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# The Determinants of Subnational Public Spending Allocation for Disaster Risk Reduction in Bangladesh


## Abstract

We examine the directly observable determinants of sub-national (central to local) public spending allocations for disaster risk reduction and climate adaptation in Bangladesh, a country with a very high exposure to weather risk. We use a comprehensive dataset for the 483 sub-districts (Upazilas) in Bangladesh, tracking disaster risk reduction and adaptation funding provided to each sub-district by the central government during fiscal years' 2010-11 to 2013-14, disaggregated by the various types of social protection programs. We assess to what extent the primary determinants of such funding flows—such as current hazard risk, socio-economic vulnerability, and political economy considerations—contribute to these funding allocation decisions. We find that flood hazard risk and socio-economic vulnerability are both positively correlated with the sub-district fiscal allocations. We find that political factors do not seem to significantly correlate with these allocations and neither does proximity to the centres of Dhaka and Chittagong. Public spending for adaptive disaster risk reduction, as investigated here, can be a useful complementary intervention tool to other DRR programs, such as insurance or broader social transfers, provided that it is allocated rationally. Broadly, this appears to be the case in Bangladesh. We leave the measuring of the relative efficacy and efficiency of each financing tool for future work.


JEL-Codes: Q540.

Keywords: subnational public spending, disasters, risk reduction, adaptation, Bangladesh.

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# 1.INTRODUCTION

Climate change impacts in the developing world are unavoidable. This realization makes adaptation to the shocks associated with the changing distribution of extreme weather events progressively more urgent and more prominent in development policy priority (e.g. Ayers and Abeysinghe, 2013; Karim and Noy, 2016a, 2016b, 2018). In particular, spending on disaster risk reduction (DRR) is perceived to be a rather neglected but important part of adaptation to climate change (e.g. World Bank, 2010; Asian Development Bank, 2019; Karim, 2018).[1] However, there is little empirical work that is examining the way disaster risk reduction spending is allocated.

Bangladesh has a long history with extreme weather events, due to its topography and geography and its location on the shores of the Bay of Bengal. In addition to already existing risks, Bangladesh is predicted to be one of the most exposed countries to climate change impacts in the coming decades (Bandyopadhyay and Skoufias, 2015). Extreme weather events in Bangladesh range from floods and tropical cyclones to river bank erosion and droughts. Flooding associated with the monsoon season occurs practically every year in some parts of the country. The monsoon rain plays, of course, also a pivotal role in securing domestic agricultural production, but it nevertheless kills people and devastates crops and livelihoods. Along the coasts, the most destructive tropical cyclones generate storm surges that can inundate vast areas of land, and have in the near past killed hundreds of thousands of people.

Given all these observations, it is obvious that the Bangladesh government has been focussed on disaster emergency planning and disaster risk reduction programs for a long time, and that an investigation into its capacity to mobilise and allocate resources rationally in these spending programs can be informative and useful. It is this intra-country allocation of DRR spending in Bangladesh that is the focus of this paper.

[1] Following convention—as adopted by the United Nations Office for Disaster Risk Reduction, and the 2015 Sendai Framework for Disaster Risk Reduction global treaty—we use the term "Disaster Risk Reduction" to broadly mean any spending on disaster risk management, and not narrowly limiting it to the spending aimed at reducing *ex ante* risks.

In this context, it is important to note that Bangladesh's policies for DRR are widely perceived as successful examples of what can be achieved in a resource-constrained developing country. In particular, Bangladesh is often mentioned for its successful intervention programs - e.g. its early warning systems for cyclones. Most recently for Tropical Cyclones *Sidr* in 2007 and *Aila* in 2009, Bangladesh managed to evacuate millions of people away from the coast and the storm's surge (see Paul and Dutt, 2010).[2] Bangladesh's successful disaster risk reduction policies are also favourably mentioned in the context of its management of the annual monsoon floods (e.g. del Ninno et al., 2003).

Some recent literature has examined the determinants' of aid allocation for climate change adaptation, especially in the international comparative context (e.g. Weiler, Klock and Dornan, 2018). We are not aware of much literature that investigates the determinants of public financing allocation for DRR, at the subnational level in lower- and middle-income countries.[3]

Here, we ask: "what determines subnational public spending for disaster risk reduction and adaptation in Bangladesh?" We aim to investigate whether the flows of DRR funding are conditional on primary determinants such exposure to local hazards, local vulnerabilities, and other local attributes such as the proximity of political affiliation between the sub-district and the center.[4] The only related work is Miller and Vela's (2014) work on Peru.

This paper contributes to the literature by offering a unique subnational analysis that aims to identify the rationale behind the central government's funding for disaster risk reduction and adaptation in Bangladesh's 483 sub-districts. We show that both climatic risk and socio-economic vulnerability are significant determining factors in the DRR fiscal allocations we examine. In contrast

[2] For further data and a comparison of *Sidr* to previous storms, see p. 502 in IPCC (2012).
[3] Vorhies (2012) summarizes the literature on fiscal spending on DRR, and also does not identify any research on the determinants of this spending.
[4] Hodler and Raschky (2014) identify political favoritism in regional allocations by examining the intensity of nighttime light in regions associated with the political leadership (but their focus is on regional development spending). Aldrich (2010) and Takasaki (2011) identify the ability of elites to capture post-disaster reconstruction spending in India and rural Fiji, respectively.

with the *ex post* disaster aid literature, political factors do not seem to be important in determining regional funding allocation for DRR.

The paper presents some implications on the implementation of disaster risk reduction policies. In the United Nations Climate Change Convention (1992, Article 4.4), the developed countries agreed to assist "particularly vulnerable" developing countries to adapt to climate change. One potential justification of prioritization of bilateral adaptation aid could be good governance; in this case interpreted as the efficient intra-state allocation of public funding (Stadelmann et al., 2014). With evidence of effective targeting of affected groups, public spending on disaster risk reduction could be a useful intervention tool to be thus funded.

The next section describes the conceptual framework linking social protection, disaster risk reduction and climate change adaptation. Section 3 provides a literature review, while Section 4 describes the social protection programs in Bangladesh. Section 5 describes the data and provides detailed description of our methodology. In Section 6, we present and analyze the estimation results along with robustness checks. Finally, in Section 7, we conclude with relevant policy implications and some suggestions about further research.

## 2. SOCIAL PROTECTION, DISASTER RISK REDUCTION AND CLIMATE CHANGE ADAPTATION: A CONCEPTUAL FRAMEWORK

To conceptualize and establish the links between social protection, disaster risk reduction and climate change adaptation, we primarily adapt two strands of the literature. The first strand focuses on the adaptation benefits of social protection; i.e. adaptive social protection.[5] As highlighted in Norton et al. (2001), most of the definitions of social protection include the need to address

[5] The term Adaptive Social Protection was formulated at the end of the 2000s by researchers from the Institute of Development Studies at the University of Sussex who realized that social protection, disaster risk reduction and climate change adaptation were three communities of practices that had evolved from different origins but were all linked by the same fundamental concern for reducing vulnerability and building resilience—be it to chronic poverty (social protection), disasters and extreme events (disaster risk reduction) or changes in the distribution of climatic conditions over time and space (climate change adaptation) - See Bene et al. (2018).

vulnerability and reduce risk, and the determination of levels of (absolute) deprivation that are deemed unacceptable. Besides the conventional perception of social protection as social welfare programs for poor communities, Devereux and Sabates-Wheeler (2004) argues that social protection should extend to the entire population as it can be socially transformative. In the adaptation literature, transformation is becoming an increasingly important concept as worsening climate change impacts are likely to demand more substantial—i.e., transformative—responses (e.g. Bonfigliolo and Watson, 2011; Park et al. 2012; Fenton et al., 2017a). Following this framework, Fenton et al. (2017a) provides evidence of the transformative capacity of microfinance to facilitate climate change adaptation through both *ex ante* risk reduction and *ex post* disaster recovery.[6] In their risk-hazard approach, weather-induced extreme events (flood risk in the current context) can be viewed as the intersection of hazard, exposure and vulnerability.[7] This framework defines clear connection between disaster risk reduction efforts and social protection as the latter is aimed at reducing vulnerability, and potentially limiting exposure as well (e.g. IPCC, 2012; Fenton et al., 2017a).

[FIGURE 1 HERE]

Figure 1 displays the conceptual framework to illustrate the links between social protection, climate change adaptation and disaster risk reduction. In this conceptualization; some social protection programs contribute to disaster risk reduction and to climate change adaptation. By placing social protection in the context of the exposure and vulnerabilty to natural hazards, Davies et al. (2009) describe a similar framework tying the three nodes together within the context of the changing climate- impacts, including the future plausible occurence of conditions that have not been experienced within the past reach of our collective memories.

Our argument is that the social protection programs we analyse in this paper, for example those whose objective is ensuring food security, have this broader scope that also includes protection

[6] See Fenton et al. (2015) for an overview of microfinance. However, Fenton et al. (2017a) also notes ways in which microfinance may be hindering adaptation by sustaining indebtedness.

[7] Fenton et al. (2017b), however, note that the risk hazard approach can sometimes undervalue an investigation of unique vulnerabilities and especially equity concerns.

in the context of longer-term adaptation to extreme weather events and other similar shocks.[8] Similar arguments are raised by several papers who evaluate these programs' effectiveness in addressing vulnerabilities in Bangladesh (e.g., Kamal and Saha, 2014; Coirolo et al. 2013; Khuda, 2011). In particular, the Vulnerable Group Development (VGD) and Food for Work (FFW) programs address social protection and disaster risk reduction through protective, preventive measures (Al-Mansur, 2011). Our aim in this paper is not to substantiate the adaptation and DRR benefits of social protection programs but to investigate the determinants' of the central government's subnational financing allocations for disaster risk reduction and adaptation, through social protection programs. We examine whether these flows of funds are conditional upon primary determinants of the risk as it manifests by the interaction of hazard, exposure, and vulnerability.

The literature, however, has also portrayed the limitations of social protection programs (e.g., Conning and Kevane, 2002; Deshingkar, Johnson and Farrington, 2005; Kamal and Saha, 2014; Coirolo et al. 2013; Al-Mansur, 2011; Khuda, 2011). Public spending on social protection programs might not result in desired outcomes as there might be mis-targeting of beneficiaries, regional disparities in the efficacy of implementation, and leakages in program funding flows. All of these may be exacerbated because disaster risk reduction and climate change adaptation are not the sole aims of some of these spending programs.

## 3. LITERATURE REVIEW

Recently, there has been an emergence of academic research on the climate adaptation benefits of social protection highlighting their preventive and transformative nature (e.g. Bene et al. 2018; Davies M., Bene, C. et al. 2013; Fenton et al. 2017a). Besides their explicitly intended role, social protection programs were found to reduce disaster risk, enhance post-disaster relief distribution

[8] Brown (2014) provided a literature review on these links while Awal (2013) and Fenton et al. (2017a) provided an examination of the integration potential of social safety nets, disaster risk reduction and climate change adaptation in Bangladesh. See also Hasan (2017) for a detailed structural breakdown of social protection in Bangladesh.

channels, and assist in recovery and rehabilitation (e.g. Bastagli and Holmes, 2014; Fiszbein, Kanbur and Yemtsov, 2014; Gehrke and Hartwig, 2018). After all, helping households cope with covariate shocks that affect entire communities is one of the objectives of social protection (i.e. Bastagli and Holmes, 2014; Bastagli et al. 2016; Barca, 2018). While many countries do not yet have a comprehensive social protection system, all have social protection elements that can be assessed for their contribution in reducing vulnerability and enhancing resilience to shocks (e.g. Clare O'Brien et al. 2018; McCord, 2013; ASEAN 2019). This is true for Bangladesh as well.

'Adaptive Social Protection' refers to efforts to integrate social protection (SP), disaster risk reduction (DRR) and climate change adaptation (CCA). The need for realizing this adaptive protection goal is increasingly being recognised by both researchers and practitioners (Davies et al., 2013). The existing literature has focussed mostly on theoretical elaboration rather than on the empirical evidence, and successfully explored the ways in which aspects of DRR, social protection and livelihood approaches contribute to increasing adaptive capacity and facilitate adaptation to climate change (e.g. Smit and Wandel, 2006; Davies et al. 2009; Jones et al. 2010). Against this background; our objective here is to investigate the determinants' of the central government's sub-national financing allocations for disaster risk reduction and adaptation through social protection programs in Bangladesh. We particularly focus on whether these flows of funds are conditional upon primary determinants of the risk as it manifests by the interaction of hazard, exposure, and vulnerability.

Jones et al. (2010) argue that a combined approach can enhance adaptive capacity within a community or system with a variety of interventions falling along the adaptation continuum. These combined programs can address longer-term stresses for different segments of the population and at different scales of spatial aggregation. For climate change adaptation, Heltberg, Jorgensen and Siegel (2008) emphasized instruments such as social funds for community-based adaptation, flexible safety nets designed to respond to climatic shocks and disasters, and microfinance. Heltberg (2007) argued that social protection—income support in particular—is less liable to be misappropriated and could be designed for greater impact.

At the local level, Jones, Ludi and Levine (2010) proposed a framework to assess this adaptive capacity by examining five parameters: the available asset base, existing institutions and entitlements, available knowledge and information, capacity for innovation, and flexible forward-looking decision-making practices. These parameters influence and determine the degree to which a community is resilient and responsive to changes in the external environment and could further be utilized to monitor progress, conduct needs assessments, and allocate development resources to enhance a system's ability to adapt to change.

The need for social protection through the provision of social safety nets has been reiterated in various papers that focus on disaster risk reduction; for example, Rahman and Choudhury (2012) and World Bank (2010). Heltberg (2007) described South Asian countries' long experience of using public workfare programs to respond to national and local disasters, focussing in particular on cash-for-work and food-for-work programmes. In Bangladesh, workfare is routinely part of the response to disasters. After the flooding of 2004, for example, safety-net programmes such as Vulnerable Group Development, Vulnerable Group Feeding, Food-for-Work, Test Relief, and Gratuitous Relief distributed a total of 0.74 million metric tons of food grains in addition to corrugated iron sheets, clothing, and cash assistance (Heltberg, 2007).

A demonstration of the crucial role that government social safety net programs can play in DRR is the comparison of the severe flood of 1998 with the equally severe flood in 1974. In 1998, the government's emergency food and financial assistance, through improved management of targeted programs such as Vulnerable Group Feeding (VGF) and Food For work (FFW), helped prevent mass starvation when compared with the impacts of the 1974 flood (Khandker, 2007).

In addition to social protection programs, we also include in our analysis 'investments in specific infrastructure' when the targeted aim of this infrastructure is disaster risk reduction. For example, the Department of Disaster Management in Bangladesh constructs bridges and culverts (up to 12 meters long) under its Annual Development Plan – the explicit aim for this spending on infrastructure is DRR, rather than development more generally or poverty alleviation.

The recent literature has mostly focused on inter-country adaptation finance allocation in the global context (e.g. Bickenbach, Mbelu and Nunnenkamp, 2019; Weiler, Klock and Dornan, 2018; Stadelmann et al. 2013) and there are very few projects investigated intra-country adaptation financing allocation (e.g. Barrett, 2014 on Malawi). Intra-country allocation is our focus here.

A burgeoning literature investigates the efficacy of public spending in lower income countries more generally. This literature examines spending on public infrastructure in Uganda and Mexico (Sennoga and Matovu, 2013; Ramirez, 2004), on public health spending in Indonesia (Kruse et al., 2012), on food aid (Clay, Molla, & Habtewold, 1999; Jayne et al., 2001; Jayne et al., 2003), on disaster response (Besley & Burgess, 2002; Morris & Wodon, 2003; Francken, Minten & Swinnen, 2012; Takasaki, 2011); education (Reinikka & Svensson, 2004); the allocation of foreign multinational assistance (Zhang, 2004); and on general fiscal spending (Rajkumar and Swaroop, 2008).

Agrawal (2010) describes how existing national plans to promote adaptation to climate change have been mostly inattentive to the role of local institutions in adaptation, and ignored the links between local populations and national policies. In his view, national-level efforts to develop adaptation plans need to consider the role of local institutions and social capacities, especially if they seek to serve the needs and interests of the most vulnerable populations. Fenton et al. (2017a) focus on a different mechanism for reducing vulnerability or exposure, microfinance. Using an in-depth climate-vulnerable village case study from Bangladesh, Fenton et al. (2017b) demonstrate that the risk-hazard approach is suitable for exploring autonomous adaptations.

Another relevent perspective for our research on the fiscal allocations is the financial/debt sustainability aspects of post-disaster fiscal management. These have been examined, for example, for Bangladesh after the 1998 flood (Benson and Clay, 2002) or for Belize (Borensztein et al., 2009). Several cross-country studies have also attempted to measure the average post-disaster fiscal costs of a proto-typical disaster (Noy and Nualsri, 2011; Lis and Nickel, 2010; Hochrainer-Stigler et al., 2014).

Miller and Vela (2014), in the paper most similar to ours, examine the allocation of disaster funding (both preventative and for recovery) for the Peruvian regions (districts in the Bangladeshi context), and focus on whether distribution of public expenditure in both the recovery and prevention categories is conditional upon the occurrence of disasters in the recent past, and on exposure and vulnerability. They find it difficult to correlate spending with measureable risk.

The future probability of exposure to hazards (and their probable intensity) is proxied here by past experience of this hazard. We focus on DRR activities that are mostly related to flood exposure, and therefore focus on flood risk. We measure the past exposure to hazards using details of rainfall record in each region. The risk associated with geological hazards is much more difficult to forecast, and this partly justifies our choice to focus on Bangladesh, where disaster risk is generally only associated with climatological events (unlike, for example, Peru) – see Kerr (2011).

The two other components of disaster risk, after the hazard itself, is the exposure of the population, and its vulnerability. Socio-economic vulnerability is as important as geographical exposure in order to more fully understand community-level adaptive capacity (Yonson et al., 2018). The past literature that has identified indicators measuring socio-economic vulnerability to natural hazards (Cutter et al. 2009; Tapsell et al. 2010) motivates our use of such socio-economic indicators. The political dimension of fiscal DRR policy has also been receiving attention in recent years with a primary focus on the evident failure of politicians' and voters' to prioritize prevention over post-event response – see Healy and Malhotra (2009) and Garrett and Sobel (2003) on US DRR funding, Cole et al. (2012) on India, and Fuchs and Rodriguez-Chamussy (2014) on Mexico. When funding is awarded *ex ante*, the evidence seems to suggest that governments favour spending in regions that are politically aligned with the party in power (e.g. Cohen and Werker, 2008). This observation motivates our investigation into the political economy of fiscal spending in the sub-districts.

## 4. SOCIAL PROTECTION SPENDING AND DISASTER RISK REDUCTION PROGRAMS IN BANGLADESH

In investigating the fiscal allocation, we examine several adaptive social protection spending programs employed by the central government to allocate funding to the sub-districts (upazilas).[9] The

[9] Rahman et al. (2011) provides an overview of the social protection programs in Bangladesh.

Test Relief (TR) program has been in place since 1975 in rural areas. This program is mainly for repairing roads, damaged infrastructure such as schools and clinics, and other rural activities. It provides employment opportunities by providing 8 kilograms of rice/wheat to every person in return for working 7 hours/day in specific projects related to disaster risk reduction and mitigation. The Gratuitous Relief (GR) program (established in 1973) is designed to provide a maximum of 20 kilograms of rice/wheat to affected poor households with no associated work requirements. Vulnerable Group Feeding (VGF) is another form of gratuitous relief (that is without work requirement) and is normally launched during or after a disaster and attempts to assist people remaining vulnerable to hunger. The GR program is used during the immediate emergency, whereas VGF is utilized later for post-disaster recovery support.

The Food For Work (FFW) program is designed for construction, maintenance, reconstruction and development of rural infrastructure. Based on government food and monetary support, various rural infrastructural projects (many of them aimed at reducing vulnerability) are financed under this program during normal times and in post-disaster scenarios. Among these infrastructure projects, the Department of Disaster Management funds construction of bridge/culverts (up to 12 meter long) under the Bridges and Culverts program.

[FIGURE 2 HERE]

Figure 2 demonstrates the link between "regular spending"–i.e., the allocations to programs that are related to shocks—and the total disaster-related spending for the time period, 2000-2013.[10] The disaster-related economic impacts (particularly from flood) are found to be significantly higher in 2002, 2003, 2004, 2007 and 2009. These years were further characterized by a major catastrophic flood in 2004 and storm surges associated with Tropical Cyclones *Sidr* and *Aila* in 2007 and 2009, respectively. On average, the 'regular' DRR funding (through social protection and cash transfer

[10] Here, regular spending includes Vulnerable Group Feeding (VGF) and other Public Works (PWs) program and Cash Transfer programs. Total disaster-related funding includes funding for recovery and rehabilitation projects, humanitarian aid and foreign aid on disaster-related emergency responses (ADB, 2015). We thank an anonymous reviewer for suggesting this analysis.

programs) has been above $200 million per year with an increasing trend. However, regular funding has been comparatively low in the disaster years of 2004 and 2007, with funding mostly allocated through recovery and rehabilitation projects, and through humanitarian and foreign aid. Intriguingly, despite an increasing trend in the allocation of regular funding during 2010-2013, an average disaster-related funding allocation of about $50 million per year suggests that some of the recovery and rehabilitation efforts following 2007 tropical cyclone *Sidr* and 2009 cyclone *Aila* spilled over to 2010-2013. It is also interesting to note here that regular spending in 2013 appears to be relatively higher than disaster-related funding (which is through humanitarian aid and foreign aid on disaster-related emergency responses) although cyclone *Mahasen* and monsoon floods affected millions of people in that year.[11] The assumption here is that higher level of allocation of "regular" spending will make allocation of emergency spending less necessary.

[FIGURE 3 HERE] [FIGURE 4 HERE]

Figures 3 and 4 display the amount of allocated and realized spending, in per capita, by program (i.e. TR, FFW, VGF, GR and Infrastructure) over the period FY 2010-11 to FY 2013-14. There are no clear trends of spending over these years by program, but the spending does vary after natural hazard events. For example, apparently the flood event in FY 2012-13 triggered an increase in the amount of allocated and realized spending for all the programs being analysed in that year.[12]

## 5. DATA AND METHODOLOGY

The data for this study were collected from various Bangladeshi government sources described below, both online and in print (see also the appendix for more details). The public spending data, at the local government level, were collected from publications of Bangladesh's Ministry of Food (former Ministry of Food and Disaster Management) – where sub-district (upazila) disaster risk

[11] See Bangladesh Report, 2013.

[12] In Bangladesh, an initial allocation is made at the beginning of the year for most of the programs listed e.g. TR, GR and VGF. Then they are activated in case of need. We thank an anonymous reviewer for clarifying this point.

reduction and adaptation funding allocation data from FY (fiscal year) 2010-11 to FY 2013-14 were available. For each year, the dataset records the "allocation" (allocated spending) and "expenses" (realized spending) for the various social protection programs - Test Relief (TR), Food For Work (FFW), Gratuitous Relief (GR) and Vulnerable Group Feeding (VGF). It also records the same information for the DRR infrastructure program (i.e. construction and repair of bridges /culverts).

(a) Dependent variables: allocated and realized spending

[FIGURE 5 HERE] [FIGURE 6 HERE]

Figures 5 and 6 demonstrate the distribution of funding allocated and realized across the 483 sub-districts in Bangladesh. Data has been aggregated by adding up allocations in general and special categories under the five programs previously described, for each of the 483 sub-districts over the four consecutive years (FY 2010-11 to 2013-14) for which we have the funding allocations data. We converted the in-kind food allocations provided in some of these programs to their monetary values using the contemporaneous (annual average) market wholesale price of rice in Dhaka. We divide total allocated and realized spending amounts for each program/sub-district by the size of the population of each corresponding sub-district to generate per capita information.

(b) Upazila flood risk index

Due to its geographical location at the confluence of three major rivers – the Ganges, the Brahmaputra and the Meghna; Bangladesh is an extremely flood-prone country. River-bank flooding occurs mostly during the monsoon period (June-September). High rainfall is primarily the reason of river-bank floods.[13] Flooding is an annual phenomenon in Bangladesh with about 20% of the country affected by floods on an average year. Floods cause considerable economic losses. On average, Bangladesh is expected to incur losses amounting $2.2 billion in 2014 dollars (equivalent to 1.5 percent of GDP) due to floods (ADB, 2015). According to ADB (2015), the 1998 flood has been the most catastrophic, affecting almost 68 percent of the country and causing losses equivalent to more than 9% of GDP.

[13] Other, less common types of flooding are the flash floods (in hilly areas) and storm surges (along the coast). See also Paul and Mahmood (2016) & Kundzewicz et al. (2014).

We calculate an Upazila Flood Risk index (UFRI) for each of the 483 sub-districts of Bangladesh. The index captures historical rainfall variability to determine local flood risk. To develop this index, we collected annual rainfall data from the Bangladesh Meteorological Department for 1948-2012 from 35 weather stations covering the whole country.[14] We use the coefficient of variation (CoV) as the measure of local rainfall variability.[15] Coefficient of variation is the ratio of standard deviation and mean.[16] We also utilize the 1998 flood as an indicator to identify the historically flood prone upazilas.[17] Therefore, our measurement of upazila flood risk (UFRI) is therefore: *UFRI = (Historical rainfall CoV) *( 1998 flood indicator).*

For the historical rainfall data, we first aggregate the total monthly monsoon rainfall (June-September) for each year-station. We next calculated the mean and standard deviation for each monsoon season for each sub-district by matching weather stations with sub-districts. In cases where a sub-district did not have a rainfall measurement station, we used the average from the nearest three rainfall stations. We interacted this measure with historical flood proneness of the particular Upazila.[18] The UFRI has a mean of 45.61 with 36.24 as the standard deviation. We note that in as much as this index is based on past experiences, it does not capture the projected future changes that are associated with climatic change.

### (c) Socio-economic vulnerabilities, political risk and other determinants

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[14] Guiteras, Jina and Mobarak (2015) use satellite data for imputed rainfall, but find that this data is poorly correlated with actual flooding.

[15] Rose (2001) and Bandyopadhyay and Skoufias (2015) also utilize the Coefficient of Variation indicator as a measure of rainfall variability.

[16] We also tried the mean and standard deviation as two separate indicators of rainfall parameters. They provide similar results and are therefore not reported.

[17] Bangladesh Water Development Board (BWDB) characterizes the 1998 flood as: ‘‘The 1998 flood in Bangladesh has been characterized as one of the catastrophic deluge on record. River water levels exceeded danger levels for country’s all of the major rivers. It was combined with local rainfall in catchment areas of small rivers. All these influences including overbank flow and drainage congestion resulted in a flood that extended over most of the country with duration of weeks to months.’’

[18] An Upazila has been considered as historically flood prone if 50% or more of the area in the Upazila were flooded during the monsoon period of 1998 for which the percent of Upazila flooded information is available (See Bandyopadhyay and Skoufias, 2015 for further details ).

Population numbers and poverty rates for each sub-district (annually) were collated from government circular orders of the Department of Disaster Management. Our proxy for "economic development" for each sub-district is a composite variable averaging the shares of the population with access to basic amenities (i.e. electricity, safe drinking water, and sanitation facilities) from the 2011 Population and Housing Census of Bangladesh.

To capture the strength of political connection in allocation of funding from the central government to the sub-regions, we construct a binary variable that measures whether the Member of Parliament (MP) representing the respective sub-district belongs to the main political party in power. To construct this variable, we link the 300 electoral constituencies to the 483 sub-districts based upon the electoral delimitation information on the Bangladesh Gazette (2013). Information regarding election results and the sub-district representatives has been collected from the Bangladesh Election Commission report of 2008.

According to the Coastal Zone Policy of the Government of Bangladesh (2005), the zone is divided into "exposed coast" (the area/upazilas that front the sea directly, and "interior coast" (the area/upazilas that are located behind the exposed coast). Here, we include both groups to create the "coastal belt binary variable." Another dummy variable has been created to capture ethnic divisions within the sub-district. Bangladesh, unlike some of its neighbours, is relatively homogenous. We include a dummy variable noting if indigenous ethnic minorities reside in a particular sub-district. To create this ethnicity dummy, we use information from the 2011 Population and Housing Census of Bangladesh. We add three more binary variables. The first identifies the central sub-district in any particular district (in most cases, this central sub-district has bigger populations, higher degree of urbanization and more industrialization). The other indicates urban sub-districts associated with the two mega-cities of Dhaka and Chittagong. The presence of a public university in each upazila has also been included.

(d) Descriptive statistics

[TABLE 1 HERE]

Table 1 reports the descriptive statistics of public spending on DRR in Bangladesh (the LHS variables in our estimations), including both allocated and realized spending for the four fiscal years' 2010-11 to 2013-14 for each of the programs described earlier. These statistics include mean, standard deviation, and the maximum of total allocated and realized spending per capita for Test Relief (TR), Vulnerable Group Feeding (VGF), Food For Work (FFW), Gratuitous Relief (GR) and Infrastructure Spending (Bridges and Culvert construction under FFW). The mean for DRR allocated (realized) spending per capita is 28.92 (23.17). On average, TR provided the highest amount of funding per capita, followed by VGF, while the maximum amount in a single sub-district has been distributed through the VGF program.

[TABLE 2 HERE]

Table 2 demontrates the descriptive statistics for all the independent (RHS) variables. The mean population size in each sub-district is 0.26 million. The Upazila Flood Risk Index (UFRI) has a mean of 45.61 with a standard deviation of 36.24. The political risk dummy indicates that approximately 77 percent of sub-districts are represented by MPs from the ruling party as a consequence of the 2008 general elections. Approximately 19 percent of the 483 sub-districts are situated in the coastal zone.

## (e) Methodological framework

We start with the following functional form: $SPEND_{ij} = f(risk_i, pop_i, pov_i, dev_i, D_i)$.

Public spending ($SPEND_{ij}$) in sub-district (*i*), for program (*j*), is a function of several variables: *risk* is calculated as an index constructed from past exposure as defined earlier; the population (*pop*) and poverty (*pov*) rates in the receiving sub-district; and a composite measure of economic development (*dev*: a composite measure indicating access to electricity, water and sanitation). The binary independent variables (vector *D*), include political affiliation with respect to ruling party representations, presence of ethnic minorities, being a district headquarter, being a sub-district in either of the two large megacities, presence of a public university and being located by the coast.

The spending variable, the dependent variable, measures either the allocated or realized amount for each sub-district, and social protection program (indicated by superscript $x$). Our theoretical prior is that the primary determinants' should have positive correlation with sub-districts' disaster risk reduction and adaptation funding allocation. Ceteris paribus, a sub-district with higher perceived risk, more poverty, less access to public services, more political connections, and a coastal location should be receiving more DRR funding (either allocated or realized). We are agnostic regarding several of the other determinants, including location as districts headquarter or as part of the two metropolitan agglomerations, and the presence of ethnic minorities.

Given the censored nature of the dependent variable, we estimate the following Tobit regression model to account for the censored data and arrive at consistent coefficient estimates:[19]

$$y^{x}{}_{ij} = \beta X_{ij} + u_{ij}$$

$$y\,^{x}_{ij} = \begin{cases} y\,^{x*}_{ij} \ if\ SPEND^{x}_{ij} > 0 \\ 0 \qquad if\ SPEND^{x}_{ij} = 0 \end{cases}$$

Where $y\,^{x}_{ij}$ is the dependent variable of the outcome equation, $X_{ij}$ is a vector of covariates, $\beta$ is a vector of coefficients and $u_{ij}$ is the random disturbance term. We estimate our model with robust standard errors clustered by sub-districts.

## 6. ESTIMATION RESULTS

We start by estimating our benchmark model with all categories of public spending for disaster risk reduction and adaptation at the sub-district level as the dependent variables. In addition to an examination of the total allocated and realized spending, we investigate these determinants for each specific program separately.

### (a) Aggregated adaptive disaster risk reduction spending: allocated vs. realized

[19] The Tobit model is the standard technique used to estimate equations with censored dependent variables. The assumption of normally distributed residual is crucial for the consistency of the Tobit estimates. See also Garrett and Sobel (2003) for an investigation of FEMA disaster payments in the US.

[TABLE 3 HERE]

Table 3 reports the identifiable determining factors for the allocation of public spending towards disaster risk reduction through social protection programs at the sub-district level. For this aggregate spending, our a priori is these are primarily determined by the flood risk factor, by coastal proximity, by socio-economic vulnerability, by political connections, and by other determining factors as highlighted in the previous literature (See Guillaumont, 2013; Guillaumont and Simonet, 2011; Duus-Otterstrom, 2016; Halimanjaya, 2014; Hoeffler and Outram, 2011; Robinson and Dornan, 2016; Francken, Minten and Swinnen, 2012). Our results show a significant positive increase in total allocated spending due to an increase in upazila flood risk. This is a re-assuring finding; the spending is allocated at least partially according to the degree of risk that each upazila is facing.

Consistently with previous papers, poverty rate, an indicator of socio-economic vulnerability, is found to be a robust indicator of adaptive disaster risk reduction funding with higher poverty associated with more funding. The coastal variable is also highly significant and positive, and allocations are less likely to be directed to the bigger urban districts (Dhaka and Chittagong). Other determinants, including the political affiliation of the local Member of Parliament do not seem to play any role in determining funding levels. This latter finding is in contrast with the previous findings about the political economy context of DRR spending in other countries (e.g. Garrett and Sobel, 2003; Francken, Minten and Swinnen, 2012). Estimation results of the total realized spending (column 2) are found to exhibit very similar patterns (in sign and significance) to the equivalent allocated aggregate spending (column 1).

(b) Disaggregated spending categories: obligatory vs. non-obligatory

[TABLE 4 HERE]

We further estimate and report our benchmark model results with disaggregated allocated and realized spending as dependent variables, in categories based on conditional requirements (work/without obligation to work). As defined earlier; obligatory public spending is dispersed through programs which include work requirements such as Test Relief, Food for Work and Bridges and Culvert construction programs. Both obligatory spending (allocated and realized) are found to be significantly (5% significance level) associated with upazila flood risk. Allocated spending through obligatory programs are found to increase by 0.183 units due to one unit increase in the risk factor of the particular sub-district.

We further show infrastructure spending (in the Bridges and Culverts program) results separately because of our particular interest in disaster risk reduction. Both allocated and realized funding in this category demonstrate a positive and significant relationship with upazila flood risk in attracting subnational funding. For the non-obligatory public spending[20] (allocated and realized) there is still a positive association with the flood risk measure, but it is not statistically significant. We note that in the time period examined here, lower amounts of funding were disbursed through the non-obligatory social protection programs included in our analysis.

Among the primary determinants, coastal effect seems to be the only consistently statistically significant variable with positive coefficients for all the disaggregated categories of funding. The poverty rate also has a positive coefficient for all disaggregated categories, but these are only statistically significant for the obligatory realized spending program. Contrary to the contemporary broader funding and relief distribution literature, the political connections variable estimates are mostly negative (but always insignificant).

### (c) The primary determinants: comparative analysis

In this section, we highlight our findings regarding the key determinants of the funding allocations we investigate. Comparison between aggregated (total allocated and realized) funding and the corresponding disaggregated ones reveals upazila flood risk (measured based on past exposure) and the coastal location are very significant determining factors in sub-districtwise distribution in Bangladesh; as is found in the cross-country case by Guillaumont (2013) and Huq et. al (2005). The poverty rate (our proxy for socio-economic vulnerability) is also a robust determinant for the

[20] Non-obligatory per capita public funding are dispersed through targeted safety net programs which do not have work requirements in their structural mechanism. Here, the non-obligatory safety net programs are Gratuitous Relief and Vulnerable Group Feeding.

subnational allocation of central government spending. This is crucial as the justification of a "need-based approach" compared to other interests (for example, interests of the political elites) has widely been examined in various contexts of adaptation finance.

Nevertheless, in the context of local government financing of adaptive disaster risk reduction through social protection programs, we find that risk and vulnerability seem to be dominant factors in the government's sub-districtwise funding allocation decision-making.[21] The political risk factor seems to be counter-intuitively, but consistently, negative (though not statistically significant) in all cases - aggregated and disaggregated (with exceptions in infrastructure spending) which seems to contrast with other funding allocation literatures in adaptation financing and disaster relief distribution (e.g. Beg, 2019).

In addition to our analysis of the primary determinants, we further analyze the findings of the other determinants. These are economic development, ethnicity, district headquarter, public university, and population. They do not seem to significantly affect regional funding allocations for disaster risk reduction and adaptation.[22] The megacity urban measure for Dhaka and Chittagong is, however, statistically significant, but negative, thus suggesting that affiliations with the bigger cities does not attract more funding (and potentially attracts less).

(d) Robustness checks

[TABLE 5 HERE]

In Table 5, we compare the results obtained from the Tobit estimation with a Ordinary Least Squares (OLS) estimates for the specifications for total spending. Our benchmark estimations are found to be quite consistent across both estimation methods in terms of the significance and the sign and magnitude of the relationship of the primary determinants (i.e. upazila flood risk, poverty rate and coastal effect) with both total allocated and realized spending. The political risk factor is again statistically insignificant. The other determinants exhibit the same consistent pattern as well.

[21] This finding, however, do not rule away the fact that different proxies and measurements could demonstrate variations in comparative results. See also Bickenbach, Mbelu and Nunnenkamp (2019).
[22] All of these variables exhibit positive and non-significant results.

## 7. CONCLUSION AND POLICY REMARKS

Our primary objective is to identify the directly observable determinants' of publicly allocated and realized spending for disaster risk reduction at the subnational (local government) level and to assess to what extent the primary determinants (i.e. flood risk, socio-economic vulnerability and politics) contributed to these allocation decisions. We collect a unique comprehensive dataset for 483 sub-districts in Bangladesh tracking disaster risk reduction and climate adaptation funding during fiscal years' 2010-11 and 2013-14 through social protection programs funded by the Bangladesh central government. Our priors are that, ceteris paribus, a sub-district with higher flood risk (based on past exposure), more poverty (as proxy for socio-economic vulnerability), more political connections, and a coastal location should be receiving more funding.

Our results strongly suggest that flood risk and coastal location and proximity are indeed significant indicators for public spending at the subnational level in Bangladesh, both aggregated and disaggregated by types of spending. This finding is consistent with the findings of the climate adaptation aid allocation literature (e.g. See Weiler, Clock and Dornan (2018); Barrett, 2014; Betzold and Weiler, 2017; Robinson and Dornan, 2016; Karim and Mimura, 2008; Huq et. Al.,2005). The other significant focus of our findings is on socio-economic vulnerability. The poverty rate is an equally consistent determinant in the subnational allocation of central government's DRR and CCA spending.

Interestingly, we consistently fail to find any significance for close political affiliation in attracting sub-district level public funding for disaster risk reduction and climate adaptation. This observation, however, is consistent with the findings of Weiler, Klock and Dornan (2018) for adaptation aid allocation, but it does contrast with some of the literature on *ex post* disaster relief distribution (e.g. Garrett and Sobel, 2003). Among the other independent variables we examine; location within the two mega-cities (Dhaka or Chittagong) is consistently negative and significant, implying that funding is more likely to go to more outlying areas. The other variables we include are never statistically significant.

The findings we present have some policy implications in terms of implementing disaster risk reduction that corresponds to the global policy agenda as it was set in the Sustainable Development Goals and the Sendai Framework for Disaster Risk Reduction. It is re-assuring that, at least in the Bangladesh Government case, much of the funding that is targeting these goals appear to be directed appropriately.

Public spending for adaptive disaster risk reduction, as investigated here, can be a useful complementary intervention tool to other DRR programs, such as insurance, or broader social transfers.[23] All these funding programs, of course, have not been without their detractors, with mis-targeting of beneficiaries and leakages in program funding being some of the main criticisms. At this point, we find little evidence of political pressures guiding funding in specific directions. Equally, the relative ability of all these programs to achieve their stated goals and sustainably assist recipients needs to be investigated. We leave the measuring of the relative efficacy and efficiency of each financing tool for future work.

[23] See Fiszbein, Kanbur and Yemtsov (2014); Duru (2016); Gehrke and Hartwig (2018).

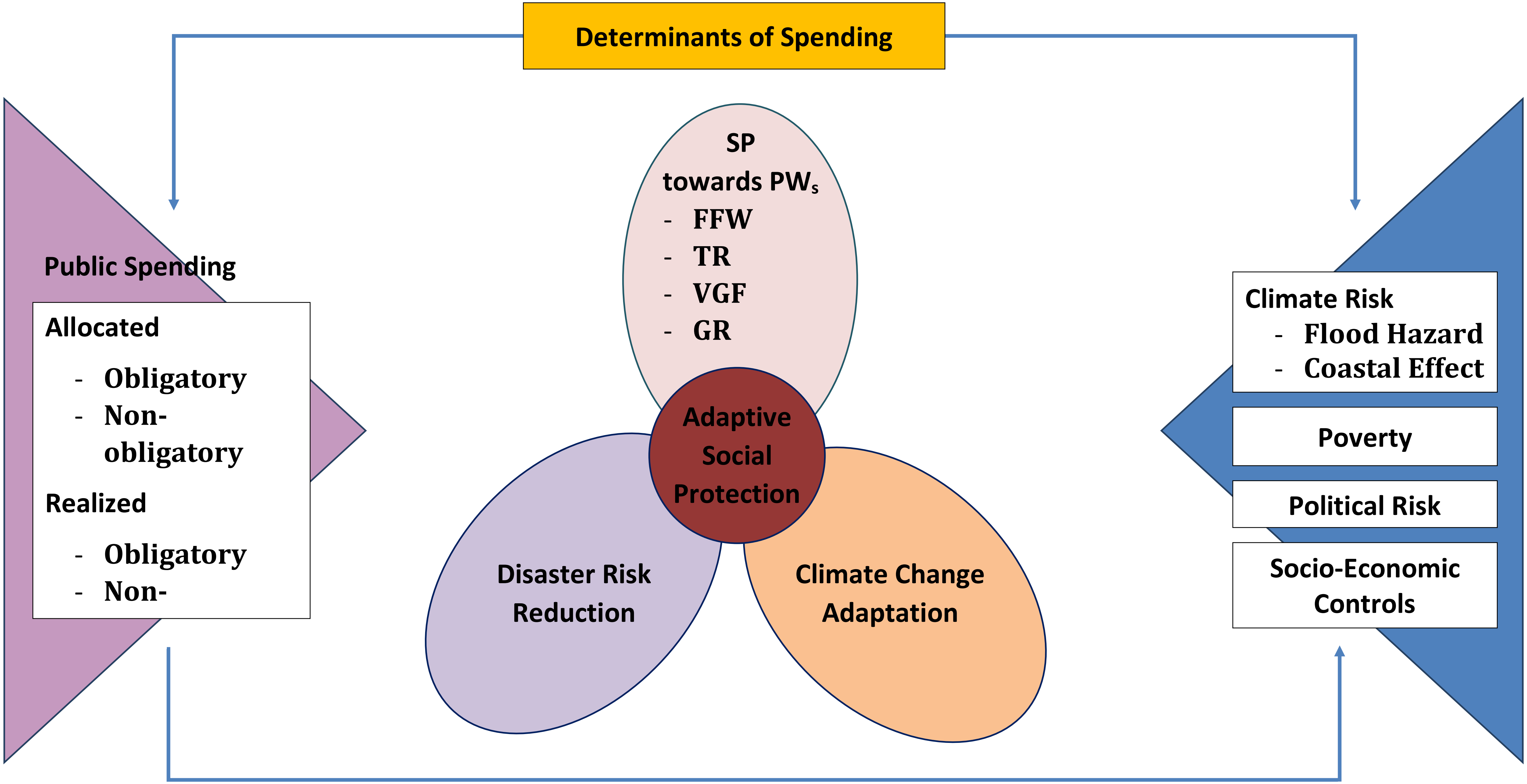


Figure 1: Authors’ elaborations of the conceptual framework based on Davies et al. (2009), IPCC (2014) and Karim (2018).

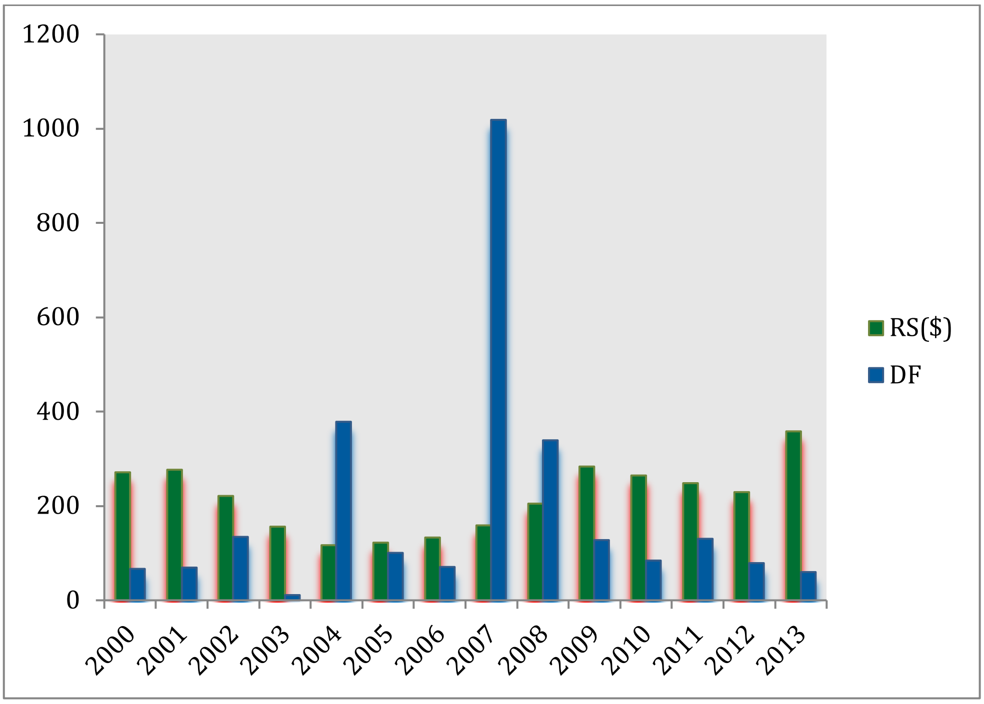


**Figure 2: Links between Regular Spending (RS) and Disaster Funding (DF), 2000-13**
*Source:* Ministry of Finance, GOB and Rahman et al. (2011).

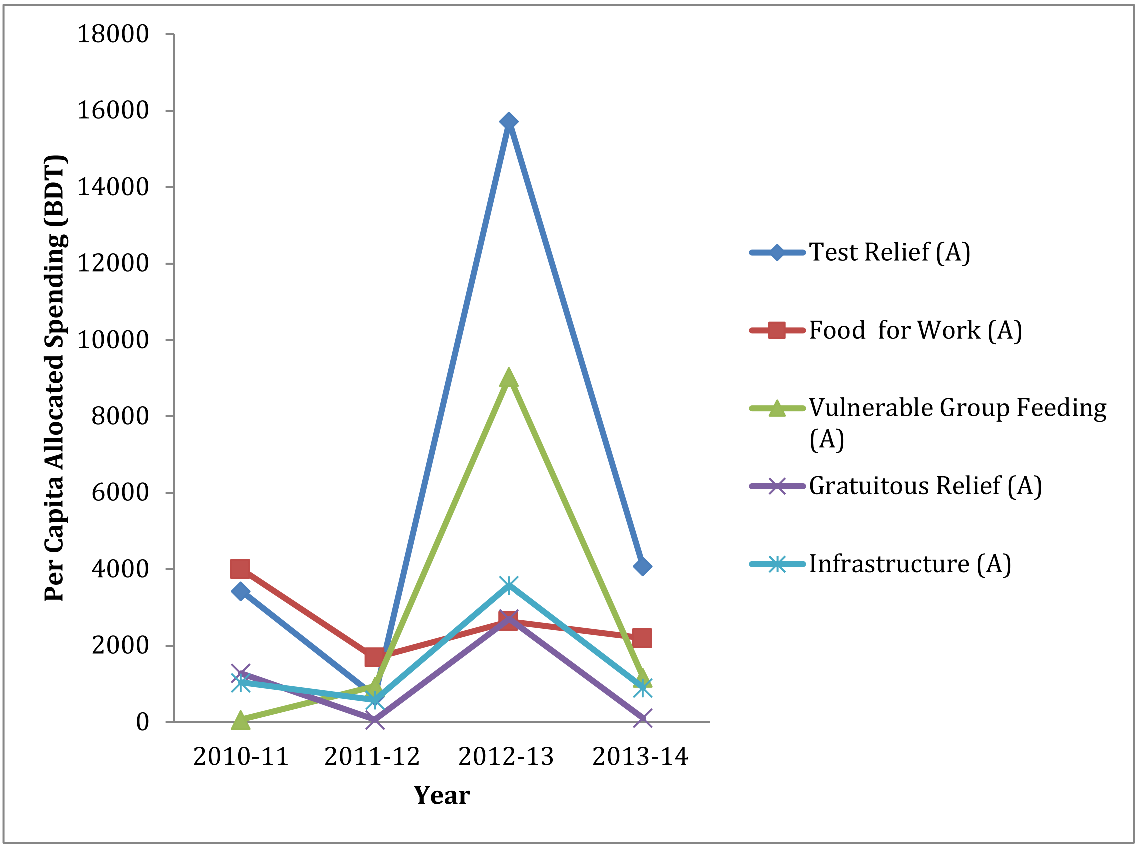


**FIGURE 3: PER CAPITA ALLOCATED SPENDING BY DRR PROGRAMS**

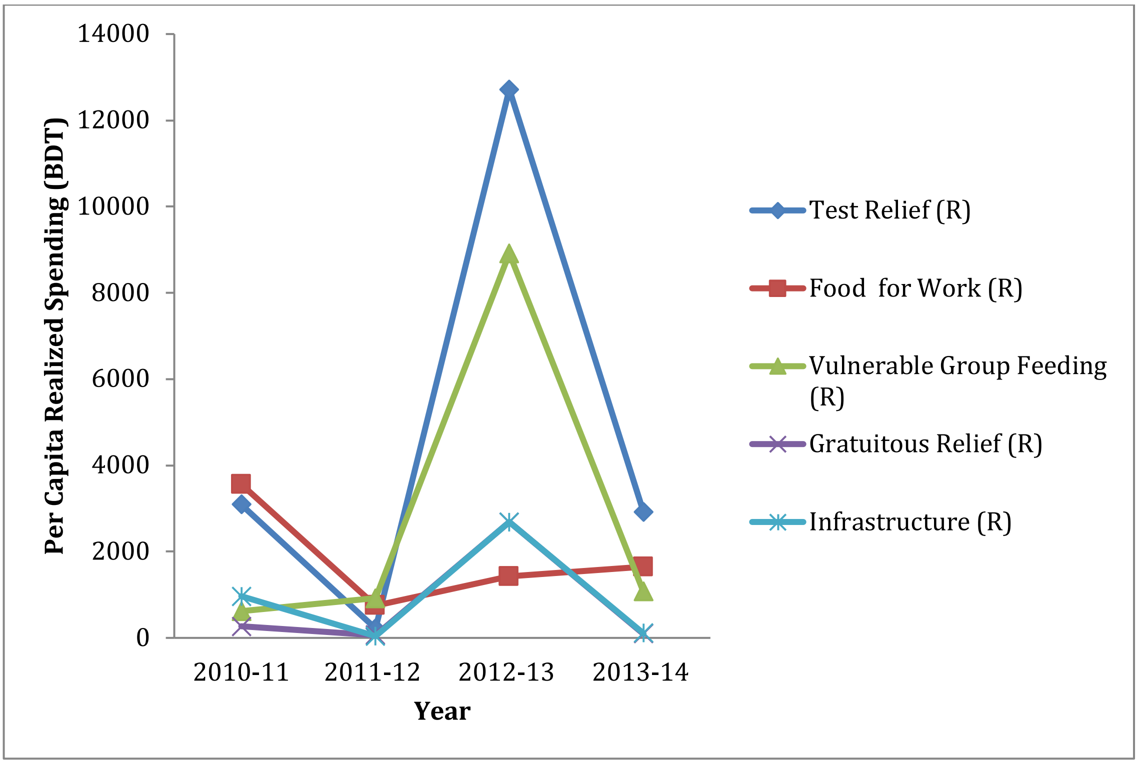


**FIGURE 4: PER CAPITA REALIZED SPENDING BY DRR PROGRAMS**

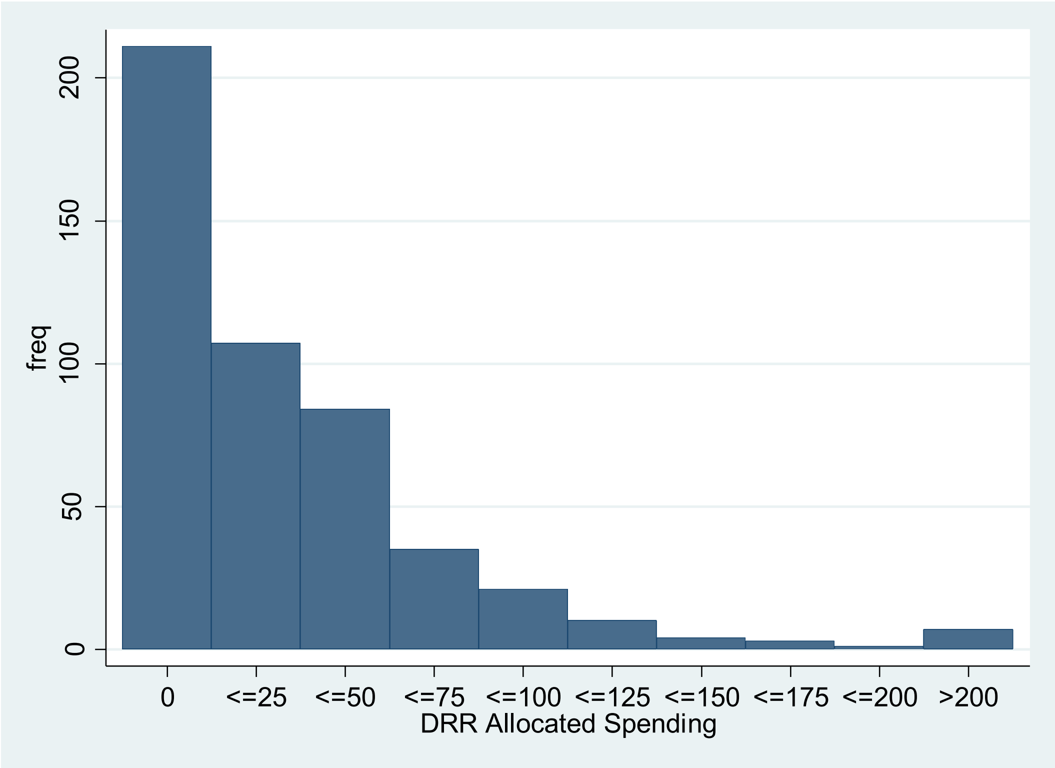


**FIGURE 5: DISASTER RISK REDUCTION PER CAPITA ALLOCATED SPENDING DISTRIBUTION**

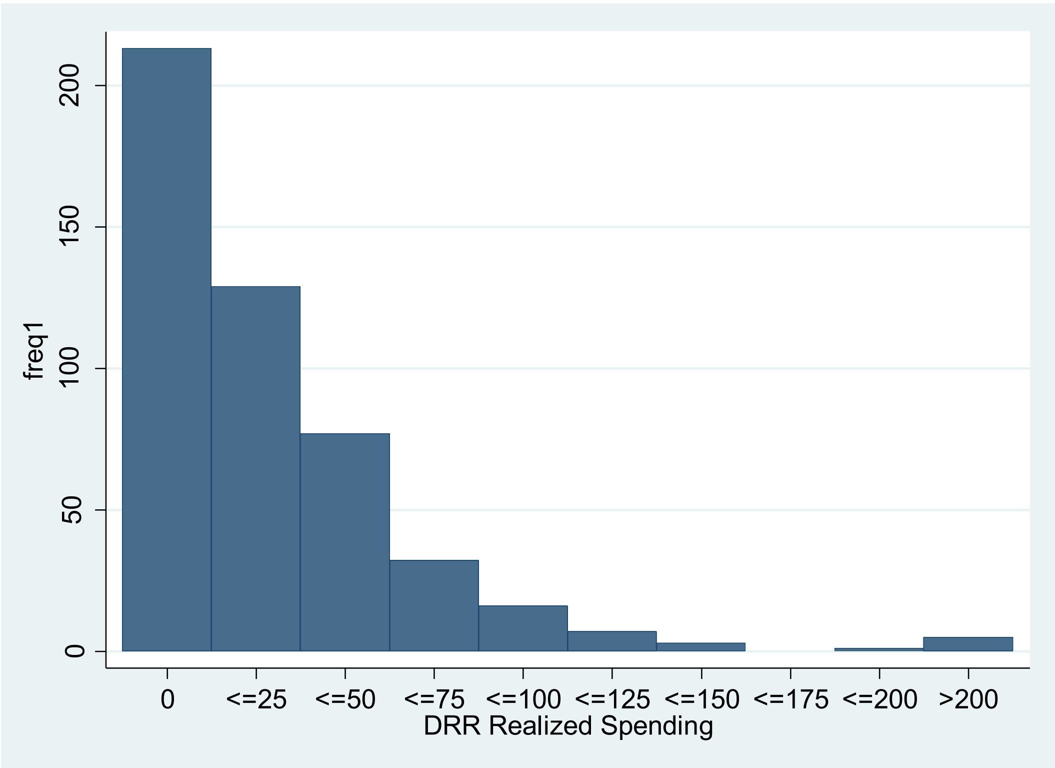


**FIGURE 6: DISASTER RISK REDUCTION PER CAPITA REALIZED SPENDING DISTRIBUTION**

### TABLE 1: DESCRIPTIVE STATISTICS FOR DEPENDENT (LHS) VARIABLES

| VARIABLES | OBSERVATION | MEAN | STANDARD DEVIATION | MAXIMUM |
|---|---|---|---|---|
| **DRR TOTAL ALLOCATED SPENDING** | 483 | 28.92 | 80.69 | 968.60 |
| **DRR TOTAL REALIZED SPENDING** | 483 | 23.17 | 73.12 | 966.68 |
| **TR ALLOCATED SPENDING** | 483 | 12.37 | 17.59 | 137.63 |
| **TR REALIZED SPENDING** | 483 | 9.81 | 14.29 | 95.31 |
| **FFW ALLOCATED SPENDING** | 483 | 5.44 | 13.48 | 126.40 |
| **FFW REALIZED SPENDING** | 483 | 3.82 | 9.06 | 90.42 |
| **INFRASTRUCTURE ALLOCATED SPENDING** | 483 | 3.16 | 9.59 | 102.81 |
| **INFRASTRUCTURE REALIZED SPENDING** | 483 | 1.96 | 7.55 | 102.81 |
| **GR ALLOCATED SPENDING** | 483 | 2.15 | 20.46 | 374.93 |
| **GR REALIZED SPENDING** | 483 | 1.61 | 17.20 | 374.93 |
| **VGF ALLOCATED SPENDING** | 483 | 5.80 | 42.97 | 921.98 |
| **VGF REALIZED SPENDING** | 483 | 5.97 | 43.01 | 921.98 |

*Source:* Authors' calculations.
*Note:* The acronyms used here represents Disaster Risk Reduction (DRR), Test Relief (TR), Food For Work (FFW), Infrastructure, Gratuitous Relief (GR) and Vulnerable Group Feeding (VGF) Allocated and Realized Spending respectively (all in per capita terms). The currency unit is BDT (Bangladeshi Taka) [1 USD = 83.90 BDT].

# TABLE 2: DESCRIPTIVE STATISTICS FOR INDEPENDENT (RHS) VARIABLES

| VARIABLES | OBSERVATION | MEAN | STANDARD DEVIATION | MINIMUM | MAXIMUM |
|---|---|---|---|---|---|
| UPAZILA FLOOD RISK | 483 | 45.61077 | 36.24235 | 0 | 115 |
| POVERTY RATE | 483 | 28.34 | 13.24 | 1.9 | 68 |
| ECONOMIC DEVELOPMENT | 483 | 52.60 | 11.12 | 8.1 | 73.5 |
| ETHNICITY | 483 | 0.46 | 0.50 | 0 | 1 |
| DISTRICT HEADQUARTER | 483 | 0.13 | 0.34 | 0 | 1 |
| URBAN EFFECT | 483 | 0.04 | 0.19 | 0 | 1 |
| COASTAL EFFECT | 483 | 0.19 | 0.39 | 0 | 1 |
| PUBLIC UNIVERSITY | 483 | 0.37 | 0.48 | 0 | 1 |
| POPULATION | 483 | 255833.4 | 138584.8 | 17152 | 941005 |
| POLITICAL RISK | 483 | 0.78 | 0.42 | 0 | 1 |

*Source:* Authors' Calculations.

### TABLE 3: DETERMINANTS OF TOTAL ALLOCATED AND REALIZED SPENDING

| VARIABLES | TOTAL ALLOCATED SPENDING | TOTAL REALIZED SPENDING |
|---|---|---|
| UPAZILA FLOOD RISK | 0.384* | 0.408** |
| | (0.201) | (0.191) |
| POVERTY RATE | 1.107* | 1.088* |
| | (0.638) | (0.571) |
| ECONOMIC DEVELOPMENT | 0.423 | 0.446 |
| | (0.489) | (0.451) |
| ETHNICITY | 1.787 | 4.659 |
| | (13.08) | (11.33) |
| DISTRICT HEADQUARTER | 10.71 | 11.38 |
| | (14.21) | (12.75) |
| URBAN EFFECT | -45.32* | -41.97* |
| | (23.16) | (22.15) |
| COASTAL EFFECT | 55.05*** | 48.38*** |
| | (18.23) | (18.19) |
| PUBLIC UNIVERSITY | 8.387 | 8.668 |
| | (8.767) | (7.160) |
| POPULATION | -1.03e-07 | -6.14e-06 |
| | (3.87e-05) | (3.32e-05) |
| POLITICAL RISK | -13.02 | -13.02 |
| | (11.80) | (10.91) |
| CONSTANT | -81.28 | -84.42* |
| | (49.80) | (48.24) |
| SIGMA | 93.12*** | 81.92*** |
| | (19.20) | (20.73) |
| OBSERVATIONS | 483 | 483 |

*Source:* Authors' Calculations.
*Note:* Robust standard errors (clustered by sub-district) in parentheses *** p<0.01, ** p<0.05, * p<0.1.

## TABLE 4: DETERMINANTS OF OBLIGATORY AND NON-OBLIGATORY SPENDING

| VARIABLES | OBLIGATORY ALLOCATED SPENDING | OBLIGATORY REALIZED SPENDING | INFRASTRUCTURE ALLOCATED SPENDING | INFRASTRUCTURE REALIZED SPENDING | NON-OBLIGATORY ALLOCATED SPENDING | NON-OBLIGATORY REALIZED SPENDING |
|---|---|---|---|---|---|---|
| **UPAZILA FLOOD RISK** | 0.183** | 0.172** | 0.0824** | 0.0765** | 0.174 | 0.234 |
| | (0.0900) | (0.0713) | (0.0396) | (0.0346) | (0.202) | (0.207) |
| **POVERTY RATE** | 0.417 | 0.382** | 0.126 | 0.116* | 0.875 | 0.901 |
| | (0.282) | (0.189) | (0.0807) | (0.0659) | (0.669) | (0.671) |
| **ECONOMIC DEVELOPMENT** | 0.171 | 0.0946 | -0.0477 | -0.0422 | 0.593 | 0.817 |
| | (0.249) | (0.205) | (0.0933) | (0.0807) | (0.632) | (0.657) |
| **ETHNICITY** | -6.305 | -3.481 | -2.286 | -1.622 | 14.56 | 14.60 |
| | (6.767) | (4.629) | (2.070) | (1.397) | (14.59) | (14.49) |
| **DISTRICT HEADQUARTER** | 8.340 | 7.761 | 4.183 | 4.272 | 0.788 | 1.484 |
| | (9.495) | (8.067) | (3.746) | (3.653) | (14.06) | (13.88) |
| **URBAN EFFECT** | -21.81** | -17.19** | -4.469 | -2.998 | -56.31 | -56.98 |
| | (9.910) | (7.854) | (3.493) | (2.900) | (37.17) | (37.29) |
| **COASTAL EFFECT** | 23.86*** | 19.99*** | 5.797*** | 4.165*** | 59.62** | 52.39** |
| | (5.677) | (4.414) | (1.357) | (1.134) | (27.32) | (26.58) |
| **PUBLIC UNIVERSITY** | 7.524 | 6.398* | 2.116 | 1.317 | -0.629 | 0.665 |
| | (5.458) | (3.772) | (1.408) | (1.049) | (9.324) | (9.085) |
| **POPULATION** | 9.49e-07 | -4.99e-06 | -7.60e-06 | -8.35e-06 | 8.18e-06 | 7.37e-06 |
| | (2.42e-05) | (1.83e-05) | (7.54e-06) | (6.82e-06) | (3.74e-05) | (3.67e-05) |
| **POLITICAL RISK** | -5.546 | -4.016 | 1.527 | 0.764 | -16.09 | -17.85 |
| | (5.729) | (4.390) | (1.576) | (1.218) | (14.65) | (14.84) |
| **CONSTANT** | -26.04 | -21.78 | -9.255* | -8.506** | -130.8* | -143.1* |
| | (19.16) | (14.08) | (5.274) | (4.003) | (73.51) | (77.30) |
| **SIGMA** | 49.04*** | 36.36*** | 14.73*** | 11.84*** | 90.48*** | 88.37*** |
| | (4.241) | (2.881) | (2.481) | (2.636) | (30.98) | (31.99) |
| **OBSERVATIONS** | 483 | 483 | 483 | 483 | 483 | 483 |

*Source:* Authors' Calculations.
*Note:* Robust standard errors (clustered by sub-district) in parentheses *** p<0.01, ** p<0.05, * p<0.1.

**TABLE 5: DETERMINANTS OF TOTAL ALLOCATED AND REALIZED SPENDING - ROBUSTNESS**

| VARIABLES | TOTAL ALLOCATED SPENDING (TOBIT) | TOTAL ALLOCATED SPENDING (OLS) | TOTAL REALIZED SPENDING (TOBIT) | TOTAL REALIZED SPENDING (OLS) |
|---|---|---|---|---|
| UPAZILA FLOOD RISK | 0.384* | 0.201* | 0.408** | 0.231** |
| | (0.201) | (0.120) | (0.191) | (0.111) |
| POVERTY RATE | 1.107* | 0.708* | 1.088* | 0.701* |
| | (0.638) | (0.413) | (0.571) | (0.359) |
| ECONOMIC DEVELOPMENT | 0.423 | -0.0260 | 0.446 | 0.0555 |
| | (0.489) | (0.252) | (0.451) | (0.221) |
| ETHNICITY | 1.787 | 5.755 | 4.659 | 7.116 |
| | (13.08) | (8.654) | (11.33) | (7.593) |
| DISTRICT HEADQUARTER | 10.71 | 10.73 | 11.38 | 10.53 |
| | (14.21) | (7.453) | (12.75) | (6.747) |
| URBAN EFFECT | -45.32* | -30.94** | -41.97* | -28.50** |
| | (23.16) | (14.41) | (22.15) | (13.87) |
| COASTAL EFFECT | 55.05*** | 28.86** | 48.38*** | 24.37** |
| | (18.23) | (11.51) | (18.19) | (10.77) |
| PUBLIC UNIVERSITY | 8.387 | -2.704 | 8.668 | -1.937 |
| | (8.767) | (5.259) | (7.160) | (4.284) |
| POPULATION | -1.03e-07 | -2.48e-05 | -6.14e-06 | -2.83e-05 |
| | (3.87e-05) | (2.17e-05) | (3.32e-05) | (1.87e-05) |
| POLITICAL RISK | -13.02 | -6.642 | -13.02 | -7.684 |
| | (11.80) | (7.656) | (10.91) | (7.117) |
| CONSTANT | -81.28 | 5.202 | -84.42* | -4.440 |
| | (49.80) | (21.06) | (48.24) | (17.64) |
| SIGMA | 93.12*** | 5.202 | 81.92*** | -4.440 |
| | (19.20) | (21.06) | (20.73) | (17.64) |
| OBSERVATIONS | 483 | 483 | 483 | 483 |

*Source:* Authors' Calculations.

*Note:* Robust standard errors (clustered by sub-district) in parentheses *** p<0.01, ** p<0.05, * p<0.1.

# APPENDIX

### APPENDIX TABLE 1: DESCRIPTION OF VARIABLES DEFINED AND THEIR SOURCES

| NO. | VARIABLES | DESCRIPTION | SOURCES |
|---|---|---|---|
| 1 | **POPULATION** | The total number of people residing in each sub-district. | Department of Disaster Management, Government of Bangladesh. |
| 2 | **TEST RELIEF ALLOCATED SPENDING** | The total (per capita) amount of public fund allocated for disaster risk reduction through test relief program. | Ministry of Food (Former Ministry of Food and Disaster Management), Government of Bangladesh. |
| 3 | **TEST RELIEF REALIZED SPENDING** | The total (per capita) amount of public fund spent for disaster risk reduction through test relief program. | Ministry of Food (Former Ministry of Food and Disaster Management), Government of Bangladesh. |
| 4 | **FOOD FOR WORK ALLOCATED SPENDING** | The total (per capita) amount of public fund allocated for disaster risk reduction through Food For Work program. | Ministry of Food (Former Ministry of Food and Disaster Management), Government of Bangladesh. |
| 5 | **FOOD FOR WORK REALIZED SPENDING** | The total (per capita) amount of public fund spent for disaster risk reduction through Food For Work program. | Ministry of Food (Former Ministry of Food and Disaster Management), Government of Bangladesh. |
| 6 | **INFRASTRUCTURE ALLOCATED SPENDING** | The total (per capita) amount of public fund allocated for bridge & culvert construction under Food For Work program. | Ministry of Food (Former Ministry of Food and Disaster Management), Government of Bangladesh. |
| 7 | **INFRASTRUCTURE REALIZED SPENDING** | The total (per capita) amount of public fund spent for bridge & culvert construction under Food For Work program. | Ministry of Food (Former Ministry of Food and Disaster Management), Government of Bangladesh. |
| 8 | **GRATUITOUS RELIEF ALLOCATED SPENDING** | The total (per capita) amount of public fund allocated for disaster risk reduction through gratuitous relief program. | Ministry of Food (Former Ministry of Food and Disaster Management), Government of Bangladesh. |
| 9 | **GRATUITOUS RELIEF REALIZED SPENDING** | The total (per capita) amount of public fund spent for disaster risk reduction through gratuitous relief program. | Ministry of Food (Former Ministry of Food and Disaster Management), Government of Bangladesh. |
| 10 | **VULNERABLE GROUP FEEDING ALLOCATED SPENDING** | The total (per capita) amount of public fund allocated for disaster risk reduction through vulnerable group feeding program. | Ministry of Food (Former Ministry of Food and Disaster Management), Government of Bangladesh. |
| 11 | **VULNERABLE GROUP FEEDING REALIZED SPENDING** | The total (per capita) amount of public fund spent for disaster risk reduction through vulnerable group feeding program. | Ministry of Food (Former Ministry of Food and Disaster Management), Government of Bangladesh. |

| | | | |
|---|---|---|---|
| 12 | **Upazila Flood Risk Index (UFRI)** | Upazila Flood Risk Index (UFRI) = Monsoon Coefficient of Variation of Rainfall * 1998 flood affected area index | Bangladesh Meteorological Department (BMD) rainfall data of 64 years (1948-2012), and Department of Disaster Management, Government of Bangladesh. |
| 13 | **1998 flood indicator** | Extent of surface flooding per Upazila during the 1998 flood. | Department of Disaster Management, Government of Bangladesh. |
| 14 | **Poverty rate** | The number of people living below the national poverty line of US$ 2 per day in each Upazila. | Department of Disaster Management, Government of Bangladesh. |
| 15 | **Economic Development** | A composite variable averaging the percentage of population in each Upazila with access to safe drinking water, sanitation facilities and electricity. | Population and Housing Census of Bangladesh, 2011. |
| 16 | **Ethnicity** | Binary variable; 1 if indigenous ethnic minorities resides the Upazila, 0 otherwise. | Population and Housing Census of Bangladesh, 2011. |
| 17 | **District Headquarter** | Binary variable; 1 if the Upazila is central (in most cases, bigger population size and main economic centre) in any particular district, 0 otherwise. | Authors' elaborations. |
| 18 | **Political Risk** | Binary variable; 1 if the Member of Parliament (MP) is from the main political party in power, 0 otherwise. | Authors' elaborations using Bangladesh Election Commission Report, 2008 and Bangladesh Gazette (2013). |
| 19 | **Urban Effect** | Binary variable; 1 if the sub-district belongs to the bigger urban cities; Dhaka or Chittagong, 0 otherwise. | Authors' elaborations. |
| 20 | **Coastal Effect** | Binary variable; 1 if the sub-district belongs to any districts situated in the coastal belts[a], 0 otherwise. | Authors' elaborations. |
| 21 | **Public University** | Binary variable; 1 if the district has got a public university, 0 otherwise. | Authors' elaborations. |

[a] 'Coastal Zone' is most frequently defined as land affected by its proximity to the sea (Kamaluddin and Kaudstaal, 2003). According to the Coastal Zone Policy (2005) of the Government of Bangladesh, the zone is divided into 'exposed coast' (the upazilas that embrace the sea directly and is subject to be affected highly by the anticipated sea level rise, also known as *first tier* coastal upazilas) and 'interior coast' (the area/upazilas that are located behind the exposed coast, can also be sub-divided into *second* and *third tier* coastal upazilas). Here, we consider the *first* and *second tier* coastal upazilas to create the 'coastal effect' dummy variable.