The (mis) Allocation of Public Spending in a Low Income Country:

evidence from disaster risk reduction spending in Bangladesh

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ABSTRACT: Rational allocation of limited public resources is critical to achieve the stated aims of government programmes. Here, we focus on the regional allocation of public spending for disaster risk reduction in Bangladesh as a case study to identify the rationale that guides public funding allocations. It is well understood that any government's public spending decision-making is also affected by considerations other than need, and our objective in this paper is to identify all of the directly observable determinants' of publicly allocated and realized spending at the local government (sub-district) level. We employ the Heckman two-stage selection model with detailed public finance and other data from 483 sub-districts (upazilas) across the country. While some of our results conform with our priors, our estimations surprisingly find that government does not respond to the sub-district's risk exposure as a factor affecting the DRR financing mechanism. This variable is consistently counter-intuitively negative and statistically significant. The DRR regional allocations do not seem to be determined by risk and exposure, only weakly by vulnerability, nor even by more transparent political economy motivations. This is surprising, as the Bangladesh DRR program is considered a poster-child of DRR investments.

Key words: Public spending, natural disasters, sub-district, Heckman selection
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1. Introduction

A burgeoning literature has emerged investigating the efficacy of public spending in lower income countries. For example, recently Sennoga and Matovu (2013) provided an investigation of public spending in Uganda, Ramirez (2004) investigated public infrastructure spending in Mexico, Kruse et al. (2012) examine public health spending in Indonesia, and Rajkumar and Swaroop (2008) focus on a cross-country statistical analysis of levels of spending, institutional structures, and relevant outcomes. This literature also uses a wide variety of methodologies to approach this efficacy question: Sennoga and Matovu (2013) use general equilibrium modeling, Ramirez (2004) uses a vector error correction empirical model with impulse response functions, and Kruse et al. (2012) use panel data regression techniques.

This literature assumes that public spending is indeed geared towards achieving the relevant favourable outcomes—productivity growth for infrastructure spending, better health service utilization for health spending, or improved literacy for education spending. More importantly, this literature implicitly assumes that funding is allocated optimally given these desired outcomes and the perceived community needs. It is this last assumption that we examine in this paper. We ask whether we can find evidence that public spending is indeed allocated rationally according to perceived needs, or whether we can identify other explanations for the pattern of *de facto* public spending.

We focus on disaster risk reduction (DRR) spending in Bangladesh for several reasons. Disaster risk reduction spending has a clearly defined policy aim, and measurable outcomes. As such, DRR spending is maybe uniquely suited to examine the rationale for the regional allocation of public resources. Bangladesh has a long history with natural disasters due to its geography and its location on the shores of the Bay of Bengal. Natural hazards in Bangladesh range from floods and cyclones to river bank erosion and droughts. Flooding associated with the monsoon season occurs each year. The monsoon rain plays a pivotal role in securing domestic agricultural production, but can also kill and devastate crops and livelihoods. Along the coasts, the most destructive cyclones generate storm surges that can inundate vast land areas, and have in the last few decades killed hundreds of thousands of people. Given all these; it is obvious that disaster planning and government-led disaster risk reduction (DRR) has been part of the Bangladeshi government's economic planning process for a long time.

Bangladesh, it is important to note, is widely perceived as poster-child for successful spending on DRR by a developing country. In particular, Bangladesh is often mentioned for its successful early warning programmes for cyclones, which is frequently favourably contrasted with neighbouring Burma after its catastrophic experience with cyclone *Nargis* in 2008. Most recently for cyclone *Sidr* in 2007, for example, Bangladesh managed to evacuate millions away from the coast and the storm's surge (Paul and Dutt, 2010).[1] Bangladesh's successful disaster risk reduction policies is also mentioned in the context of the management of the annual monsoon floods (del Ninno et al., 2003).

A demonstration of the crucial role that government safety net policies can play in DRR is the comparison of the severe flood of 1998 in comparison to an equally severe flood in 1974.[2] In this case, in 1998, the government's substantial disaster management facilities and emergency food and financial assistance through better management of targeted

[1] For further data and a comparison of *Sidr* to previous storms, see p. 502 in IPCC (2012).
[2] The severity of the 1998 flood has been identified in terms of area affected (affecting two-thirds of the country) and lasted for a prolonged period (from early July till mid-September) in many areas and direct damages were estimated at US$2 billion (Khandker, 2007).

programs such as Vulnerable Group Feeding (VGF) and Food For work (FFW), it is claimed, helped prevent mass starvation and other associated risks compared with the severe flood impacts of 1974.[3]

Besides the already mentioned ease of determining the aim of DRR spending in the Bangladeshi context, its importance is also well established. Ex ante spending choices on disaster risk management has been advocated for by all the international aid multilaterals, as DRR's importance in reducing mortality, morbidity, and risk to livelihoods is undisputed in Bangladesh, and elsewhere. The most recent example of this emphasis is the Philippines' decision to initiate a US$293 million national disaster risk reduction and management fund that is targeted to be used for pre-disaster risk reduction activities. In Bangladesh, as well as in the Philippines, one of the more important decisions the central government consistently needs to make is how to allocate DRR program spending across communities to minimize and mitigate the risks associated with the natural hazards both countries are exposed to.

Our focus here amounts to answering a basic question: 'what determines public spending in disaster risk reduction and mitigation in Bangladesh?' We believe that this particular question has important implications not only for DRR spending in Bangladesh—as important as that is—but also to DRR spending elsewhere, and more generally for government spending in low income countries and its challenges.

We identify the determinants' of per capita public spending on disaster risk reduction and mitigation at the local government (sub-district/upazila[4]) level in Bangladesh. The

[3] For discussions and analysis of the impacts of floods in Bangladesh, see Khandker (2007) and Banerjee (2007).
[4] Bangladesh is divided into 7 administrative regions (Divisions), 64 districts (Zila) and 483 sub-districts (Upazila). Our primary focus in this investigation includes all 483 sub-districts.

objective of this study is to identify the rationale behind the allocation of public spending based on the stated aims of these DRR safety net programs.

After describing the, admittedly very limited, literature that examines the determinants of public expenditure, we discuss our data in detail. Section 4 provides relevant descriptive and summary statistics of the variables we use, while section 5 presents the methodological framework and justifies our use of the Heckman two-step selection model. Section 6 examines the estimation results and interprets them. Finally, in Section 7 we conclude, identify potential caveats, and discuss possible future research.

2. The Determinants of Fiscal Spending?

Oftentimes, natural disasters are perceived as an exogenous shock to the economy resulting in additional fiscal expenditure or re-adjustment of existing expenditure to finance rehabilitation and reconstruction activities. The financial aspects of post-disaster fiscal management has been examined in country-specific policy papers (e.g. Bangladesh after the 1998 flood is examined in Benson and Clay, 2002, while Belize is analysed in Borensztein et al., 2009). Several cross-country studies have also attempted to measure the average *ex post* fiscal costs (in lost revenue and increased expenditures) of a proto-typical disaster (e.g. Noy and Nualsri, 2011 and Lis and Nickel, 2010) and a global assessment is provided in Hochrainer-Stigler et al. (2014). Yet, none of these papers examine *ex-ante* disaster risk financing.

As we have already noted in the introduction, we are not aware of any literature that attempts to examine the rationale behind central government's financing to the regions; neither in the context of disaster risk financing, nor in other contexts. We aim to investigate the determinants of regional financing for DRR activities and examine whether these flows of funds are conditional upon actual (or perceived) regional hazards, vulnerabilities, other socio-economic regional attributes, and political affiliations at the local government level.[5] Aldrich (2010) and Takasaki (2011) identify the ability of elites to capture post-disaster reconstruction spending in India and Samoa, respectively.

The research project most closely related to our own work is Miller and Vela (2014). They examine the allocation of disaster funding (both preventative and for recovery) for Peruvian regions (districts in the Bangladesh context), and focus on whether distribution of public expenditure in both recovery and prevention categories is conditional upon the occurrence of natural disasters in the recent past and on exposure and vulnerability. The data they use, their empirical approach, and the questions they ask are all quite different, but ultimately they also find it difficult to correlate the spending they examine with measureable risk.

3. What we define as DRR?

We interpret the term DRR spending fairly broadly, given the often repeated insight that 'an ounce of prevention is worth a pound of cure' and the increased awareness that social and socio-economic vulnerability is as important in determining a disaster's impact as is the natural hazard itself. The need for social protection through the provision of social safety nets has been reiterated in various papers that focus on DRR (e.g. Pelham et al, 2011; Rahman and Choudhury, 2012; and World Bank, 2010). Relevant examples of disaster safety net[6] programs

[5] Indirectly, Hodler and Raschky (2014) identify political favoritism in regional allocations by examining the intensity of nighttime light in regions associated with the political leadership.

[6] In this paper, the term 'Disaster Safety Net' refers to particular social safety net programs that has embedded structural mechanism to participate in disaster risk reduction activities.

incorporated into a country's DRR policies are Bangladesh's National Disaster Management Prevention Strategy and Ethiopia's Productive Safety Net Program.[7]

An additional type of DRR activity that we include in our analysis is Investments in specific infrastructure whose aim is disaster prevention; again this type of DRR spending is widely recognized in the DRR literature (e.g. World Bank, 2010). For example, the Department of Disaster Management (DDM) in Bangladesh constructs bridges/culverts (up to 12 meter long) under its Annual Development Plan – the main aim for this infrastructure is DRR rather than development or poverty alleviation more broadly.

The connection between the climate and disaster occurrence is obvious, but the causality from climatic change to disasters has only been emphasized in the past few years, and most forcefully by the IPCC in their Special Report on Extreme Events (IPCC, 2012). Another international organization that has emphasized the link between DRR and climate change adaptation is the United Nations International Strategy for Disaster Risk Reduction (e.g. UNISDR, 2009).[8] We therefore also include an investigation of the US$350 million allocated by the Government of Bangladesh in fiscal years 2009-2013 to tackle climate change impacts.

4. The possible determinants of DRR

The future probability of exposure to hazards (and their probable intensity) is proxied in this paper by past experience of this hazard. In this case, we focus on DRR activities that

[7] See Pelham et al (2011) for discussion of these two programs.
[8] See also Shamsuddoha et al. (2013).

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.[9]

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. The past literature has identified indicators of socio-economic vulnerability to natural hazards and emphasizes the importance of integrating them into national disaster prevention planning (Cutter et al. 2009; Tapsell et al. 2010). This widely discussed need to insert this socio-economic perspective into DRR planning motivates our use of socio-economic indicators.

The political dimension of natural disaster 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 for example Healy and Malhotra (2009) and Garret and Sobel (2003) on US post-disaster 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), and this is the focus of our investigation into the political economy of fiscal spending on the regions.

[9] 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, for example, Kerr (2011).

5. The Data

The data for this study were collected from various Bangladeshi government sources described below, both online and in print. Appendix table 1 provides the precise definition of all the variables and their data sources.

5.1 DRR Programs in Bangladesh

The disaster risk reduction public spending data at the local government level was collected from publications of Bangladesh's Ministry of Food (former Ministry of Food and Disaster Management) – the information was collected from the Ministry's web portal where sub-district (upazila) disaster risk reduction and mitigation funding allocation data from FY (fiscal year) 2010-11 to FY2013-14 was available. For each year, the dataset records the *'allocation'* (allocated spending) and *'expenses'* (realized spending) for the various disaster safety net programmes - 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 programme (bridges and culvert construction) and the climate change fund (also known as the climate investment fund). These various programs are described below.

The *Test Relief* (TR) program has been implemented every year since 1975 in rural areas. This programme 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) programme (established in 1973) is designed to provide a maximum of 20 kilograms of rice/wheat to worst affected poor households with no associated work requirements. *Vulnerable Group Feeding*

(VGF) is another form of gratuitous relief (i.e. without work requirement) and is normally launched during or after a disaster and attempts to assist people remaining vulnerable to hunger.

The *Food For Work* (FFW) program has been implemented since 1975 and 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 with work requirements. Among these infrastructure projects, the Department of Disaster Management funds construction of bridge/culverts (up to 12 meter long) under the Annual Development Programme of the Bangladesh Government (*Bridges and Culverts programme*).

Data has been aggregated by adding up allocations in general and special categories under each DRR programme for each of the 483 sub-districts. We converted the food allocations in some of these programs into its monetary value using the contemporaneous (average) market price of rice in Dhaka (wholesale price). We aggregate both food and cash amount to get total allocation under each particular DRR activity for each sub-district. We then divide total allocated and realized spending amounts for each program/sub-district by the size of the population of each corresponding sub-district.

5.2 Rainfall Hazard Data

Due to its geographical location in the South-Eastern part of Hindu-Kush Himalayan region and being at the confluence of three major rivers – the Ganges, the Brahmaputra and the Meghna, Bangladesh is an extremely flood-prone. River-bank flooding occurs mostly during the monsoon period (May-October) is the most frequent case.[10] High rainfall is primarily the reason of river-bank floods. Here, we calculate a rainfall-based flood risk probability index for 483 sub-districts of Bangladesh to examine the sensitivity government DRR spending to flood risks. The index captures historical rainfall variability to determine local (sub-district) flood risks. 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.

To develop this index, we collected annual rainfall data for 64 years for 35 weather stations covering the whole country from the Bangladesh Meteorological Department (BMD).[11] The BMD records daily rainfall data since 1948 for all available weather stations across the country. We first calculated total monthly rainfall for each year under each weather station. We next calculated the mean and standard deviation for each month for each sub-district by matching weather stations with sub-districts.[12] We develop two indexes of low- and high-risk indices. For the low flood risk, we count the number of months over the 64 years for which we have data with extreme rainfall using two thresholds: monthly rainfall exceeding 15% of average annual rainfall for this sub-district; and monthly rainfall exceeding one standard deviation above the mean for that month throughout the available time period.[13]

We calculate the average number of months with extreme rainfall to obtain the probability of flooding occurring annually in that particular weather station (and consequently sub-district). The mean probability is 0.93 with 0.16 standard deviation. The second index,

[10] Other, less common types of flooding are the flash floods (in hilly areas) and storm surges (along the coast).
[11] The available data were for the years 1948-2012.
[12] In cases where a sub-district did not have a rainfall measurement station, we used an average of the three nearest stations.
[13] The historical coverage of rainfall data in BMD weather stations varies depending upon their establishment year. Therefore, we calculate the average number of months with extreme rainfall by dividing with the total number of rainfall years available to calculate the probability of annual flooding in that particular weather station.

high flood risk, is constructed similarly, but in this case the two thresholds are 20% of average annual rainfall and more than two standard deviation above the monthly mean. For the high-risk measure, the mean probability is 0.26 with 0.08 standard deviation.

5.3 Other Variables

Population numbers and poverty rates for each the 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 (electricity, safe drinking water, and sanitation facilities). This data were collected from the 2011 Population and Housing Census of Bangladesh.

To capture the importance of politics in allocation of funding from the central government to the regions, we construct a political binary variable that measures whether the Member of Parliament (MP) representing the sub-district belongs to the main political party in power. To construct this variable, we divide the 300 electoral constituencies with respect to 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 variable noting if indigenous ethnic minorities reside in the sub-district. To create this ethnicity dummy, we use information from the 2011 Population and Housing Census of Bangladesh. We add two more binary variables. The first identifies the central sub-district in any particular district (in most cases that implies bigger populations, higher degree of urbanization and more industrialized). The other binary measures indicate urban sub-districts associated with the two mega-cities in Bangladesh (Dhaka and Chittagong).

6. Descriptive Statistics and Model Specification

Table 1 reports the descriptive statistics of public spending on DRR in Bangladesh, including both allocated and realized spending for the fiscal year 2010-11 to 2013-14 for each of the programmes described earlier. These statistics include mean, standard deviation, maximum and minimum of allocated and realized spending for Test Relief (TR), Vulnerable Group Feeding (VGF), Food For Work (FFW), Gratuitous Relief (GR), Infrastructure Spending (Bridges and Culvert construction under FFW) and Climate Investment Fund (CIF). On average, TR received 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 documents the descriptive statistics of all the independent (RHS) variables. The mean population size in each sub-district is 0.26 million. The mean probability of low and high flood-risk assigned to each sub-district is 0.935 and 0.258 respectively. Although the current ethnic population size is just over 2 million people, 46% of the sub-districts include some ethnic minorities indicating their dispersal across a wide range of sub-districts. The political risk dummy indicates that fully 77% of sub-districts are represented by MPs from the ruling party as a consequence of the 2008 general election. 19% of the 483 sub-districts are in the coastal zone.

We also examine the difference, in the Bangladeshi government's accounts, between the allocated vs. realized spending, and whether the two are determined differently. We do not have a pre-conceived notion of the types of influences that affect the regional allocation of public spending, but for DRR spending, we assume that these are determined by the perception of risk, by socio-economic vulnerability, and by political and geographic factors.

Some sub-districts do not receive any funding for some of the DRR programs we investigate over some fiscal years. Due to this truncation of the data, we employ a two-stage Heckman selection model to identify the determinants' of public spending on disaster risk reduction and mitigation. To construct this two-stage Heckman selection model, we start with the following premise:

$$SPEND_{ijt}^{x} = f(risk^{v}, pop_{it}, pov_{it}, dep_{i}, D_{i}) \quad [1]$$

Public spending (*SPEND*) in sub-district (*i*), for program (*j*), at fiscal year (*t*), is a function of several variables. The perceived risk (*risk*) which is calculated as an index constructed from past exposure, with low and high thresholds (*v*). Spending is also a function of the population (*pop*) and poverty (*pov*) rates in the receiving sub-district, and measures of socio-economic deprivation (*dep*: measured as access to certain assets – see the data discussion earlier in section 5). This public spending is also a function of a set of characteristics, measured as binary variables (vector *D*), that include political affiliation with the centre, presence of ethnic minorities, being a district headquarter, belonging to either of the two large metropolitan areas, and a coastal location. The spending variable measures either the allocated or realized equivalent for each sub-district, fiscal year, and DRR programme (indicated by superscript *x*).

Our theoretical prior is that these determinants' should have positive relationship with sub-district DRR funding allocation. *Ceteris paribus*, a sub-district with higher perceived risk, more poverty, less access to assets, more deprivation, 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 controls, including location as a district headquarter or as part of the two metropolitan agglomerations, and the presence of ethnic minorities.

Given the truncated nature of this allocation (many sub-districts get nothing), we estimate the model in two stages. In the first stage, we estimate the probability of getting funding ($SPEND_{ijt}^{x} > 0$). More formally, the funding selection equation defines the cases where a particular sub-district has received or been allocated funding in any targeted program:

$$z_{ijt} = \begin{cases} 1\ if\ SPEND_{ijt} > 0 \\ 0\ if\ SPEND_{ijt} = 0 \end{cases} \quad \text{and} \quad z_{ijt} = \alpha W_{ijt} + \varepsilon_{ijt} \qquad [2]$$

Where, z_{ijt} is a latent variable indicating funding, and is the dependent variable of the selection equation [2]. W_{ijt} is a vector of covariates, and ε_{ijt} is the random disturbance term. The selection variable z_{ijt} is binary and we therefore use a probit regression specification to estimate the first stage selection equation [2]. The second stage specifies the outcome (public spending) equation where public spending (allocated or realized) is the dependent variable. The model specification for the second stage equation is as follows:

$$Y_{ijt} = \beta X_{ijt} + u_{ijt} \qquad [3]$$

Where Y_{ijt} is the dependent variable of the outcome equation, X_{ijt} is a vector of covariates, β is a vector of coefficients and u_{ijt} is the random disturbance term. The selection equation (first stage) includes the population variable which is not included in the outcome equation (second stage).[14]

7. Estimation Results

The estimation results for the two-stage Heckman selection model for allocated spending are documented in tables 3-4. The first two columns show the estimated coefficients of low and high flood risks along with a set of socio-economic and geo-political controls with the dependent variable being total allocated spending for per capita disaster risk reduction spending.[15] Columns (3) and (4) present the estimated coefficients for non-obligatory public funding[16] for low- and high- flood risks consecutively, while columns (5) and (6) do the same for obligatory public funding.[17]

Table 3 reports the results from the first stage selection regression. Among the independent (RHS) variables; poverty rate, socio-economic status, coastal location, and population size are found to be sign consistent with our previous predictions. In terms of statistical significance, coastal location is significant at 1% level in all cases, while economic development is significant at the 10% level. Interestingly; ethnic minority presence, district

[14] Heckman (1979) suggests that the outcome and selection equation are correlated and dependent variable (public spending) of the outcome equation is observed only if the a particular sub-district has received funding in any targeted program which also indicates: $u_i \sim N(0, \sigma)$, $\varepsilon_i \sim N(0, 1)$, corr $(u_i, \varepsilon_i) = \rho$; where ρ denotes the correlation between errors of the two stages been defined.

[15] This refers to the summation of all public funds (per capita) that were allocated for disaster risk reduction in all the previously described programmes except the climate investment fund. We estimated the impacts on the climate fund separately.

[16] 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.

[17] Obligatory public funding are dispersed through programmes which include work requirements. Here, the obligatory programmes are Test Relief, Food For Work and Bridges and Culvert construction.

headquarter and urban centre indicator variables all have negative coefficient estimates (though these are statistically insignificant). The most striking results are for the risk and political variables. Both perception of low and high flood risk variables appear to have a counter-intuitive negative relationship with DRR funding allocation with consistent statistical significance. The political connection to the centre indicator also has a counter-intuitive negative sign but this estimate is statistically insignificant.

Table 4 presents the second stage estimation where the dependent variable is DRR per capita allocated funding of the sub-districts which have received funding. The poverty rate, economic development, and coastal effect again show positive signs (consistently with our priors) with statistical insignificance. In contrast to our selection estimation, the outcome for ethnicity and district headquarter showed positive association with DRR funding allocation. However, as in the first-stage estimations, political connections and flood risks showed negative association with allocated spending patterns. In particular, a one standard deviation increase in high flood risk leads to 0.33 standard deviation decrease in predicted per capita DRR allocated spending compare to 0.38 s.d. decrease in case of low flood risk. This result is the most intriguing, and we view it as the most important. Taken overall, and in particular this finding about flood risk measure, our findings suggest there is no evident logic to the way the Bangladeshi government allocated its DRR funding.

We report the same set of first- and second-stage Heckman selection regressions for realized funding (rather than allocated funding) in appendix tables 2 and 3 respectively. All columns in these two tables represent the same set of variables with the dependent variable being per capita realized funding in DRR. To a large extent, the results are very similar. In particular, we observe a similar pattern for the two variables we singled out earlier: flood risks and political connection. Again, low and high flood risks tend to show negative relationship with statistically significant coefficient estimates, while the political connection variable appears to have a negative association with funding but with statistical significance at 10% level observed in only one case. A one standard deviation increase in high flood risk leads to 0.39 standard deviation decrease in predicted per capita DRR realized spending compare to 0.38 s.d. decrease in case of low flood risk.

We report Heckman two stage regression results for climate investment fund separately in tables 5 and 6. The first two columns in table 5 display the determinants of sub-district wise per capita allocated public spending on climate change. Columns (3) and (4) portray the impacts on per capita realized public spending for the same set of independent variables as in columns (1) and (2). In table 5 and among the independent variables; coastal location, urban centre, and district headquarter shows, once again, sign consistency with our priors, but with only the coastal location indicator coefficient being highly significant (at 1% level) in all cases. Poverty rate, socio-economic status, ethnicity and population size are not similarly consistent. As before, the most intriguing of the reported results are negative coefficients for flood risk measures and the political connection variable; in this case, however, the coefficients are not always statistically significantly different from zero.

The second stage regression results for the climate investment fund, in table 6, shows similar patterns of the earlier table 5. Among the RHS variables; poverty rate, ethnicity, and the urban centre show sign consistency with no statistical significance. Socio-economic status, district headquarter, and the coastal location measures show sign inconsistency with the latter two in contrast with the selection equation results. For the climate investment fund, we no longer observe the counter-intuitive and statistically significant negative coefficients for flood risks. However, these estimates are also not statistically different from zero.

8. Conclusion

Bangladesh is a low-income country. Its natural disaster risk will not change dramatically in the near future, though its risk clearly extends beyond the immediate disaster effects to future impacts associated with climate change. As is true for almost any public programme of fiscal spending, rational allocation of limited public resources is critical to the stated aims of the programmes we examine (i.e., enhance households' coping abilities to reduce and mitigate disasters risks). Clearly, the effectiveness of prevention spending is important, and equally obviously the first pre-condition for any effective spending, not exclusively for DRR, is that this spending is allocated rationally across space.

It is well understood that any government's public spending decision-making processes are affected by other considerations rather than need, but the balance between these competing pressures is not obviously clear. Our objective in this paper is to identify the determinants' of publicly allocated and realized spending at the local government (sub-district) level in Bangladesh. We employ the Heckman two-stage selection model to empirically estimate the covariates where we assume public spending is a function of the probability of flood risks, population size, poverty rate, socio-economic development, political connections, ethnic composition, and details about the geo-location of the sub-district.

While some of our results conform with our priors (where these priors are well formed), it is surprising to note that the presence of the ruling party's elected candidates fails to become a statistically important factor when it is time to attract DRR funding.

The most intriguing finding of this study, however, is the response to the sub-district flood risk probabilities as a factor affecting the DRR financing mechanism. This variable is consistently counter-intuitively negative and statistically significant. This result, we should add, is also observed when we do not control for coastal location, when we add other variables, and when we estimate a simpler linear model.

To summarize, we find little evidence (and some counter-evidence) of any rationale in the regional funding allocation decisions of the Bangladeshi government. The DRR regional allocations do not seem to be determined by risk and exposure, and only weakly by vulnerability. Even obvious and transparent political economy motivations do not seem to explain much of the variation in inter-regional funding. These funding decisions appear to be much murkier than we expected them to be. This surprised us, as the Bangladesh DRR program is considered a poster-child of DRR investments. Of course, our result are about DRR funding. Whether the same can be said of other types of central government funding in Bangladesh, or whether this is indeed typical of regional allocations in lower-income countries are all still open questions that require evidence-based answers.

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TABLE 1: DESCRIPTIVE STATISTICS A: LEFT-HAND SIDE VARIABLES

VARIABLES	OBSERVATION	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
TR_ALLOCATED	483	12.37298	17.5886	0	137.6302
TR_REALIZED	483	9.809799	14.28539	0	95.31361
FFW_ALLOCATED	483	5.443759	13.4828	0	126.3999
FFW_REALIZED	483	3.819665	9.05842	0	90.41516
INFRA_ALLOCATED	483	3.15629	9.593239	0	102.8087
INFRA_REALIZED	483	1.96463	7.554146	0	102.8087
GR_ALLOCATED	483	2.145435	20.45798	0	374.9262
GR_REALIZED	483	1.607032	17.19828	0	374.9262
VGF_ALLOCATED	483	5.799361	42.9692	0	921.9801
VGF_REALIZED	483	5.967508	43.00797	0	921.9801
CIF_ALLOCATED	483	1.28391	5.476021	0	58.71323
CIF_REALIZED	483	0.9925554	4.739405	0	58.46924

Source: Authors' Calculations.

Note: The acronyms used here represents test relief, food for work, infrastructure, gratuitous relief, vulnerable group feeding and climate investment fund respectively. Allocated and realized for each safety net program indicates total (per capita) amount of public fund been allocated and total (per capita) amount of public fund been spent out of total allocation in disaster risk reduction consecutively. The currency unit is in BDT (Bangladeshi Taka) [1 USD = 75.79 BDT].

TABLE 2: DESCRIPTIVE STATISTICS B: RIGHT-HAND SIDE VARIABLES

VARIABLES	OBSERVATION	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
POPULATION	483	255833.4	138584.8	17152	941005
FLRISK_LOW	483	0.9347943	0.156718	0.6818	1.909
FLRISK_HIGH	483	0.2577505	0.078411	0.123	0.7272
POVERTY RATE	483	28.3388	13.23799	1.9	68
ECONOMIC DEVELOPMENT	483	52.60449	11.12422	8.1	73.5
ETHNICITY	483	0.4637681	0.499203	0	1
DISTRICT HQ	483	0.1325052	0.339391	0	1
POLITICAL RISK	483	.7763975	.4170906	0	1
URBAN EFFECT	483	0.0393375	0.194598	0	1
COASTAL EFFECT	483	0.1904762	0.393084	0	1

Source: Authors' Calculations.

TABLE 3: ALLOCATED SPENDING: HECKMAN FIRST STAGE REGRESSION RESULTS

	ALLOCATED SPENDING – HECKMAN FIRST STAGE REGRESSION					
VARIABLES	**DISASTER RISK REDUCTION_TOTAL**	**DISASTER RISK REDUCTION_TOTAL**	**RELIEF _NON-OBLIGATORY**	**RELIEF _NON-OBLIGATORY**	**RELIEF _OBLIGATORY**	**RELIEF _OBLIGATORY**
FLRISK_LOW	-0.668*		-1.336***		-0.668*	
	(0.387)		(0.450)		(0.387)	
FLRISK_HIGH		-1.760**		-1.058		-1.760**
		(0.816)		(0.880)		(0.816)
POVERTY RATE	0.00581	0.00691	0.00598	0.00489	0.00581	0.00691
	(0.00526)	(0.00533)	(0.00541)	(0.00545)	(0.00526)	(0.00533)
ECONOMIC DEVELOPMENT	0.0109*	0.0117*	0.0114*	0.0115*	0.0109*	0.0117*
	(0.00601)	(0.00605)	(0.00645)	(0.00646)	(0.00601)	(0.00605)
ETHNICITY	-0.0173	-0.0498	0.0437	0.0241	-0.0173	-0.0498
	(0.136)	(0.137)	(0.141)	(0.141)	(0.136)	(0.137)
DISTRICT HQ	-0.0602	-0.0763	-0.0564	-0.0691	-0.0602	-0.0763
	(0.206)	(0.206)	(0.212)	(0.210)	(0.206)	(0.206)
POLITICAL RISK	-0.210	-0.228	-0.239	-0.215	-0.210	-0.228
	(0.149)	(0.150)	(0.149)	(0.148)	(0.149)	(0.150)
URBAN EFFECT	-0.102	-0.110	-0.553	-0.615*	-0.102	-0.110
	(0.346)	(0.346)	(0.341)	(0.339)	(0.346)	(0.346)
COASTAL EFFECT	0.730***	0.693***	0.628***	0.690***	0.730***	0.693***
	(0.176)	(0.179)	(0.164)	(0.167)	(0.176)	(0.179)
POPULATION	6.73E-07	7.58E-07	4.20E-07	5.19E-07	6.73E-07	7.58E-07
	(5.30E-07)	(5.30E-07)	(5.38E-07)	(5.35E-07)	(5.30E-07)	(5.30E-07)
CONSTANT	-0.0644	-0.292	-0.0358	-1.022**	-0.0644	-0.292
	(0.542)	(0.452)	(0.607)	(0.487)	(0.542)	(0.452)
OBSERVATIONS	483	483	483	483	483	483

Source: Authors' Calculations.

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

TABLE 4: ALLOCATED SPENDING: HECKMAN SECOND STAGE REGRESSION RESULTS

	ALLOCATED SPENDING – HECKMAN SECOND STAGE REGRESSION					
VARIABLES	**DISASTER RISK REDUCTION_TOTAL**	**DISASTER RISK REDUCTION_TOTAL**	**RELIEF _NON-OBLIGATORY**	**RELIEF _NON-OBLIGATORY**	**RELIEF _OBLIGATORY**	**RELIEF _OBLIGATORY**
FLRISK_LOW	-162.3		-262.0		-97.41	
	(126.5)		(382.8)		(72.45)	
FLRISK_HIGH		-282.5		-226.3		-126.2
		(257.8)		(277.3)		(128.8)
POVERTY RATE	1.651	1.729	1.876	1.667	0.652	0.597
	(1.362)	(1.298)	(2.066)	(1.536)	(0.780)	(0.649)
ECONOMIC DEVELOPMENT	0.752	0.804	1.260	1.134	0.362	0.256
	(2.104)	(1.908)	(3.552)	(2.814)	(1.205)	(0.954)
ETHNICITY	15.70	12.43	35.07	31.93	-3.257	-5.000
	(25.73)	(23.76)	(35.83)	(29.86)	(14.73)	(11.87)
DISTRICT HQ	15.50	15.09	4.756	5.749	12.03	11.08
	(34.87)	(32.34)	(42.29)	(37.71)	(19.97)	(16.16)
POLITICAL RISK	-39.52	-39.02	-51.82	-46.43	-19.00	-15.95
	(39.84)	(36.94)	(68.66)	(52.19)	(22.81)	(18.46)
URBAN EFFECT	-35.03	-36.91	-97.73	-97.80	-13.65	-14.88
	(59.25)	(55.23)	(148.6)	(128.1)	(33.93)	(27.60)
COASTAL EFFECT	91.51	84.87	110.1	107.9	41.50	34.06
	(92.61)	(74.96)	(153.2)	(130.9)	(53.03)	(37.46)
CONSTANT	-32.05	-103.1	-107.6	-254.1	10.87	-24.05
	(217.3)	(204.3)	(303.9)	(423.3)	(124.4)	(102.1)
LAMBDA	216.9	202.7	228.4	204.4	124.2	101.3
	(232.7)	(195.6)	(358.6)	(274.1)	(133.2)	(97.76)
OBSERVATIONS	483	483	483	483	483	483

Source: Authors' Calculations.

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

TABLE 5: CLIMATE INVESTMENT FUND: HECKMAN FIRST STAGE REGRESSION RESULTS

	CLIMATE INVESTMENT FUND - HECKMAN FIRST STAGE REGRESSION			
VARIABLES	**ALLOCATED SPENDING**	**ALLOCATED SPENDING**	**REALIZED SPENDING**	**REALIZED SPENDING**
FLRISK_LOW	-0.653		-0.353	
	(1.011)		(0.995)	
FLRISK_HIGH		-1.773		-1.764
		(2.096)		(2.201)
POVERTY RATE	-0.00991	-0.0105	-0.00940	-0.00948
	(0.00903)	(0.00893)	(0.00908)	(0.00899)
ECONOMIC DEVELOPMENT	-0.0191*	-0.0181*	-0.0212**	-0.0198*
	(0.00975)	(0.00991)	(0.0100)	(0.0101)
ETHNICITY	-1.155***	-1.189***	-1.022***	-1.055***
	(0.373)	(0.376)	(0.368)	(0.372)
DISTRICT HQ	0.191	0.178	0.244	0.236
	(0.375)	(0.375)	(0.379)	(0.378)
POLITICAL RISK	-0.460*	-0.480*	-0.344	-0.358
	(0.277)	(0.279)	(0.283)	(0.287)
URBAN EFFECT	0.120	0.119	0.132	0.152
	(0.473)	(0.469)	(0.472)	(0.469)
COASTAL EFFECT	2.044***	2.014***	2.054***	2.009***
	(0.262)	(0.266)	(0.266)	(0.267)
POPULATION	-1.36e-06	-1.30e-06	-1.19e-06	-1.15e-06
	(1.08e-06)	(1.07e-06)	(1.08e-06)	(1.08e-06)
CONSTANT	0.604	0.433	0.214	0.277
	(1.084)	(0.830)	(1.079)	(0.842)
OBSERVATIONS	483	483	483	483

Source: Authors' Calculations.
Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

TABLE 6: CLIMATE INVESTMENT FUND: HECKMAN SECOND STAGE REGRESSION RESULTS

	CLIMATE INVESTMENT FUND - HECKMAN SECOND STAGE REGRESSION			
VARIABLES	**ALLOCATED SPENDING**	**ALLOCATED SPENDING**	**REALIZED SPENDING**	**REALIZED SPENDING**
FLRISK_LOW	7.311		28.92	
	(26.69)		(25.74)	
FLRISK_HIGH		67.83		73.88
		(53.90)		(60.44)
POVERTY RATE	0.208	0.201	0.232	0.223
	(0.201)	(0.214)	(0.186)	(0.226)
ECONOMIC DEVELOPMENT	-0.163	-0.251	-0.329	-0.274
	(0.318)	(0.317)	(0.357)	(0.382)
ETHNICITY	5.920	5.936	3.200	5.636
	(16.04)	(17.06)	(14.71)	(17.64)
DISTRICT HQ	-6.950	-6.612	-4.799	-5.124
	(5.857)	(6.068)	(5.345)	(6.469)
POLITICAL RISK	8.735	9.068	8.268	8.481
	(6.698)	(7.123)	(5.468)	(6.791)
URBAN EFFECT	3.509	3.966	6.888	5.218
	(8.478)	(8.574)	(7.912)	(9.158)
COASTAL EFFECT	-16.35	-17.99	-10.78	-20.71
	(28.15)	(28.08)	(30.36)	(32.97)
CONSTANT	32.25	31.07	10.40	31.30
	(30.26)	(20.98)	(33.93)	(24.59)
LAMBDA	-14.71	-16.39	-11.47	-17.28
	(17.77)	(18.32)	(18.71)	(21.27)
OBSERVATIONS	483	483	483	483

Source: Authors' Calculations.

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

APPENDIX TABLE 1: DESCRIPTION OF VARIABLES DEFINED AND THEIR SOURCES

No.	Variables	Description	Source
1	POPULATION	The total number of people residing in each sub-district.	Department of Disaster Management, Government of Bangladesh.
2	TR_ALLOCATED	The total (per capita) amount of public fund been allocated in disaster risk reduction through test relief program.	Ministry of Food (Former Ministry of Food and Disaster Management), Government of Bangladesh.
3	TR_REALIZED	The total (per capita) amount of public fund been spent out of total allocation in disaster risk reduction through test relief program.	Ministry of Food (Former Ministry of Food and Disaster Management), Government of Bangladesh.
4	FFW_ALLOCATED	The total (per capita) amount of public fund been allocated in disaster risk reduction through Food For Work program.	Ministry of Food (Former Ministry of Food and Disaster Management), Government of Bangladesh.
5	FFW_REALIZED	The total (per capita) amount of public fund been spent out of total allocation in disaster risk reduction through Food For Work program.	Ministry of Food (Former Ministry of Food and Disaster Management), Government of Bangladesh.
6	INFRA_ALLOCATED	The total (per capita) amount of public fund been allocated in bridges and culvert construction under Food For Work program.	Ministry of Food (Former Ministry of Food and Disaster Management), Government of Bangladesh.
7	INFRA_REALIZED	The total (per capita) amount of public fund been spent out of total allocation in bridges and culvert construction under Food For Work program.	Ministry of Food (Former Ministry of Food and Disaster Management), Government of Bangladesh.
8	GR_ALLOCATED	The total (per capita) amount of public fund been allocated in disaster risk reduction through gratuitous relief program.	Ministry of Food (Former Ministry of Food and Disaster Management), Government of Bangladesh.
9	GR_REALIZED	The total (per capita) amount of public fund been spent out of total allocation in disaster risk reduction through gratuitous relief program.	Ministry of Food (Former Ministry of Food and Disaster Management), Government of Bangladesh.

10	**VGF_ALLOCATED**	The total (per capita) amount of public fund been allocated in disaster risk reduction through vulnerable group feeding program.	Ministry of Food (Former Ministry of Food and Disaster Management), Government of Bangladesh.
11	**VGF_REALIZED**	The total (per capita) amount of public fund been spent out of total allocation in disaster risk reduction through vulnerable group feeding program.	Ministry of Food (Former Ministry of Food and Disaster Management), Government of Bangladesh.
12	**CIF_ALLOCATED**	The total (per capita) amount of public fund been allocated in climate investment fund to combat climate change induced risks.	Ministry of Food (Former Ministry of Food and Disaster Management), Government of Bangladesh.
13	**CIF_REALIZED**	The total (per capita) amount of public fund been spent out of total allocation in climate investment fund to combat climate change induced risks.	Ministry of Food (Former Ministry of Food and Disaster Management), Government of Bangladesh.
14	**FLRISK_LOW**	Also defined as 'low flood risk'. The number of times each sub-district is likely to incur flood risk each year. The threshold is the number of months each sub-district has total rainfall higher than 15% of average annual rainfall and more than 1 standard deviation above the mean divided by the number of years' rainfall data has been recorded for each weather station corresponding to each sub-district out of 64 year time span.	Bangladesh Meteorological Department (BMD) rainfall data of 64 years (1948-2012) for 35 weather stations of Bangladesh.
15	**FLRISK_HIGH**	Also defined as 'high flood risk'. The number of times each sub-district is likely to incur flood risk each year. The threshold is the number of months each sub-district has total rainfall higher than 20% of average annual rainfall and more than 2 standard deviation above the mean divided by the number of years' rainfall data has been recorded for each weather station corresponding to each sub-district out of 64 year time span.	Bangladesh Meteorological Department (BMD) rainfall data of 64 years (1948-2012) for 35 weather stations of Bangladesh.
16	**POVERTY RATE**	The number of people living below the national poverty line of US$ 2 per day.	Department of Disaster Management, Government of Bangladesh.
17	**ECONOMIC DEVELOPMENT**	This is a composite variable averaging the percentage of population under each sub-district to get access to safe drinking water, sanitation facilities and electricity.	Population and Housing Census of Bangladesh, 2011.

18	**ETHNICITY**	Dummy variable; 1 if indigenous ethnic minorities resides in any sub-district, 0 otherwise.	Authors' elaborations using Population and Housing Census of Bangladesh, 2011.
19	**DISTRICT HQ**	Dummy variable; 1 if the sub-district is central (in most cases, bigger population size and main economic centre) in any particular district, 0 otherwise.	Authors' elaborations.
20	**POLITICAL RISK**	Dummy 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).
21	**URBAN EFFECT**	Dummy variable; 1 if the sub-district belongs to the bigger urban cities; Dhaka or Chittagong, 0 otherwise.	Authors' elaborations.
22	**COASTAL EFFECT**	Dummy variable; 1 if the sub-district belongs to any districts situated in the coastal belts [a], 0 otherwise.	Authors' elaborations.

Source: Authors' elaborations.

Note: [a] 'Coastal Zone' is most frequently defined as land affected by its proximity to the sea and that part of the sea affected by its proximity to the land (Kamaluddin and Kaudstaal, 2003). According to the Coastal Zone Policy (2005) of the Government of Bangladesh (GOB), the zone is divided into 'exposed coast' (the area/upazilas that embraces 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.

APPENDIX TABLE 2: REALIZED SPENDING: HECKMAN FIRST STAGE REGRESSION RESULTS

	REALIZED SPENDING – HECKMAN FIRST STAGE REGRESSION					
VARIABLES	**DISASTER RISK REDUCTION_TOTAL**	**DISASTER RISK REDUCTION_TOTAL**	**RELIEF_NON-OBLIGATORY**	**RELIEF_NON-OBLIGATORY**	**RELIEF_ OBLIGATORY**	**RELIEF_ OBLIGATORY**
FLRISK_LOW	-0.732*		-1.269***		-0.726*	
	(0.388)		(0.448)		(0.388)	
FLRISK_HIGH		-1.887**		-0.923		-1.582*
		(0.818)		(0.878)		(0.815)
POVERTY RATE	0.00608	0.00721	0.00591	0.00475	0.00586	0.00654
	(0.00526)	(0.00533)	(0.00541)	(0.00546)	(0.00525)	(0.00532)
ECONOMIC DEVELOPMENT	0.00987	0.0107*	0.0130**	0.0131**	0.00908	0.00970
	(0.00601)	(0.00605)	(0.00649)	(0.00649)	(0.00600)	(0.00604)
ETHNICITY	0.00491	-0.0300	0.0612	0.0439	0.00713	-0.0227
	(0.136)	(0.137)	(0.141)	(0.142)	(0.136)	(0.137)
DISTRICT HQ	-0.0443	-0.0618	-0.0498	-0.0619	-0.0809	-0.0973
	(0.207)	(0.206)	(0.211)	(0.210)	(0.206)	(0.206)
POLITICAL RISK	-0.191	-0.210	-0.256*	-0.231	-0.142	-0.151
	(0.149)	(0.149)	(0.149)	(0.148)	(0.148)	(0.149)
URBAN EFFECT	-0.0910	-0.100	-0.541	-0.602*	-0.0764	-0.0914
	(0.346)	(0.346)	(0.341)	(0.339)	(0.346)	(0.346)
COASTAL EFFECT	0.737***	0.699***	0.575***	0.641***	0.762***	0.741***
	(0.176)	(0.179)	(0.164)	(0.167)	(0.176)	(0.178)
POPULATION	7.08E-07	8.00E-07	4.10E-07	5.04E-07	7.73E-07	8.58E-07
	(5.30E-07)	(5.31E-07)	(5.38E-07)	(5.35E-07)	(5.30E-07)	(5.30E-07)
CONSTANT	-0.00818	-0.266	-0.176	-1.131**	-0.0395	-0.356
	(0.543)	(0.453)	(0.608)	(0.489)	(0.543)	(0.452)
OBSERVATIONS	483	483	483	483	483	483

Source: Authors' Calculations.

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

APPENDIX TABLE 3: REALIZED SPENDING: HECKMAN SECOND STAGE REGRESSION RESULTS

	REALIZED SPENDING – HECKMAN SECOND STAGE REGRESSION					
VARIABLES	DISASTER RISK REDUCTION_TOTAL	DISASTER RISK REDUCTION_TOTAL	RELIEF_ NON-OBLIGATORY	RELIEF_ NON-OBLIGATORY	RELIEF_ OBLIGATORY	RELIEF_ OBLIGATORY
FLRISK_LOW	-144.2		-242.2		-77.22	
	(131.9)		(380.7)		(64.50)	
FLRISK_HIGH		-292.0		-196.5		-123.6
		(265.5)		(281.5)		(108.9)
POVERTY RATE	1.665	1.767	1.874	1.681	0.612	0.605
	(1.367)	(1.307)	(2.145)	(1.669)	(0.668)	(0.582)
ECONOMIC DEVELOPMENT	0.834	0.904	1.745	1.671	0.243	0.217
	(1.960)	(1.794)	(4.102)	(3.413)	(0.921)	(0.782)
ETHNICITY	22.23	18.37	39.15	36.52	0.993	-0.781
	(26.47)	(24.13)	(39.73)	(34.43)	(13.55)	(11.43)
DISTRICT HQ	17.06	16.47	6.029	6.977	10.67	10.14
	(35.62)	(33.08)	(43.66)	(40.99)	(17.75)	(15.31)
POLITICAL RISK	-39.40	-40.08	-57.33	-53.14	-14.69	-14.03
	(37.55)	(35.14)	(75.73)	(60.39)	(16.92)	(14.69)
URBAN EFFECT	-31.40	-32.29	-100.4	-104.3	-9.222	-10.44
	(59.03)	(55.39)	(152.8)	(139.5)	(29.93)	(25.94)
COASTAL EFFECT	93.27	84.62	103.2	106.7	41.59	35.43
	(90.62)	(73.34)	(148.6)	(135.8)	(44.75)	(34.85)
CONSTANT	-68.70	-121.4	-157.1	-308.3	-6.978	-33.44
	(205.1)	(195.7)	(352.5)	(492.6)	(100.0)	(91.88)
LAMBDA	216.7	203.7	234.9	221.4	110.1	95.49
	(224.6)	(188.6)	(374.6)	(303.2)	(106.5)	(83.93)
OBSERVATIONS	483	483	483	483	483	483

Source: Authors' Calculations.

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.