90% of the observations) have been added with 1 unit to avoid truncation. Parameter estimates for each amount of rainfall are presented in Appendix Table A1. Robust standard errors are in parentheses. * denotes statistical significance at 10%, ** denotes statistical significance at 5%, and *** denotes statistical significance at 1%. The F statistic tests the null hypothesis that the regression coefficients, $\tau(s)$, on rainfall dummies for period t-s are all statistically indistinguishable from zero. The estimated coefficients for $\tau(s)$ are presented in Appendix Table A1.
Source: Authors' calculation based on national aid transfer receipt data from Government of the Philippines (2009–2018). Rainfall data from Government of the United States (1992–2013).

B. What Is the Effect of Extreme Rainfall?

In this section, we briefly discuss the effect of the amount of rainfall to municipality-level outcome variables. To do this, we run equation (1) and calculate the marginal effect of moving from a normal amount of rainfall (i.e., no deviation from the long-run mean precipitation) to other relatively more extreme conditions as defined in Table 1, holding the level of aid and transfers constant. For example, the figures corresponding to extremely low rainfall denote the move from normal to less than −2 standard deviation from the long-run mean precipitation during the sample period. Results are summarized in Figure 4.

Figure 4: Effect of Amount of Rainfall and Municipality-Level Outcomes



Notes: The figure illustrates the impulse response of each outcome variable moving to relatively more extreme amounts of rainfall, holding all other variables constant. The solid black line denotes the point estimates, while the gray bands denote the 95% confidence interval. Extremely low = <−2 standardized deviation (SD) from the long-run trend of precipitation; Low = −2≤ to <−1 SD; Normal = −1 to +1 SD; High = +1< to ≤+2 SD; and Extremely high = >+2 SD.
Source: Authors' calculation based on national aid transfer receipt data from Government of the Philippines (2009–2018). Rainfall data from Government of the United States (1992–2013).

In panel (a), we find that minor deviations from normal rainfall (i.e., moving from normal to either high or low) had no strong contemporaneous effect on the growth of local government income. Quite surprisingly, we find that a shift to extremely high amounts of rainfall can cause a significant increase in locally sourced income of the locality. This can be explained by the nature of rainfall and wind direction. Based on historical trends, typhoons normally land in the northern part of the country, in mostly agricultural areas. In these areas, an abnormally high amount of rainfall translates to a good

cropping season, as most areas are just partially irrigated or rainfed paddy fields. The effect of this extreme rainfall lasts for a year and dissipates thereafter.

We also observe the same trend for areas experiencing a shift to extremely low rainfall. There are cases wherein low rainfall can spur increase in local government revenues, such as an increase in oil prices (Cashin, Mohaddes, and Raissi 2016) and perhaps due to less dependence on hydropower, thus increasing coal- and oil-based revenues. This can happen in the southern region of the country, which was mainly dependent on hydropower for its energy use.

There seems to be have lagged effects of extremely low rainfall on per capita LGU expenditure. In particular, we find that LGU expenditure reduces by about 4%, 1 year after the locality experienced extremely low rainfall. The effect seems to sustain up to 5 years and grow up to about 5%. Meanwhile, only low levels of rainfall significantly reduce contemporaneous growth in per capita LGU expenditure, and the effect is still felt up to 3 years. This is consistent with the documented damage of drought associated with the El Niño phenomenon, which includes disruption in agricultural production (namely rice), water shortages, and energy cost push associated with more dependence on costly coal- and oil-based power plants.

In terms of poverty incidence, we observe an increase in the growth of poverty incidence when a locality experiences relatively low levels of rainfall and this is sustained even after a year (panel c). The growth of poverty incidence, in contrast, fell significantly with extremely high amount of rainfall, which is quite consistent with and corroborates the observation on local income and expenditures. Panel (d) generally supports the major findings, with extremely low levels of rainfall inducing a decline in economic activity, while higher than normal amount of rainfall essentially promotes economic growth.

Overall, the findings in this exercise suggest that lower than normal rainfall, which can cause dry spells and drought, has a strong negative effect on the locality's income and economic condition. The negative effect, although slightly statistically weak, is still felt up to 5 years after the initial impact. In contrast, higher than normal rainfall translates to an improvement in the economic condition of the locality. This trend explains why the national government has put more aid and extraordinary transfers toward municipalities experiencing lower than normal amount of rainfall over the years.

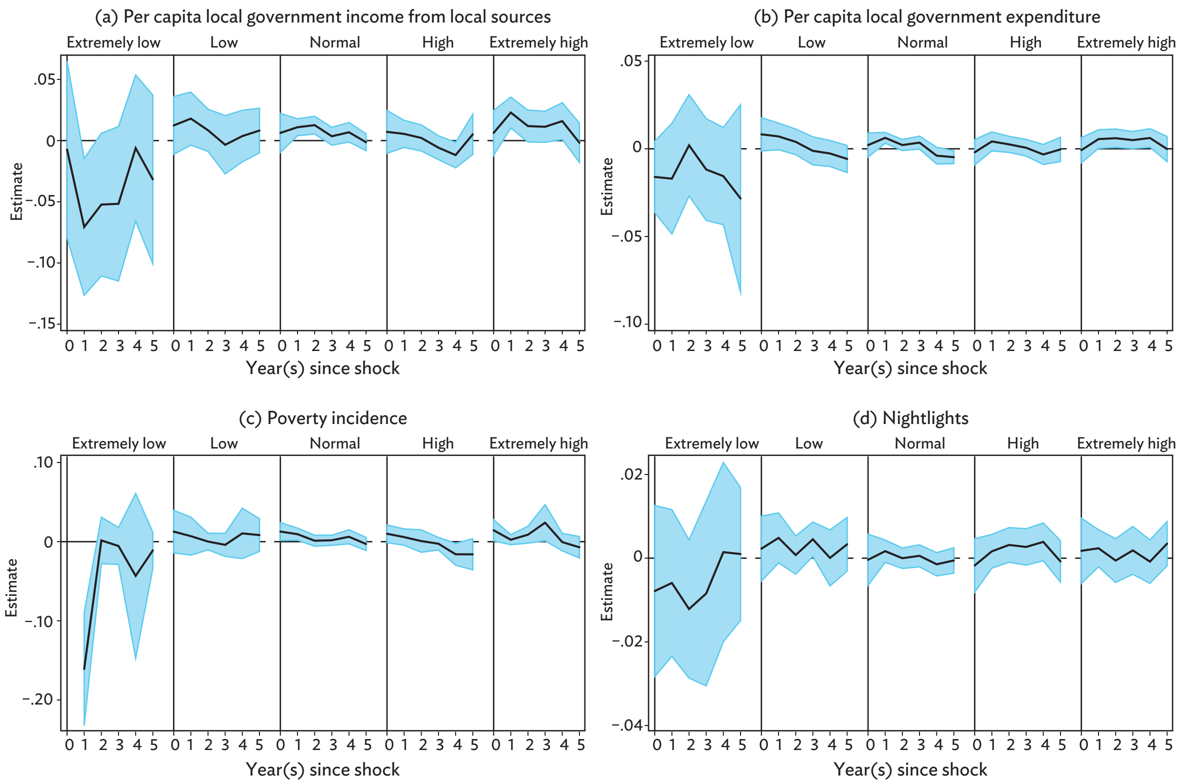
We also attempted to measure differences in the outcome variable associated with varying intensities of extreme weather events, which we measured based on the locality's declaration of a state of calamity (SOC). To do this, we augmented equation (1) by adding another interaction term between aid and the localities' declaration of SOC. The variable takes the value of 1 when the locality was declared in an SOC; 0 otherwise. Results are summarized in Appendix Figure A1.2. The estimates and the confidence intervals generally overlap between the "with SOC" and "without SOC" settings, suggesting no strong evidence for the difference between the two scenarios.

C. What Is the Effect of National Aid and Transfers?

After identifying the effect of experiencing a disturbance in the amount of rainfall on a locality's income and economic activity, we now move to determining the effect of a change in aid and transfers inflow. To do this, we run equation (1) and calculate the marginal effect of a percent increase in aid and transfers inflow under certain levels of rainfall (i.e., a deviation from the long-run mean precipitation) as defined in Appendix Table A1, holding other variables constant.

As shown in Figure 5, we find no strong evidence to suggest that national aid and transfers have significant influence on the contemporaneous growth of the income and/or economic activities of affected localities. This result holds for any amount of rainfall a locality has received during the sample period. Quite surprisingly, however, we see a decline in the LGU's income from local sources a year after a locality experienced extremely low rainfall and received aid, although the effect is quite small (about 0.75% decline in response to a 1% increase in aid inflows) (panel a). At the moment, we do not have a sensible explanation for this observation.

Figure 5: Marginal Effect of a Percent Increase in National-to-Local Aid and Transfers on Municipality-Level Outcomes



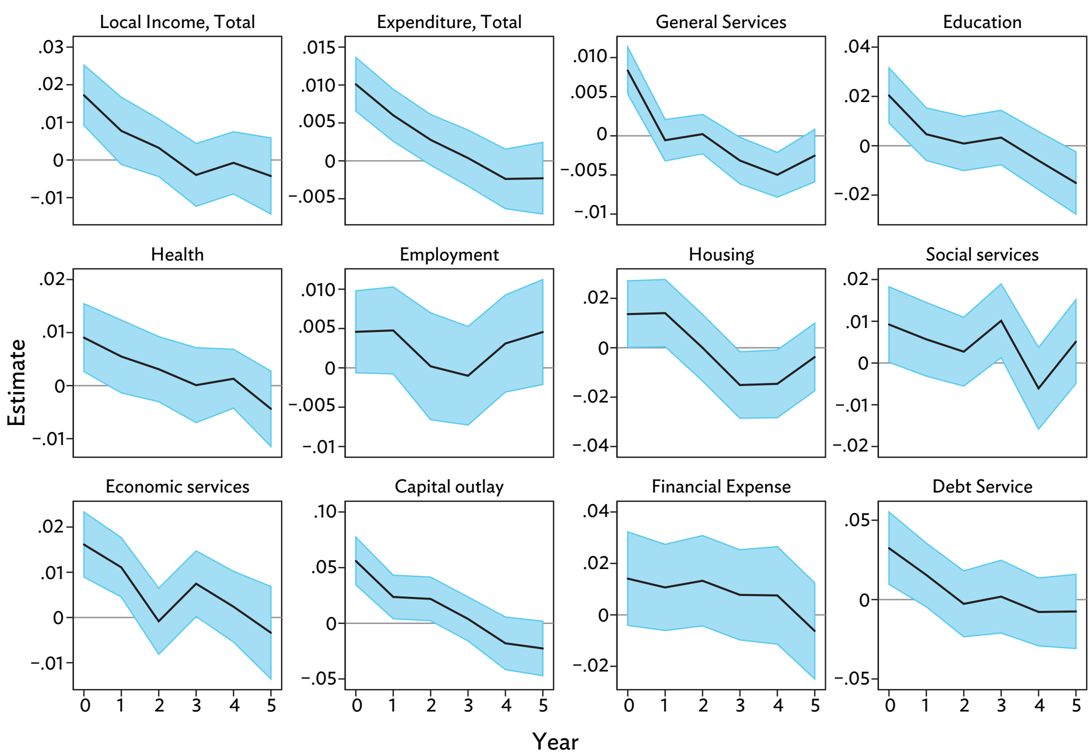
Notes: The figure illustrates the impulse response of each outcome variable to a percent increase in national aid and transfers under different rainfall scenarios, holding all other variables constant. The solid black line denotes the point estimates, while the gray bands denote the 95% confidence interval.
Source: Authors' calculation based on national aid transfer receipt data from Government of the Philippines (2009–2018). Rainfall data from Government of the United States (1992–2013).

In contrast, we see a slight increase in both local income and expenditure beginning 1 year to 4 years after the locality experienced an abnormally high amount of rainfall. This is quite consistent with the previous findings, that higher than usual precipitation generates sluggish increases in local income and expenditure. Further inflow of funds through aid will generate prolonged, though lagged, effects on the locality's financial condition.

One issue that may raise concerns in our estimation procedure is that the rainfall dummies actually washed out the effects. What we obtained may have been actually aid that is not induced by rainfall. That is, our estimate is net of rainfall, which may not be as useful, since what we want is aid in response to disaster. To test this hypothesis, we bind our estimate by adding regressions without rainfall. In this case, the coefficient on aid should be upward biased and should significantly deviate from the baseline estimates. Results are presented in Appendix Figure A1.1. We do not see any significant deviations between our baseline estimates and the estimates without the rainfall variable.

Finally, we examine where aid is usually used by the local government. To do this, we run equation (1) on different local expenditures (e.g., housing, education, health) (without the interaction) and adding IRA in the specification. The idea is that we want to know which of the local public expenditures increase when aid inflows increase, holding other variables constant. These control variables include the amount of rainfall the locality received in a year and all other locality-specific controls in the previous specification.

Figure 6: Marginal Effect of a Percent Increase in National-to-Local Aid and Transfers on Specific Local Government Expenditures



Notes: The figure illustrates the impulse response of each outcome variable to a percent increase in national aid and transfers under different rainfall scenarios, holding all other variables constant. The solid black line denotes the point estimates, while the gray bands denote the 95% confidence interval.
Source: Authors' calculation based on national aid transfer receipt data from Government of the Philippines (2009–2018). Rainfall data from Government of the United States (1992–2013). (See reference list for full citations).

Results are summarized in Figure 6. Results show that total income increased higher than expenditure. In particular, a 10% increase in aid resulted in about a 2% increase in the contemporaneous income of the affected locality, which is a percent higher than local expenditure. However, the effect on expenditure lasted much longer, up to 2 years after the shock, while the effect on income dissipates in a year's time.

Specific local expenditures that experienced an instantaneous increase in response to an increase in aid inflows include general services, education, health, social services, economic services, capital outlay, and debt services. Debt services seem to record the highest response (about 2.5% to a 10% increase in aid inflows) while economic services had the most prolonged effect.

D. Sensitivity Tests

In this subsection, we explore potential heterogeneity effects of weather disturbances and national aid and transfers of select outcome variables at the municipality level, depending on a number of municipality-specific characteristics.

Intensive Margins. We wanted to explore if there were differences in the effectiveness of national aid and transfers on local income and expenditure, poverty incidence, or economic state—conditional on whether the locality declared SOC at the time of weather disturbance. To do this, we added a dummy variable that turns to unity when the municipality declared SOC, and an interaction with the SOC variable and the amount of rainfall. In doing so, we are practically estimating intensive margins; that is, we are estimating the effects of aid and transfers on the condition that a certain locality had incurred more damage with the same amount of rainfall. Results are illustrated in Appendix Figure A1.3. We find no discernible change in the parameter estimates when compared to baseline results, suggesting that national aid and transfers do not seem to have significant effect on the municipality-level outcome variables, even when under more intense weather-induced situations.

Heterogeneity in economic structure. One issue that may raise concerns regarding our findings is that perhaps the effectiveness of aid depends on the type of location. A city, which may have a more vibrant economy and less reliance on agriculture, may behave differently than less urbanized localities when provided with aid in response to an extreme weather occurrence. This may be due to several factors, including the level of sophistication of the city government, relative to a less urbanized government, and the difference in resilience of city dwellers compared to less urbanized citizens, among others. To shed light on this, we augment our baseline estimation equation with a dummy variable that is equal to 1 if a locality is a city in a certain time period and 0 otherwise. Results are summarized in Appendix Figure A1.4. We find no significant difference from our baseline estimates, suggesting that the type of locality does not influence the effectiveness of aid in influencing the outcome variables.

Heterogeneity in terms of governance. Another issue that may raise concerns about our findings is that the effect of national aid and transfers may also be different depending on the type of government managing the funds. High-functioning governments may have the capacity and the political makeup to better allocate aid and transfer funds to where they could have higher returns and perform tasks in a more efficient manner. To validate this hypothesis, we augmented our baseline estimating equation to include a variable that will indicate whether a locality received the Seal of Good Local Governance award in 2014–2018. The award, given by the Department of the Interior and Local

Government, symbolizes integrity and good performance of local governments.[9] We then interacted this variable with the amount of rainfall to determine whether we could find a significant effect on the influence of national aid and transfers on key outcome variables, conditional on the type of weather disturbance the locality has experienced and the type of governance a locality has. Results of the analysis are summarized in Appendix Figure A1.5. We find no strong evidence to suggest that the type of local governance has influence on the effectiveness of trade in improving the situation of affected areas.

V. CONCLUSION

Following the nascent literature examining the link between extreme weather events and aid surges, we deviate from the existing literature in several respects. First, we focus on examining the link at the local level using the combined data of national aid and transfers to local government units in the Philippines and long-run deviations in the amount of rainfall a locality receives in a particular year. Second, we have addressed important issues such as the effectiveness of postdisaster aid allocation in mitigating the consequences of disasters. Third, we also looked at where exactly in the subcomponents of public finance these aid and transfers go, which can provide insights on the priorities of local governments in the event of disaster.

Results of our analysis show that national government aid and transfers are given more in areas that experienced lower-than-usual precipitation. This shows that the national government is more active in providing aid during dry spells and droughts, as opposed to during events of higher-than-usual rainfall. This could mean a number of things. First, it could be that the perceived damage of drought is more significant than torrential rains and to some extent flooding. Second, this could also reflect the difficulty in addressing threats relating to typhoons and hurricanes, of which occurrences are quite hard to predict. In contrast, dry spells and droughts are predicted ahead of time, making it easier for the government to program public funds and national interventions. Third, and in relation to the second issue, this could also reflect the difficulties in disbursing national government funds.

Further analysis suggests that the damage from dry spells and droughts are more significant and prolonged, making the threats of abnormally low precipitation more salient than extremely high-level events. Quite consistently, we also observe that extremely high precipitation is associated with higher income and expenditure and low poverty levels, suggesting that these events are generally a boon rather than a bane. This could be explained by the geographic and economic makeup of localities that often experience these extreme weather patterns.

In relation to the effectiveness of aid in mitigating the adverse effect of extreme weather patterns, we do not see any significant link between aid and local economic public finance or economic development. This is probably due to the extremely small amount of aid relative to the damage incurred by the locality (and its individuals) due to extreme weather shocks.

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[9] During the initial phase of the program, local governments must meet two standards to be conferred with the award: (i) compliance with full disclosure policy by posting budgetary documents online and in their bulletin boards, and (ii) absence of serious negative findings in its annual audit report published by the Commission on Audit. As a means of providing incentives, awardees will receive a grant from the new Performance Challenge Fund, which they can use to supplement funding for local development projects. The Performance Challenge Fund program provides a subsidy of ₱1 million (~$19,100) for municipalities, ₱3 million (~$57,200), and ₱7 million (~$133,550) for provinces. Projects to be funded must contribute to the attainment of the Millennium Development Goals, tourism, and local economic development, disaster risk reduction and management, and solid waste management.

In this paper, we have unpacked a number of interesting issues to understand postdisaster reconstruction. While laudable, a number of pressing issues need to be resolved. For example, we did not explicitly look at the foreign aid response. To the extent that they go through the national government and down to the local government, our analysis has included them already. However, most of this foreign aid is given directly to the community, charitable institutions, or international donor agencies and/or organizations. Thus, it would be interesting to see how this foreign aid influences local recovery process in the future.

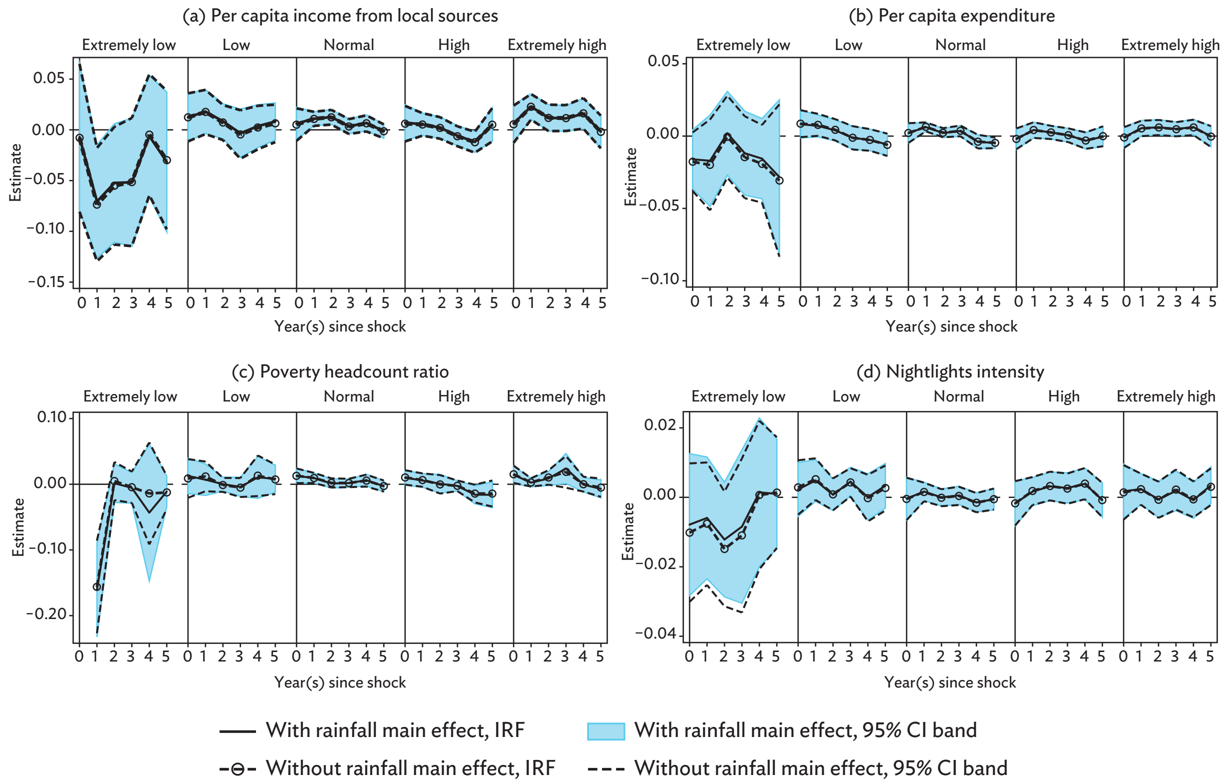
APPENDIX

Table A1: Estimated Parameters of Rainfall and Corresponding Lags on National-to-Local Transfers Per Capita

	t	*t*–1	*t*–2	*t*–3	*t*–4	*t*–5
A. National aid per capita, log						
Extremely low	–0.106**	–0.081	0.033	0.174***	0.177***	0.031
	(0.054)	(0.059)	(0.059)	(0.061)	(0.062)	(0.047)
Low	–0.059*	–0.036	0.027	0.065*	0.081**	0.047
	(0.035)	(0.036)	(0.035)	(0.035)	(0.036)	(0.035)
High	–0.001	0.064**	0.043	0.005	–0.013	0.013
	(0.028)	(0.029)	(0.028)	(0.027)	(0.027)	(0.026)
Extremely high	–0.059*	0.063*	0.112***	0.094***	0.056	0.039
	(0.035)	(0.038)	(0.034)	(0.034)	(0.036)	(0.035)
B. Internal revenue allotment per capita, log						
Extremely low	–0.010	0.000	–0.006	0.007	0.017***	–0.014
	(0.011)	(0.009)	(0.006)	(0.006)	(0.006)	(0.010)
Low	0.000	0.010**	0.003	0.003	0.003	–0.006
	(0.005)	(0.005)	(0.004)	(0.005)	(0.004)	(0.003)
High	–0.002	0.003	0.006*	0.004	0.007**	–0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Extremely high	–0.001	0.003	0.009**	0.005	0.006**	0.003
	(0.003)	(0.004)	(0.004)	(0.005)	(0.003)	(0.004)

Notes: The table presents the parameter estimates for the amount of rainfall defined in Table 1. * denotes significance at 10%, ** denotes significance at 5%, and *** denotes significance at 1% level.
Source: Authors' calculation based on national aid transfer receipt data from Government of the Philippines (2009–2018). Rainfall data from Government of the United States (1992–2013).

Figure A1.1: Marginal Effect of National Aid and Transfers Inflow, With and Without the Rainfall Variable

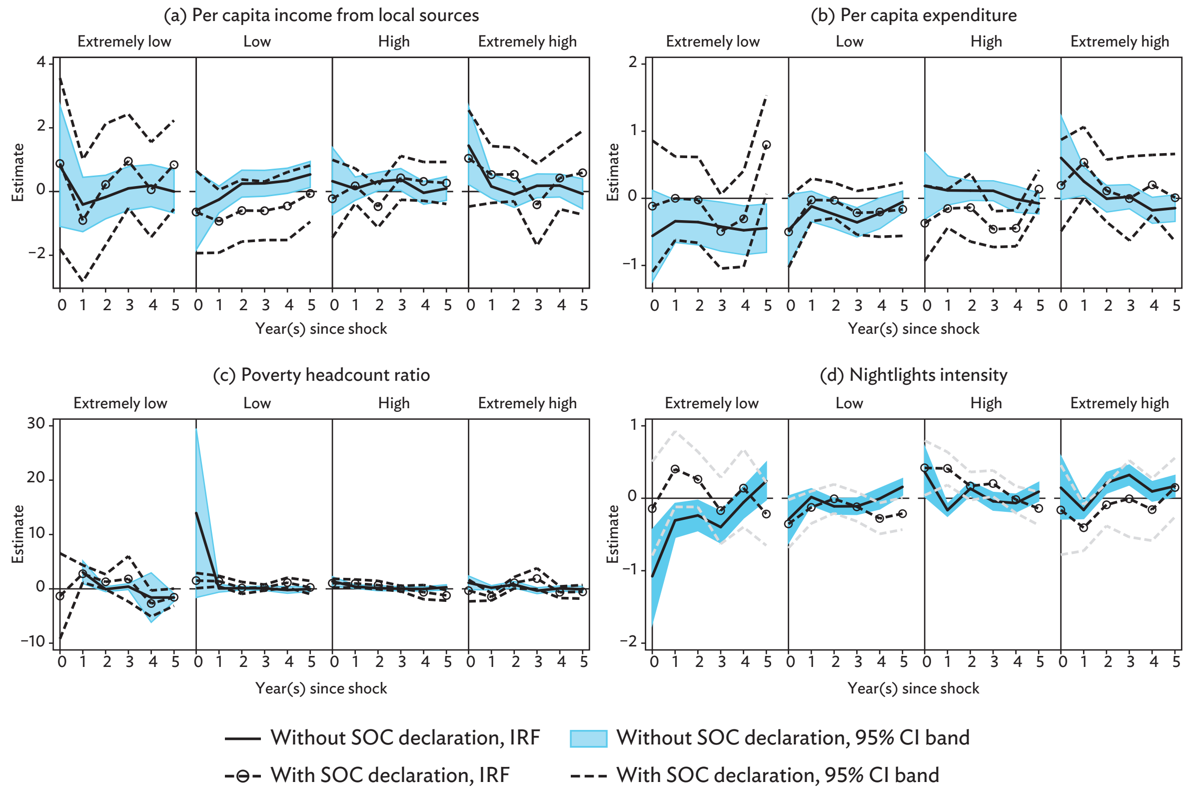


CI = confidence interval, IRF = impulse response function.

Notes: The figure illustrates the impulse response of each outcome variable to a percent increase in national aid and transfers under different rainfall scenarios, with and without the rainfall main effect variable, holding all other variables constant. The solid black line denotes the point estimates with rainfall variable, the dashed connected line denotes the point estimates without the rainfall variable, while the gray bands (dashed lines) denote the 95% confidence interval.

Source: Authors' calculation based on national aid transfer receipt data from Government of the Philippines (2009–2018). Rainfall data from Government of the United States (1992–2013).

Figure A1.2: Marginal Effect of Rainfall Conditional on the State's Declaration of a State of Calamity

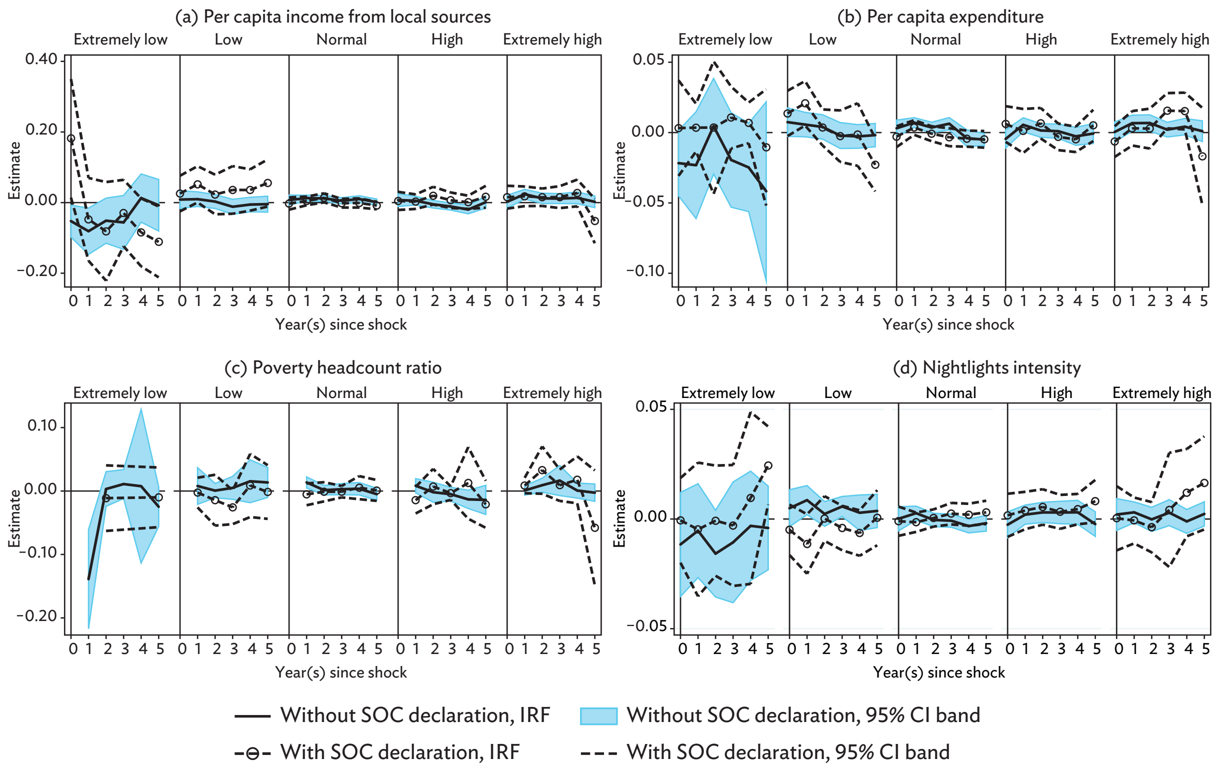


CI = confidence interval, IRF = impulse response, SOC = state of calamity.

Notes: The figure illustrates the impulse response of each outcome variable to a percent increase in national aid and transfers under different rainfall scenarios, with and without the declaration of an SOC, holding all other variables constant. The solid black line denotes the point estimates with rainfall variable, the dashed connected line denotes the point estimates without the rainfall variable, while the gray bands (dashed lines) denote the 95% confidence interval.

Source: Authors' calculation based on national aid transfer receipt data from Government of the Philippines (2009–2018). Rainfall data from Government of the United States (1992–2013).

Figure A1.3: Marginal Effect of National Aid and Transfers Inflow Conditional on the State's Declaration of a State of Calamity

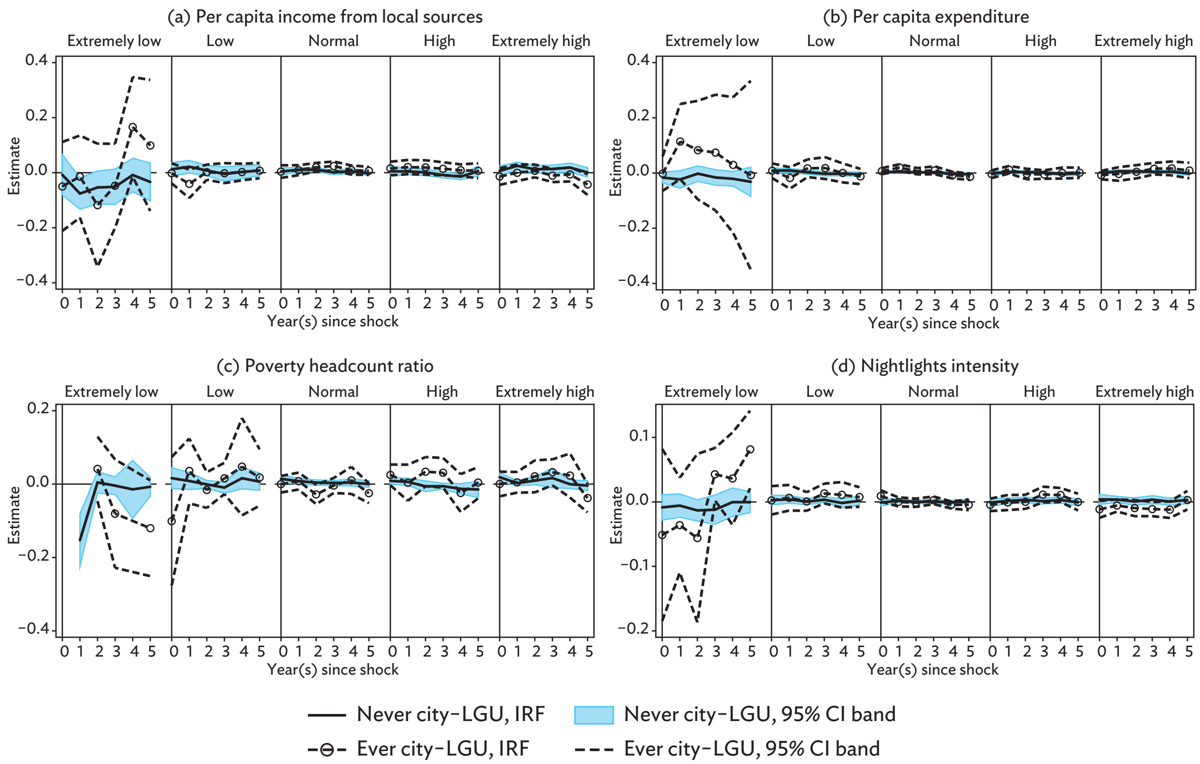


CI = confidence interval, IRF = impulse response function, SOC = state of calamity.

Notes: The figure illustrates the impulse response of each outcome variable to a percent increase in national aid and transfers under different rainfall scenarios, with and without SOC declaration, holding all other variables constant. The solid black line denotes the point estimates with SOC declaration, the dashed connected line denotes the point estimates without SOC declaration, while the gray bands (dashed lines) denote the 95% confidence interval.

Source: Authors' calculation based on national aid transfer receipt data from Government of the Philippines (2009–2018). Rainfall data from Government of the United States (1992–2013).

Figure A1.4: Marginal Effect of National Aid and Transfers Inflow Conditional on the Type of Locality

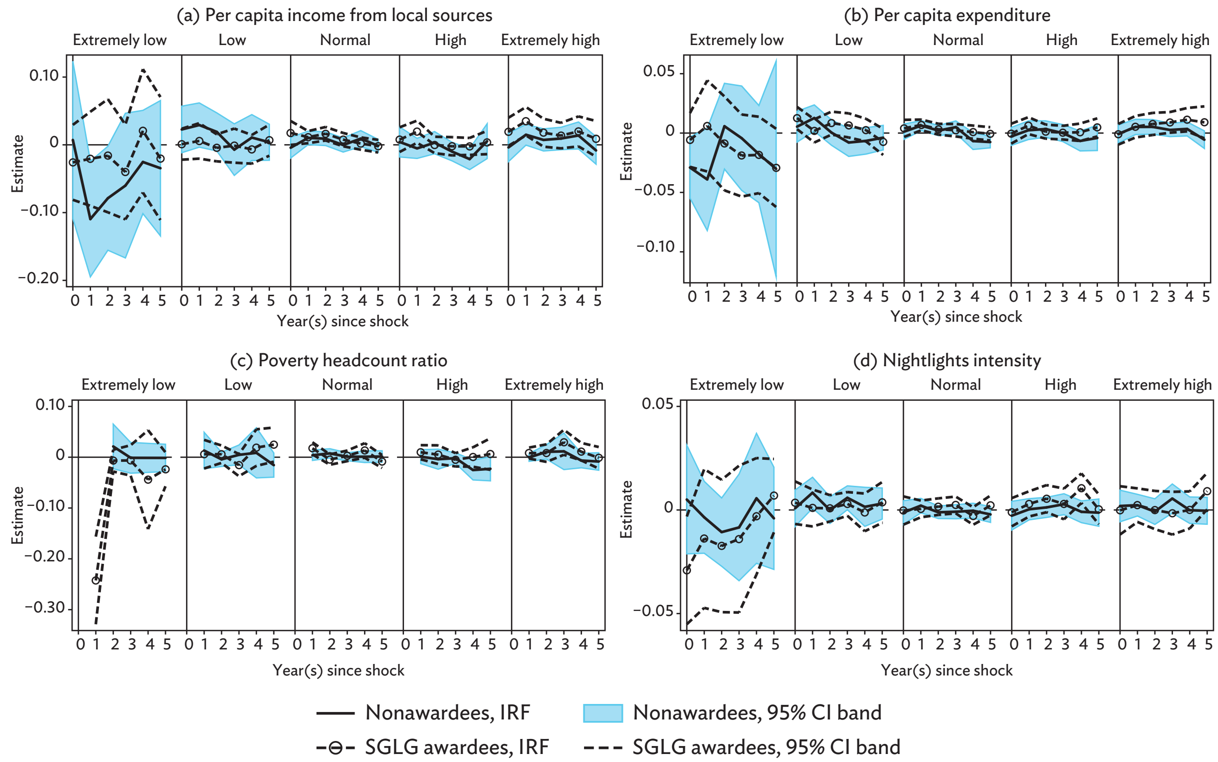


CI = confidence interval band, IRF = impulse response function, LGU = local government unit.

Notes: The figure illustrates the impulse response of each outcome variable to a percent increase in national aid and transfers under different rainfall scenarios, by cityhood, holding all other variables constant. The solid black line denotes the point estimates for local government units with city status, the dashed connected line denotes the point estimates for local government units without city status, while the gray bands (dashed lines) denote the 95% confidence interval.

Source: Authors' calculation based on national aid transfer receipt data from Government of the Philippines (2009–2018). Rainfall data from Government of the United States (1992–2013).

Figure A1.5: Marginal Effect of National Aid and Transfers Inflow Conditional on the Type of Local Governance



CI = confidence interval, IRF = impulse response function, SGLG = Seal of Good Local Governance.

Notes: The figure illustrates the impulse response of each outcome variable to a percent increase in national aid and transfers under different rainfall scenarios, by SGLG award receipt, holding all other variables constant. The solid black line (dashed connected line) denotes the point estimates for local government units with (without) SGLG awards, while the gray bands (dashed lines) denote the 95% confidence interval.

Source: Authors' calculation based on national aid transfer receipt data from Government of the Philippines (2009–2018). Rainfall data from Government of the United States (1992–2013).

REFERENCES

Aldrich, Daniel P. 2010. *Building Resilience: Social Capital in Post-Disaster Recovery*. Chicago, USA and London, UK: The University of Chicago Press.

———. 2017. "The Importance of Social Capital in Building Community Resilience." In *Rethinking Resilience, Adaptation and Transformation in a Time of Change,* edited by W. Yan and W. Galloway. Cham, Switzerland: Springer Nature.

Alipour, Fardin, Hamidreza Khankeh, Husain Fekrazad, Mohammad Kamali, Hassan Rafiey, and Shokoufeh Ahmadi. 2015. "Social Issues and Post-Disaster Recovery: A Qualitative Study in an Iranian Context." *International Social Work* 58 (5): 689–703.

Armah, Frederick Ato, David Oscar Yawson, Genesis T. Yengoh, Justice Odoi, and Ernest Amankwa Afrifa. 2010. "Impact of Floods on Livelihoods and Vulnerability of Natural Resource Dependent Communities in Northern Ghana." *Water* 2 (2): 120–39.

Bachmair, Sophie, Cecilia Svensson, Ilaria Prosdocimi, Jamie Hannaford, and Kerstin Stahl. 2017. "Developing Drought Impact Functions for Drought Risk Management." *Natural Hazards and Earth System Sciences* 17 (11): 1947–60.

Bagtasa, Gerry. 2017. "Contribution of Tropical Cyclones to Rainfall in the Philippines." *Journal of Climate* 30 (10): 3621–33.

Becerra, Oscar, Eduardo Cavallo, and Ilan Noy. 2014. "Foreign Aid in the Aftermath of Large Natural Disasters." *Review of Development Economics* 18 (3):445–60.

———. 2015. "Where is the Money? Post-Disaster Foreign Aid Flows." *Environment and Development Economics* 20 (5): 561–86.

Bruederle, Anna, and Roland Hodler. 2018. "Nighttime Lights as a Proxy for Human Development at the Local Level." *PloS one* 13 (9): e0202231.

Cabrera, Jonathan Salar, and Han Soo Lee. 2018. "Impacts of Climate Change on Flood-Prone Areas in Davao Oriental, Philippines." *Water* 10 (7): 893. https://doi.org/10.3390/w10070893.

Cashin, Paul, Kamiar Mohaddes, and Mehdi Raissi. 2016. "China's Slowdown and Global Financial Market Volatility: Is World Growth Losing Out?" IMF Working Paper WP/16/63. Washington, DC: International Monetary Fund.

Cruz, Faye Abigail, Lourdes Tibig, Jose Ramon Villarin, Rosalina de Guzman, Thelma Cinco, Gemma Teresa Narisma, and Flaviana Hilario. 2016. *The Philippine Climate*. The Oscar M. Lopez Center for Climate Change Adaptation and Disaster Risk Management Foundation Inc., 1st edition. Ch. 3, pp. 18–28.

Dado, Julie Mae B., and Hiroshi G. Takahashi. 2017. "Potential Impact of Sea Surface Temperature on Rainfall over the Western Philippines." *Progress in Earth and Planetary Science* 4: 23. https://doi.org/10.1186/s40645-017-0137-6.

Dahal, Vaskar, Sudip Gautam, and Rabin Bhattarai. 2018. “Analysis of the Long-Term Precipitation Trend in Illinois and Its Implications for Agricultural Production.” *Water* 10 (4): 433. https://doi.org/10.3390/w10040433.

Domingo, Sonny N. 2017. “Institutional Issues on Disaster Risk Reduction and Management.” Technical Report 2017–50, PIDS Discussion Paper Series.

Eguchi, Ronald T., Charles K. Huyck, Shubharoop Ghosh, and Beverly J. Adams. 2008. “The Application of Remote Sensing Technologies for Disaster Management.” The 14th World Conference on Earthquake Engineering, p. 17.

Elvidge, Christopher D., Kimberly E. Baugh, Mikhail Zhizhin, and Feng-Chu Hsu. 2013. “Why VIIRS Data are Superior to DMSP for Mapping Nighttime Lights.” Proceedings of the Asia-Pacific Advanced Network v. 35.

Emergency Events Database (EM-DAT). The OFDA/CRED International Disaster Database. www.em-dat.net.

Ghesquiere, Francis, and Olivier Mahul. 2010. “Financial Protection of the State against Natural Disasters: A Primer.” World Bank Policy Research Working Paper No. WPS 5429.

Gillespie, Thomas W., Elizabeth Frankenberg, Kai Fung Chum, and Duncan Thomas. 2014. “Night-Time Lights Time Series of Tsunami Damage, Recovery, and Economic Metrics in Sumatra, Indonesia.” *Remote Sensing Letters* 5 (3): 286–94.

Global Research Institute. 1901–2001. “Yearly Precipitation – CRUTS.” Williamsburg, VA: The College of William and Mary. www.aiddata.org/.

GMA News Online. 2007. “The El Nino Phenomenon.” 26 July. http://www.gmanetwork.com/news/news/content/52900/the-el-ni-o-phenomenon/story/ for details.

Goodman, Seth, Ariel Benyishay, and Daniel Runfola. 2017. “Overview of the Geo Framework.” Williamsburg, VA: AidData, College of William and Mary. http://geo.aiddata.org/. DOI: 10.13140/RG.2.2.28363.59686 (accessed on 3 October 2018).

Government of the Philippines. 2009–2018. “LGU Fiscal Data.” Manila: Bureau of Local Government Finance, Department of Finance database. http://blgf.gov.ph/lgu-fiscal-data/ (accessed on 3 October 2018).

———. 2018. “Philippine Disaster Risk Reduction and Management System Act of 2018. S. No. 1735 2018.” Manila: Philippines Senate.

Government of the United States. 1992–2013. “DMSP-OLS Nighttime Lights Composites, Version 4.” Boulder: National Oceanic & Atmospheric Administration. National Center for Environmental Information. ngdc.noaa.gov/eog/dmsp/downloadV4composites.html.

Hamilton, James Douglas. 1994. *Time Series Analysis*. Princeton: Princeton University Press.

Harris, I., Philip D. Jones, Timothy John Osborn, and David H. Lister. 2014. "Updated High-Resolution Grids of Monthly Climatic Observations–The CRU TS3.10 Dataset." *International Journal of Climatology* 34 (3):623–42. https://www.aiddata.org/ (accessed 3 October 2018).

Hudson, Paul, W. Wouter Botzen, Jeffrey Czajkowski, and Heidi Kreibich. 2017. "Moral Hazard in Natural Disaster Insurance Markets: Empirical Evidence from Germany and the United States." *Land Economics* 93 (2):179–208.

Institute for Economics and Peace. 2019. *Global Peace Index 2019: Measuring Peace in a Complex World.* Sydney. http://visionofhumanity.org/reports (accessed 11 October 2019).

Jayasuriya, Sisira, and Peter McCawley. 2008. "Reconstruction after a Major Disaster: Lessons from the Post-tsunami Experience in Indonesia, Sri Lanka, and Thailand." ADBI Working Paper No 125. Tokyo: Asian Development Bank Institute.

Jing, Xin, Xi Shao, Changyong Cao, Xiaodong Fu, and Lei Yan. 2015. "Comparison between the Suomi-NPP Day/Night Band and DMSP-OLS for Correlating Socio-economic Variables at the Provincial Level in China." *Remote Sensing* 8 (1): 17. https://doi.org/10.3390/rs8010017.

Jorda, Oscar. 2005. "Estimation and Inference of Impulse Responses by Local Projections." *American Economic Review* 95 (1): 161–82.

Kreft, Sönke, David Eckstein, and Inga Melchior. 2015. "Global Climate Risk Index 2015: Who Suffers Most from Extreme Weather Events? Weather-Related Loss Events in 2013 and 1994 to 2013." Technical report. Bonn: Germanwatch.

Koop, Gary, M. Hashem Pesaran, and Simon M. Potter. 1996. "Impulse Response Analysis in Non-linear Multivariate Models." *Journal of Econometrics* 74 (1): 119–47.

Li, Xi, Huimin Xu, Xiaoling Chen, and Chang Li. 2013. "Potential of NPP-VIIRS Nighttime Light Imagery for Modeling the Regional Economy of China." *Remote Sensing* 5 (6): 3057–81.

Lund, Jay, Josue Medellin-Azuara, John Durand, and Kathleen Stone. 2018. "Lessons from California's 2012–2016 Drought." *Journal of Water Resources Planning and Management* 144 (10): 04018067.

Mall, Rajesh, S. Attri, and Santosh Kumar. 2011. "Extreme Weather Events and Climate Change Policy in India." *Journal of South Asia Disaster Studies* 4 (2):27–76.

Nagy, Gustavo, Ulisses Azeiteiro, Johanna Heimfarth, Jose Verocai, Chunlan Li, and Walter Leal Filho. 2018. "An Assessment of the Relationships between Extreme Weather Events, Vulnerability, and the Impacts on Human Wellbeing in Latin America." *International Journal of Environmental Research and Public Health* 15 (9): 1802.

National Statistical Coordination Board. 2009. "The 2003 Municipal and City Level Poverty Estimates." Makati City, Philippines.

———. 2013. "The 2006 and 2009 Municipal and City Level Poverty Estimates." Makati City, Philippines.

Phaup, Marvin, and Charlotte Kirschner. 2010. "Budgeting for Disasters." *OECD Journal on Budgeting* 10 (1): 1–24.

Philippine Statistics Authority. 2016. "2012 Municipal and City Level Poverty Estimates." Quezon City, Philippines. https://psa.gov.ph/psa-press-release-tags/poverty-small-area-estimate for details (accessed on 10 November 2018).

———. 2018. 2018 Philippine Standard Geographic Code. Philippine Statistics Authority Database. http://psa.gov.ph/classification/psgc/ (accessed on 3 October 2018).

Poapongsakorn, Nipon, and Pitsom Meethom. 2013. "Impact of the 2011 Floods, and Flood Management in Thailand." ERIA Discussion Paper Series 34. Jakarta: Economic Research Institute for ASEAN and East Asia.

Ranson, Matthew, Lisa Tarquinio, and Audrey Lew. 2016. "Modeling the Impact of Climate Extreme Weather Losses." Washington, DC: National Center for Environmental Economics, US Environmental Protection Agency.

Rózsa, Szabolcs, Tamás Weidinger, Andras Zeno Gyöngyösi, and Ambrus Kenyeres. 2012. "The Role of GNSS Infrastructure in the Monitoring of Atmospheric Water Vapor." Special Issue: Application of Remote Sensing and Geoinformatics in Environmental Sciences and Agriculture. *Időjárás* 116 (1): 1–20.

Small, Christopher, and Christopher D. Elvidge. 2013. "Night on Earth: Mapping Decadal Changes of Anthropogenic Night Light in Asia." *International Journal of Applied Earth Observation and Geoinformation* 22: 40–52.

Small, Christopher, Francesca Pozzi, and Christopher D. Elvidge. 2005. "Spatial Analysis of Global Urban Extent from DMSP-OLS Night Lights." *Remote Sensing of Environment* 96 (3–4): 277–91.

Stahl, Kerstin, Irene Kohn, Veit Blauhut, Julia Urquijo, Lucia De Stefano, Vanda Acácio, Susana Dias, James H. Stagge, Lena M. Tallaksen, Eleni Kampragou, Anne F. Van Loon, Lucy J. Barker, Lieke A. Melsen, Carlo Bifulco, Dario Musolino, Alessandro de Carli, Antonio Massarutto, Dionysis Assimacopoulos, and Henny A. J. Van Lanen. 2016. "Impacts of European Drought Events: Insights from an International Database of Text-Based Reports." *Natural Hazards and Earth System Sciences* 16 (3): 801–19.

Strömberg, David. 2007. "Natural Disasters, Economic Development, and Humanitarian Aid." *Journal of Economic Perspectives* 21 (3): 199–222.

Suarez, Pablo, and Joanne Linnerooth-Bayer. 2011. "Insurance-Related Instruments for Disaster Risk reduction." In *Global Assessment Report on Disaster Risk Reduction. Geneva:* United Nations Office for Disaster Risk Reduction.

United Nations Office for the Coordination of Humanitarian Affairs Financial Tracking Service Database. 1980–2019. "About FTS." [Website, and series of records published online]. https://fts.unocha.org/content/about-fts-1 (accessed on 20 November 2018).

Versluis, Anna. 2014. “Formal and Informal Material Aid Following the 2010 Haiti Earthquake as Reported by Camp Dwellers.” *Disasters* 38 (s1): S94–S109.

Villacin, Deanna T. 2017. “A Review of Philippine Government Disaster Financing for Recovery and Reconstruction.” Technical Report 2017–21. PIDS Discussion Paper Series. Quezon City: Philippine Institute for Development Studies.

Wang, S.-Y. Simon, Jin-Ho Yoon, Emily Becker, and Robert Gillies. 2017. “California from Drought to Ddeluge.” *Nature Climate Change* 7 (7): 465.

Wei, Jianwen, and Yang Han. 2018. “Pre-disaster Social Capital and Disaster Recovery in Wenchuan Earthquake-Stricken Rural Communities.” *Sustainability* 10 (6): 2046.

Yang, Dean. 2008. “Coping with Disaster: The Impact of Hurricanes on International Financial Flows, 1970–2002.” *The B.E. Journal of Economic Analysis & Policy* 8 (1): 1935–62.

Yumul Jr., Graciano P., Carla B. Dimalanta, Nathaniel T. Servando, and Flaviana D. Hilario. 2010. “The 2009–2010 El Niño Southern Oscillation in the Context of Climate Uncertainty: The Philippine Setting.” *Philippine Journal of Science* 139 (1): 119–26.

National-to-Local Aid and Recovery from Extreme Weather Events

Evidence from the Philippines

Using local-level data on public income and expenditures, precipitation, poverty incidence, and satellite-based night-light luminosity, this paper examines the link between extreme weather events and national aid and transfers in the Philippines between 1992 and 2015. It finds that the national government allocates more national aid and transfers during dry spells when damage is significantly higher and more prolonged compared to periods of higher-than-usual precipitation. The paper also finds no significant link between national-to-local aid and local public finance and economic development to mitigate the adverse effects of extreme weather patterns.

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