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Distortions in Aid Allocation of United Nations Flash Appeals: Evidence from the 2015 Nepal Earthquake

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Abstract
We examine the role of local need and various distortions in the design and implementation of United Nations flash appeal triggered in response to the destructive 2015 Nepal earthquake. Specifically, we investigate the extent to which the allocation of this humanitarian assistance follows municipalities' affectedness and their physical and socio–economic vulnerabilities, as rapidly reducing suffering is the intended goal of flash appeals. We then analyze potential ethnic, religious, and political distortions. We alternatively consider the proposed project number, the proposed financial amount, and the subsequent funding decision by aid donors. Our results show that aid allocation is associated with geophysical estimates of the disaster's destructiveness, but shows little regard for the specific socio–economic and physical vulnerabilities conditional on destruction. It is worrisome that the allocation of the flash appeal commitments favors municipalities dominated by higher castes and disadvantages those with a greater distance to the Nepali capital Kathmandu.

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1 Introduction

On April 25, 2015 an earthquake of magnitude 7.8 struck central Nepal.[1] With more than 100 subsequent aftershocks, of which the largest reached an intensity of 7.3 on May 12, it was one of the most destructive natural disasters in the history of Nepal. The disaster triggered substantial international attention. It is estimated to have killed 8,800 people and affected more than 5.6 million (Guha-Sapir et al., 2016a), which constituted almost a fifth of Nepal's inhabitants.

Four days after the earthquake, the United Nations Office for the Coordination of Humanitarian Affairs (UNOCHA), in collaboration with the Office of the Humanitarian Coordinator (OHC), the Nepalese government, and humanitarian partners, issued a strategic response plan for Nepal, a so-called flash appeal.[2] The 2015 UN Nepal Earthquake Flash Appeal identified 184 projects and requested US$ 422 million in order to provide life-saving assistance and protection for the Nepalese people in the five months after the earthquake (AidData, 2016a).[3] Although 77 donor organizations responded to the Flash Appeal, a third of the requested amount remains unmet as of May 2018 (UNOCHA, 2018).[4] However, the spatial heterogeneity is large. This holds with respect to the number of aid projects, the proposed financial amount, and the degree to which proposed projects obtained funding commitments by international donors. This raises the question: what explains the selection of project locations and the provision of the requested funds?

[1] Nepal, a landlocked country situated between China and India, has 29 million inhabitants, of which 15 percent live below the poverty line of US$1.90 (PPP) a day (World Bank, 2018). It is home to 125 ethnic (caste) groups. After a civil war (1996-2006), the country became a secular republic in 2008. It now is a multi-party democracy with the Communist Party of Nepal and Nepali Congress being the dominant parties. The new political constitution has been in force since September 2015. According to the "Polity Score" of the Polity IV dataset, Nepal is coded as a democracy with a value of 6 on a 21-point scale from -11 (full autocracy) to 10 (full democracy) (Marshall et al., 2018).

[2] While a flash appeal responds to new disasters, annually consolidated appeals cover protracted crises. This study only covers the former. The decision to issue an appeal is primarily left to field staff but the affected government should be consulted (UNGA, 1991).

[3] The revised flash appeal of May 4, 2015 is available at https://www.humanitarianresponse.info/system/files/documents/files/nepal_earthquake_2015_revised_flash_appeal_final_0.pdf (accessed January 27, 2017).

[4] The largest five official donors are the United States of America, the Central Emergency Response Fund, Norway, Canada, and the United Kingdom (see https://fts.unocha.org/appeals/486/summary, accessed December 13, 2018).

This paper is the first to investigate the allocation of proposed and funded humanitarian aid projects in the framework of a United Nations flash appeal. Flash appeals have become important components of humanitarian relief in emergency situations, as demonstrated by the 76 flash appeals the UN has issued over the 2005-2016 period. In sum, the international donor community has spent US$190 billion over this period alone to satisfy humanitarian needs and stimulate economic reconstruction. As can be seen from the list of the 20 largest events in Table 1, the 2015 Nepal earthquake triggered the seventh largest flash appeal in terms of its financial size. Common hope and expectation is that disaster affectedness and the specific vulnerabilities of municipalities are the criteria for choosing the location of aid projects. A meaningful aid allocation is particularly salient since 9 of 10 flash appeals are underfunded (UNOCHA, 2018).

Studying the allocation of emergency aid is important as these flows are intended to improve the humanitarian situation of the population living in disaster-affected areas. Beyond the mere humanitarian aspect, empirical findings suggest that post-disaster aid can boost economic growth (Bjørnskov, 2013), speed up the recovery process of microenterprises (Mel et al., 2012), and play a role in reducing the likelihood of escalating government repression in democracies (Wood and Wright, 2016). Even critics of 'general' development aid support the continued provision of emergency relief following devastating disasters (Moyo, 2009). Since humanitarian aid flows are surprisingly small in comparison to the damages caused (Becerra et al., 2014, 2015), a need-oriented aid allocation is particularly salient.

By analyzing the humanitarian response triggered by the 2015 Nepal earthquake, this study addresses two (sequentially) related aspects of flash appeals. We study the municipality characteristics that influence the number of emergency aid projects and financial amount committed to a particular municipality. First, we analyze what determines the choice of project-locations in the design stage of the 2015 UN Nepal Earthquake Flash Appeal across municipalities. Second, we investigate which proposed project locations obtain funding from international donors.

Our study makes use of a new, and so far unexploited, geo-referenced aid dataset from AidData that contains information on proposed and ultimately funded aid projects that have been a part of the 2015 UN Nepal Earthquake Flash Appeal (AidData, 2016a). These data cover 156 out of 184 projects in more than 850 locations. We combine these aid data with data on nighttime light intensity and rainfall, survey data, and electoral statistics at the local level, to evaluate whether the allocation and subsequent financing of humanitarian aid projects in Nepalese municipalities are based on actual disaster impact and the population's specific vulnerabilities or rather biased by particular interests. To assess the disaster impact, we use peak ground acceleration maps provided by USGS (2017b) combined with damage functions, which—as we argue below—provide a suitable indicator for potential destruction from earthquakes to short buildings up to seven stories (USGS, 2017c). To evaluate whether aid allocation decisions also reflect socio-economic and physical vulnerabilities of the affected population, we add measures of municipalities' level of development, their exposure to rainfall, and their distance to the Nepalese capital Kathmandu, amongst others. Finally, we test for ethnic, religious, and political distortions in aid giving by analyzing the role of a municipality's share of Hindus and privileged caste population, as well as the vote share of Nepal's two dominant parties in the 2013 Constituent Assembly elections.

By studying the allocation of UN flash appeal aid, we contribute to the broader literature on the allocation of humanitarian aid. A first strand investigates aid allocation *across* countries and emergencies, where emergency aid has been shown to increase with disaster severity but is also driven by media coverage and is prone to political bias (Drury et al., 2005; Eisensee and Stromberg, 2007; Fink and Redaelli, 2011; Raschky and Schwindt, 2012; Fuchs and Klann, 2013; Bommer et al., 2018). A much smaller second strand analyzes the allocation of disaster relief *within* disaster-affected areas. For example, Benini et al. (2009) and Wiesenfarth and Kneib (2010) study relief supply to earthquake-affected communities in Pakistan after the 2005 earthquake and find that needs and logistical convenience of locations affect aid delivery. Francken et al. (2012) investigate politico-economic factors underlying aid allocation across communities in Madagascar in the aftermath of cyclone Gafilo in 2004. They uncover that domestic aid is provided to regions where governments have stronger incentives to respond, specifically those with higher radio coverage and with stronger political support from the ruling administration. At the same time, their results suggest that foreign aid is distributed to poorer areas and to those that are more easily accessible. Our study adds to this smaller and less developed second strand of the literature by examining the role of UN flash appeals. To the best of our knowledge, no existing study analyzes the geographic pattern of proposed and funded projects following UN flash appeals despite their importance in the immediate aftermath of a disaster.[5]

Our empirical results show that aid allocation in the framework of the 2015 Nepal Earthquake Flash Appeal lacks need orientation and shows ethnic and political biases. At the design stage, the location choice is not guided by municipalities' level of development and shows little regard for other socio-economic and physical vulnerabilities—the exception being that less urban municipalities receive more aid projects. Municipalities populated by upper castes receive more projects and the strongholds of the two major Nepali parties benefit from larger aid amounts in the design stage. On the positive side, the initial appeal project proposals correlate positively with the extent of earthquake damages. Similarly striking, the funding decisions of the international donor community show little regard of socio-economic and physical vulnerabilities.

We conclude that the geographic selection of aid projects is distorted at all levels of decision-making. Therefore, the need orientation of geographic project selection and funding should be strengthened. This would involve different actors: UNOCHA, the OHC, and the national government during the design of flash appeals, as well as donor countries, multilateral donors, and non-state donors during the funding and coordination phase.

The remainder of the paper proceeds as follows. In Section 2, we outline the decision-making process that underlies the 2015 UN Nepal Earthquake Flash Appeal. We also discuss the factors that should (not) guide the selection and funding of project locations according to the flash appeal document and from a humanitarian perspective. Section 3 presents our research design and the data. We use various proxies for the needs and vulnerabilities of Nepalese municipalities to analyze whether these factors guide aid distribution. We then explore alternative allocation rules, which could explain the lack of need orientation. Specifically, we test for ethnic, religious, and political distortions. In Section 4 we present and discuss our empirical results. Finally, Section 5 summarizes our findings and outlines potential avenues for future research.

[5] This article also adds to a burgeoning literature on the subnational allocation of development aid (Dreher and Lohmann, 2015; Dreher et al., 2016; Strandow et al., 2016). However, emergency aid is distinct from other development aid given its goal and time horizon. Emergency aid is relatively "high-speed" assistance, especially after fast-onset disasters. Donors react in days if not hours rather than the years that it takes to develop and implement more long-term development strategies.

2 The 2015 Nepal Earthquake Flash Appeal

The United Nations initiates flash appeals in the direct aftermath of large-scale sudden-onset disasters, which require a fast and coordinated response that exceeds the capacity of the affected government, plus any single UN agency (UNOCHA, 2013). The appeal document outlines a strategy on relief and rehabilitation plans for the months following the disaster, lists specific emergency aid projects, and determines the required resources (UNOCHA, 2015a, 2015b). The United Nations Resident Coordinator and/or Humanitarian Coordinator (HC) initiate the appeal process in consultation with the affected government and a so-called Humanitarian Country Team, which is a strategic, operational decision-making and oversight forum led by the HC. The decision to start an appeal process is, on the one hand, based on a rapid assessment of the scale and severity of the disaster and, on the other hand, a function of the respective national government's capacity to cope with the consequences. While the permission of a local government is not required for issuing a flash appeal, in practice the government plays a key role in designing the appeal.[6]

One of the financially largest emergency appeals was the Flash Appeal for the Response to the Nepal Earthquake, which was issued on April 29, 2015, i.e., four days after the first earthquake hit central Nepal.[7] At that point in time, government sources estimated a death toll of 5,006 people and the number of injured people amounting to 10,194. The appeal document called the donor community to collect US$ 415 million "to reach over 8 million people with life-saving assistance and protection in the next three months" (UNOCHA, 2015a). This estimate of the required resources was based on initial results of damage assessments, earthquake intensity mapping, and secondary data analysis.

One month later, on May 29, 2015, the UNOCHA issued a revision of the Flash Appeal (UNOCHA, 2015b). The update intended to strengthen linkages between the recovery and rehabilitation program of the Nepali government and extended the appeal duration from three to five months. This also allowed the Flash Appeal to account for the damage caused by the severe aftershock on May 12, 2015. The goal was now to collect US$ 422 million for 2.8

[6] The website https://fts.unocha.org/content/guide-funding-response-plans-and-appeals (accessed May 11, 2018) provides more information on humanitarian response plans and appeals.

[7] Appendix 1 provides a timeline of the events surrounding the 2015 Nepal earthquake flash appeal.

million affected and vulnerable people. The appeal document emphasizes that "[r]elief efforts will need to continue to identify and respond to distinct structural and situational factors that increase vulnerabilities at both local and community levels, including for women, children, the elderly, minorities and people with disabilities" (UNOCHA, 2015b: 6). UNOCHA based its assessment of the severity of needs on a severity index that "combines indicators that measure earthquake impact (damaged buildings, injured persons, migration), physical vulnerability (landslide and flood risk, road accessibility), and socio-economic vulnerability (caste/ethnicity, gender inequality, Human Development Index)" (UNOCHA, 2015b: 9).

The context just described suggests a number of different aspects, which were important to the allocation of aid after the earthquake. First, it highlights that the degree to which certain areas were affected by the earthquake is intended to be an important criterion for aid allocation. The physical intensity of the earthquake showed considerable spatial variation across and within the five Nepali development regions. More specifically, the earthquake triggered the worst consequences in the Central and Western Region, including the Kathmandu Valley. Importantly, housing conditions played a crucial role in how the severity of the earthquake translated into damages. Many Nepalese homes are characterized by fragile outer walls and bad foundations. As the revised appeal emphasizes, "the condition of houses is considered to be the most relevant proxy indicator for people in need" (UNOCHA, 2015b: 53).[8] We will test below whether municipalities that had been more severely affected by the earthquake received more proposed and subsequently funded projects.

Beyond the degree to which certain areas are affected by the catastrophe, the Flash Appeal attributes an important role to the protection of the most vulnerable populations (UNOCHA, 2015a). As the updated appeal document emphasizes, "[m]any people affected by the disaster are highly vulnerable on the basis of socio-economic, language, religious, caste, ethnic and geographic factors" (UNOCHA, 2015b: 6). Starting with socio-economic vulnerabilities, the original document explicitly demands that "the diversity of affected communities is addressed when engaging the community" (UNOCHA, 2015b: 3). Relief activities should explicitly cover "all vulnerable groups, including internally displaced persons (IDPs), host communities, ethnic and indigenous groups and other affected people" (UNOCHA, 2015a:

[8] See also, for instance, Rota et al. (2008) and Ruiter et al. (2017) in the context of other earthquakes.

4).[9] Biases in favor of privileged groups in the Flash Appeal proposal and subsequent allocation of aid would thus thwart this principle.

In spite of the appeal's stated goal to prioritize the most vulnerable population groups, Amnesty International (2015) expressed its concern that "the Government of Nepal and humanitarian agencies had still not adequately factored social and economic disparities into their relief operations." Dissatisfaction with the distribution of relief aid within Nepal also sparked protests (Bhagat, 2015). Indeed, the Asia Foundation (2017) warns that Dalits, of which 90 percent live below the poverty line, and other lower-ranked castes suffer particularly from obstacles that prevent their economic recovery. While the report also presents evidence that lower-caste people are not less likely to access aid, they do appear to struggle to receive relief aid according to their needs.[10] We will test below whether the design and financing of flash appeal projects are indeed targeted at poor municipalities and (dis)favors municipalities populated by Hindus, the dominant religion, and high-caste people. To analyze whether aid giving in the framework of the Flash Appeal is considering socio-economic vulnerabilities, we will investigate whether the level of development and the religious and caste composition of a municipality are associated with the number of proposed and funded projects. Given Nepal's track record of socio-economic exclusion (e.g., Murshed and Gates, 2005; Sharma, 2006), one is likely to expect at least some biases in favor of privileged groups in the allocation of flash appeal aid.[11]

Turning from socio-economic to physical vulnerabilities of municipalities, the appeal documents express concerns that rural and remote areas are disadvantaged in the receipt of aid. The Kathmandu International Airport, for example, played the dominant role in delivering aid to Nepal. Since it is the only Nepalese airport that could handle medium to large aircrafts, nearly all international aid arrived in Kathmandu. This may have made it less likely

[9] A report by the Asia Foundation (2017: vi-vii) concludes that "[h]igher demand for food is found among disadvantaged groups: people in more remote areas, of low income, low education, low caste and Janajatis [Nepal's indigenous peoples] and those with a disability."

[10] A case study carried out at Dartmouth College discusses this issue: "Already exposed to lower standards of healthcare, these [low-caste] people were often offered help last although their need was generally greatest – more low-caste people lived in poorly constructed houses, which collapsed. The majority of Nepali doctors and volunteers were high-caste, so sometimes prone to prioritize high-caste victims over Dalits." See details at https://journeys.dartmouth.edu/NepalQuake-CaseStudies/caste-based-inequality/ (accessed May 11, 2018).

[11] Paudel and Ryu (2018) find that ethnic differences were already prevalent in how Nepalese ethnic groups were affected by the 1988 Nepal earthquake. Using a difference-in-differences setting, they show that human capital of low-caste groups deteriorated more permanently compared to high-caste groups.

that projects were carried out in remote areas populated by poor people. In this regard, the updated appeal document highlighted that "864,000 people in remote villages are in immediate need as they have lost their homes and live below the poverty line" (UNOCHA, 2015b: 5). Moreover, the arriving monsoon had implications for needs across all sectors: "Reaching these most vulnerable communities is a priority to ensure that they are provided with adequate shelter and basic needs to strengthen their resilience ahead of the heavy monsoon rains which begin in June and can last until September" (UNOCHA, 2015b). In the empirical analysis below, we will thus explore whether particular attention in the design and financing of the Flash Appeal was given to municipalities that are geographically remote and vulnerable to heavy monsoon rain.

Finally, anecdotal evidence suggests that domestic political favoritism and patronage bias aid allocation. For example, Amnesty International (2015: 12) documents such claims according to which "the official distribution of tarpaulins favored those with familial, political or other institutional connections and loyalties" and reports that parliamentarians abstract tents intended for disaster victims. The human rights organization is particularly worried about political favoritism and patronage in municipalities that are dominated by a single party and that are demographically heterogeneous with respect to their religious, caste, and ethnic composition. In addition to the analysis of ethnic and religious biases mentioned above, we will thus test whether municipalities governed by one of Nepal's leading parties are more likely to obtain projects within the proposed Flash Appeal, and whether they are more likely to obtain aid funds under the Flash Appeal. Since the official procedures for flash appeals recommend a strong coordination between UN agencies, NGOs, and the local government, the involvement of Nepalese parliamentarians and government officials opens the door for a potential impact of local politicians on the design and implementation of the appeal.

We now turn to our empirical framework used to test whether disaster affectedness, socio-economic and physical vulnerabilities, as well as political favoritism are reflected in the 2015 Nepal Earthquake Flash Appeal.

3 Data and Method

(a) Empirical Design

Our study combines data on the location of emergency aid projects proposed and funded in the framework of the 2015 UN Nepal Earthquake Flash Appeal with measures of earthquake impact collected through remote sensing and census data. Our unit of analysis are municipalities, so-called village development committees (VDCs).[12] The VDCs correspond to the fourth subnational administrative level (ADM4) in Nepal and are grouped into 75 districts (ADM3) in 14 zones (ADM2) located in five regions (ADM1).

We proceed in two steps. In the first step, we analyze the spatial distribution of aid projects in the design stage of the Flash Appeal. Specifically, we analyze the spatial distribution of proposed appeal locations by constructing the *no. of proposed projects*. In a variant of this first step, we also analyze the spatial distribution of financial amounts as requested by the OHC using *proposed financial amount (ln)*. This variable is the logged aggregated financial value in US dollars of all appeal projects proposed for a municipality.

In the second step, we analyze the funding decision. The humanitarian aid obtained by a VDC is the outcome of individual funding decisions by international donors. As first dependent variable, we use *no. of funded projects*, which is the number of funded project locations in a given VDC. In addition to this count variable, we also analyze the financial amount of donor support provided. The variable *funded financial amount (ln)* is the logged aggregated financial value in US dollars of all funded appeal projects committed to a municipality. To isolate the factors shaping the decision-making at the funding stage, we include the number of proposed projects or the requested project amount, respectively, as a covariate to explain deviations from the proposal.

Finally, we use with the *share of funding obtained* an alternative dependent variable to shed light on decision-making at the funding stage. This is the ratio of the funded aid amount to the proposed aid amount. In this final specification, we are restricted to the sample of those

[12] We use VDC and municipality interchangeably throughout the paper.

1,290 municipalities that were proposed by the UNOCHA and the OHC as a location for at least one appeal project.[13]

For each stage in the appeal process, we run Negative Binomial (NB) regressions whenever the project number is the dependent variable and Ordinary Least Squares (OLS) regressions otherwise. NB regression is appropriate for count outcome variables that are non-negative and over-dispersed.[14] NB regression is a generalization of the Poisson estimation and based on a Poisson gamma mixture distribution. This allows the variance to be larger than the mean as is the case in our data. We estimate the following cross-sectional NB regression:

$$E(Project\ Number_i\ |\boldsymbol{D_i}, \boldsymbol{X_i}, PP_i) = \alpha_i * \exp(\boldsymbol{D'_i}\,\beta + \boldsymbol{X}_i'\gamma + \delta PP_i\,) \qquad (2)$$

where α_i, the latent exposure of a municipality i, is estimated from the data. The matrix $\boldsymbol{D}$ includes both the physical intensities of the first earthquake and the main aftershock, while $\boldsymbol{X}$ includes the remaining covariates described below. As mentioned earlier, the proposed number of projects PP is included in models analyzing the funding stage. Our unit of analysis i consists of the 2,796 Nepalese municipalities.[15] Standard errors are calculated to be robust to heteroscedasticity and clustered at the level of Nepalese districts (ADM3), within which errors are thus allowed to correlate.

For the continuous dependent variables, we deploy the following cross-sectional OLS equation where:

$$y_i = \alpha + \boldsymbol{D'_i}\,\beta + \boldsymbol{X}_i'\gamma + \delta PA_i\, + \varepsilon_i\,, \qquad (2)$$

where the y alternatively refers to any of the three continuous dependent variables, the *proposed financial amount (ln)*, the *funded financial amount (ln),* or *the ratio of funding obtained.* As mentioned above, the proposed project amount PA is included in models analyzing the funding stage.

[13] We use this restricted sample because the ratio is undefined when the proposed aid amount is zero.

[14] We do not use zero-inflated negative binomial regression to model the excessive zeros because this would require the assumptions that excess zeros are generated by a separate process from the count values and that these excess zeros can be modeled independently. We do not believe that these assumptions hold for our data.

[15] We drop VDCs within zones (ADM2) that were unaffected by the immediate earthquake according to the destruction index defined below.

The nature of our cross-sectional data and the lack of a clean identification strategy do not always allow for a causal interpretation. However, our disaster impact measures are constructed from physical measures and from damage functions. They are thus exogenous to emergency aid. Most other variables – such as religion and geographical features – cannot be affected by post-earthquake disaster aid as they were collected prior to the earthquake. Reverse causality is unlikely to be a concern in our setting. It is however possible that measurement error in the disaster impact measures is systematically related to the dependent variable in a spatial sense. We cannot estimate the size of such a potential bias but do not believe that the measurement error is large and systematically related to the dependent variable. In spite of the exogeneity of the earthquake, omitted-variables might still affect our results. We attempt to mitigate this concern by including a rich set of covariates in our baseline model and by running regressions with fixed effects at the ADM2 level in robustness checks.

(b) Data on the 2015 UN Nepal Earthquake Flash Appeal

The primary data source for the dependent variables is UNOCHA's Financial Tracking Service (FTS) (UNOCHA, 2018).[16] The database collects international humanitarian funding flows since 1992 and has frequently been used in empirical analyses of humanitarian aid (e.g., Fink and Redaelli, 2011; Raschky and Schwindt, 2012; Fuchs and Klann, 2013; Fuchs and Öhler, 2019). A major innovation over previous work using FTS data is that we analyze subnational rather than cross-country variation in the allocation of humanitarian aid. Specifically, we use a new, and so far unexploited, geospatial dataset by AidData (2016a). It contains the geographic location of 156 of the total 184 Nepal Earthquake Flash Appeal projects registered in FTS, of which funding was requested for 142 in the revised Flash Appeal of May 29, 2015.[17] These 142 projects were assigned to 821 project locations.[18] We use these data to build the five dependent variables described above.

[16] The stated goal of FTS "is to give credit and visibility to donors for their generosity and to show the total amount funding and resource gaps in humanitarian appeals" (UNOCHA, 2015a). Humanitarian funding is usually reported to FTS by the recipient organization and not the donor because the former is best informed about the final usage of funds.

[17] 184 – 156 = 24 of the proposed appeal projects could not be geocoded because of the nature of the project or a lack of information on the location of implementation.

[18] For projects geocoded with precision at the ADM3 level, i.e., one layer above our spatial unit of analysis, we attribute a project to all VDCs in this ADM3 unit and evenly split the requested and proposed project amount

While the upper panel of Figure 1 shows the spatial distribution of the proposed appeal projects, the lower panel displays the number of funded projects by municipality. Only 64 (56) out of the 184 (142) proposed appeal projects (with geocoded locations) obtained any funding from donors. In total, the 156 geocoded appeal projects received US$ 280 million. Appendix 2 lists the 20 largest flash appeal projects funded by the international donor community.

(c) Disaster impact

The need for emergency aid increases with the severity of the catastrophe. To capture disaster impact, we employ physical measures of disaster severity.[19] The disaster literature makes increasing use of geo-referenced physical variables to measure the intensity of natural disasters (Hsiang, 2010; Strobl, 2011, 2012; Bertinelli and Strobl, 2013; Felbermayr and Gröschl, 2014; Fisker, 2014; Berlemann 2016; Kunze, 2018). These measures have the advantage that they are exogenous to economic outcomes of interest such as economic development, thus allowing for causal inference. To measure the physical intensity of the earthquake in Nepal, we use peak ground acceleration (PGA) maps provided by USGS (2017b), which is arguably a suitable indicator for potential destruction from earthquakes to buildings up to seven stories tall (USGS 2017c).

Importantly, the damage suffered from earthquakes will not only be determined by the physical features of the event, but also depends on the type of building affected. To take account of this, we use information on the housing building types provided by the 2011 Census (Central Bureau of Statistics 2011) in conjunction with fragility curves by building types developed by the Global Earthquake Safety Initiative project (GESI) (Geohazards International and United Nations Centre for Regional Development, 2001). More specifically, building

across all these VDCs. This implies that 3023 of 3957 ADM4 locations are recipient of a proposed project. If a project is coded both at the ADM3 level and at the ADM4 level, we only keep the ADM4 location.

[19] Most of the cross-country literature uses the number of fatalities or the total number of affected people from the International Disasters Database EM-DAT as a measure of disaster impact (Lazzaroni and van Bergeijk, 2014; Guha-Sapir et al., 2016b). What is more, the EM-DAT data has been criticized for various reasons (e.g., ; Felbermayr and Gröschl, 2014; Felbermayr and Gröschl, 2014). However, for our study, we need subnational variation of disaster severity and EM-DAT has to date only been geo-referenced for the Philippines by AidData.

types are classified into nine different categories.[20] Each building type itself is then rated according to the quality of the design, the quality of construction, and the quality of materials. Total quality is measured on a scale of zero to seven, depending on the total accumulated points from all three categories. According to the type of building and the total points acquired through the quality classification, each building is then assigned one of nine vulnerability curves, providing estimates of the percentage of building damage for a set of 28 peak ground acceleration intervals. In order to use these vulnerability curves for Nepal, we first allocate each of the five building types given in the 2011 Census to one of the less aggregate categories of the GESI building classification.[21] Given that we have no information as to the quality of buildings in Nepal in terms of design, construction, and materials, we instead assume that building quality is homogenous across building types but experiment with two different sets of vulnerability curves, one for the highest and one for the lowest quality rating scenario.

In order to derive an administrative region i-specific earthquake destruction index, *ED*, we compute the following:

$$ED_{q,i} = \sum_{s=1}^{5} w_{si} DR_s^q(pga_i) \quad \text{with} \quad q \in \{low, high\}$$

where w is the share of building type s in region i, *DR* is the damage ratio of the building type s given the observed local peak ground acceleration *pga* in region i, defined for quality, q, high- and low-quality buildings. For our analysis, we construct two variables, *immediate damage*, which captures the destruction of the main earthquake, and *aftershock damage*, which reflects the destruction of the major aftershock. For both variables, we use the more restrictive scenario of high-quality buildings as benchmark measures.

Figure 2 shows the spatial variation of our measures of disaster impact, *immediate damage* (panel a) and *aftershock damage* (panel b) across municipalities. The stars mark the respective epicenter of the two shakes. The different colors stand for different damage experiences according to our earthquake destruction index, ranging from blue ("weak") to red ("extreme").

[20] Wood, steel, reinforced concrete, reinforced concrete or steel with unreinforced masonry infill walls, reinforced masonry, unreinforced masonry, adobe and adobe brick, stone rubble, and lightweight shack or lightweight traditional.

[21] For those buildings in the other or unassigned category, we assumed they were of the most vulnerable type, namely, lightweight shack (e.g., corrugated iron sheet) or lightweight traditional (e.g., bamboo).

Around 2.75 percent of our sample villages experience extreme damages with 87.5% to 100% of all buildings predicted by the index as being destroyed by the immediate earthquake. Both panels demonstrate that the majority of destruction occurs in VDCs northwest and northeast of Kathmandu, whereas the relatively highly populated southern regions experience only weak or light damages.

(d) Socio-economic and physical vulnerabilities

One the one hand, poorer municipalities are more vulnerable to the consequences of the earthquake and have a higher self-aid capacity. One the other hand, economically more important VDCs might have a higher ability to make their needs heard. To account for the level of development of municipalities, we use the average monthly nighttime light intensity (*average nightlight pre-earthquake)* from January 2012 to March 2015. In doing so, we are following a growing literature that proxies local economic output with nighttime light intensity (Chen and Nordhaus, 2011; Michalopoulos and Papaioannou, 2014; Hodler and Raschky, 2014; Alesina et al., 2016). In the absence of accurate GDP data, nighttime light offers a viable alternative since it correlates highly with survey-based measures of wealth (Weidmann and Schutte, 2016). Furthermore, Bertinelli and Strobl (2013) have provided evidence that nighttime light intensity is able to capture reported destruction from hurricanes in Caribbean countries.

Previous studies have mostly used the nighttime light series for stable light from the Defense Meteorological Satellites Program (DMSP), which offers stable and filtered yearly average data. However, it has several drawbacks, including overglow effects around cities (Small et al., 2005) and top-coding problems of city centers (Doll, 2008; Bluhm and Krause, 2018). Instead, we use data from the recently launched Visible Infrared Imaging Radiometer Suite (VIIRS) satellite, which offers stable and filtered, and uncensored, data on a monthly basis since April 2012. For our analysis, we downloaded the Version 1 Nighttime VIIRS Day/Night Band Composites available from the Earth Observations Group at NOAA/NDGC for January 2012 until August 2016 (NOAA, 2017). Importantly, the VIIRS images overcome most of the stated criticism of the DMSP images (Levin and Zhang, 2017). As a matter of fact, Li et al. (2013) provide evidence that the VIIRS nighttime light images have a substantially higher correlation with regional economic activity in China than the DMSP images. Moreover, with a ground footprint of 742 meters * 742 meters, VIIRS data provides a resolution 45 times higher than the DMSP images (Elvidge et al., 2013). This allows us to identify nighttime light luminosity even in a low electrified country such as Nepal, as can be seen in Appendix 3. The figure furthermore shows that most of the nighttime light intensity is concentrated in the Kathmandu Valley and the southern part of Nepal, whereas the northern regions only have a little luminosity. These spatial differences in nighttime light intensity correspond to the actual distribution of economic activities and population in the country.

Second, as another measure of self-aid capacity, we calculate the percentage of households within each VDC with a *solid house foundation* using the 2011 census data to proxy the degree of urbanization (Central Bureau of Statistics, 2011). We define solid house foundations as houses built on a cement foundation. As the map in Appendix 4 demonstrates, more solid houses are situated within cities. Hence, this measure is a proxy for the degree of urban areas, for which we expect a higher self-aid capacity.

Third, larger and more populated municipalities are more likely to host more affected people and suffer from larger damages. This follows from pure logic of scale. Thus, they are not only more likely to receive emergency aid in general but also more of it. Therefore, we control for the area, *admin 4 area*, and the (logged) population size of the VDCs, *population*, using data from the 2011 Census in Nepal (Central Bureau of Statistics, 2011). The map in Appendix 5 shows the population density of municipalities in Nepal in 2011. Accordingly, most of Nepal's population lives in the Kathmandu Valley or in southern Nepal, which corresponds to our observation concerning nighttime light intensity (see Appendix 3).

Fourth, transport infrastructure plays a crucial role for aid delivery and we thus account for each municipality's distance to the nearest airport and to Nepal's capital Kathmandu with its particularly important Kathmandu International Airport. Specifically, we include the distance from each municipality to the nearest airport in (logged) kilometers (*distance to closest airport*), as measured from its centroid. The Tribhuvan airport in Kathmandu is the only international airport that can handle medium- to large-sized planes, but there are various smaller airports in Nepal. These are crucial for getting supplies to the respective areas the respective areas since roads are non-existent or in a bad condition, especially after the earthquake(s) in 2015. The closest airport from the epicenter of the earthquake in Ghalychok VDC is 34 kilometers away. Moreover, the distance to Kathmandu is an indicator for accessibility of affected municipalities to international relief teams, as much of the international help was stranded at the international airport in Kathmandu. The distance to Kathmandu from the Ghalychok VDC is around 60 kilometers. To take care of the remoteness of the individual VDC, we add the logged *distance to Kathmandu* as additional control variable for our regression. Our distances variables can thus be interpreted as proxies for delivery costs. Remote municipalities might receive less aid money since it is more efficient to allocate more aid to easy-to-reach locations.

Finally, because of the monsoon season, which typically starts in June each year and lasts until September each year, VDCs with a higher mean rainfall will have a greater need for humanitarian aid if the earthquake destroyed their houses and roads. Thus, we add *mean rainfall* over the period 1998-2014, measured in millimeter for each VDC, and, to account for simple non-linear effects, the *mean rainfall squared*. To derive this measure, we use the monthly precipitation raster maps of the Tropical Rainfall Measuring Mission (TRMM), which are available from 1998 with a spatial resolution of 0.25° (Huffmann et al., 2014).

(e) Ethnic, religious, and political distortions

Despite being a secular democracy today, a social and religious caste system still characterizes the daily life of the former Hindu kingdom of Nepal. In the Nepalese society, the upper-castes consists of the Bahun and Chetri groups (who together correspond to Brahmins in Indian Hinduism), and the Newari group (see, for example, Murshed and Gates, 2005). Although the caste system was officially abolished in 1963, caste-based discrimination remains an issue. The upper castes still have an overproportioned influence on many decisions in Nepal and are disproportionally represented in governance institutions (DFID and World Bank, 2006; Dalit Civil Society Organizations' Coalition for UPR and International Dalit Solidarity Network, 2015). It is therefore likely that the upper castes are well represented in the offices guiding the allocation of humanitarian aid. They might thus favor those VDCs where a high percentage of their fellow caste members live. To measure possible ethnic and religious favoritism, we calculate the percentage of *privileged castes* within each VDC of our sample using the 2011 Census (Central Bureau of Statistics, 2011). Panel (a) of Figure 3 displays the spatial distribution of *privileged castes*, which varies considerably within our sample. Furthermore, we include the percentage of Hindu households at the district level (*Hin-*

du), also constructed from the 2011 Census data. Panel b of Figure 3 demonstrates that Hindus are mostly concentrated in the middle and lower districts of Nepal, therefore they are less likely to live in the Himalaya regions.

To measure possible political favoritism and patronage in the allocation and funding of humanitarian aid, we use district-level data from the 2013 Constituent Assembly elections, the last national elections before the earthquake in 2013 to compute the respective percentage of the two largest parties in Nepal, the *Nepali Congress Party* and the *Nepal Communist Party* (Election Commission Nepal, 2018). Figure 4 shows the spatial distribution of both variables.

(f) Existing aid networks

It is possible that the OHC plans to make use of the existing aid infrastructure to implement emergency projects quickly and effectively and thus chooses project locations accordingly. In addition, better information on post-disaster needs might be available to the OHC from places where (local) aid staff work or have worked. To test whether municipalities where international donors have a track record of aid activities are more or less likely to be selected as destinations of emergency aid, we use information on the locations of these general development aid projects from AidData (2016b). The data has been geo-referend by using the project information contained in the Aid Management Platform (AMP) within the Aid Information Management System (AIMS) of Nepal's Ministry of Finance. This includes 148 projects, which were implemented in more than 15,088 locations. Their aggregate value amounts to more than US$ 1.32 billion. For our analysis, we calculate the probability of receiving aid in a given year over the 2002-2014 period, *general aid probability*, for each VDC in our sample.

Table 1 provides descriptive statistics, Appendix 6 lists all definitions with data sources, and Appendix 7 provides a correlation matrix for all variables employed in this paper.

4 Results

(a) Design stage: Proposed projects

We start by examining the factors associated with the number of proposed Flash Appeal projects per VDC. Column 1 of Table 3 presents the marginal effects at the mean of the covariates, where we exclude the variables proxying ethnic, religious, and political distortions in the design of the Flash Appeal. Apart from our measures of the earthquake's destructiveness, column 1 also includes measures of socio-economic vulnerabilities (logged population; degree of urbanization, and average nighttime light before the earthquake), and of physical vulnerabilities (the municipality's logged area in square kilometers, mean rainfall and its square in the years before the earthquake; logged distance to Kathmandu and to the nearest airport), and existing aid networks (the probability of receiving general development aid projects in the decade before the earthquake). As expected, a municipality's likelihood to obtain a proposed appeal project increases with the earthquake destruction index of the major shake (April 25, 2015) and the major aftershock (May 12, 2015). This is indicated by the statistically significant marginal effects of *immediate damage* and *aftershock damage*. Quantitatively, a one-standard-deviation increase in immediate damage corresponds to an increase in the number of proposed projects by 0.8. Put differently, a VDC that is completely damaged (index value of one) receives 4.3 more projects than a VDC that is unaffected by the major shake. The impact of the aftershock still receives economically and statistically significant but less attention. A completely damaged VDC obtains only 2.7 more projects than one completely unaffected by the aftershock. These results for the exogenous proxies of earthquake damage show that the location choice of the Flash Appeal follows actual needs on the ground—but only to a certain extent as we will see when we analyze potential distortions below.

It is also reassuring that, according to Column 1 of Table 3, geographically larger and areas that are less urban still receive more aid, as indicated by the respective statistically significant marginal effects on *admin 4 area (ln)* and *solid house foundation (%)*. While it seems at first sight that poorer regions get more projects in the proposal, the significant negative effect of *pre-earthquake nightlight* disappears once we control for ethnic, religious, and political biases later on. Moreover, the marginal effects on *population (ln)* and *mean rainfall* (and its squared term) do not reach statistical significance at conventional levels. This implies that more populous municipalities, those that were more affected by an intense monsoon in the past, and those that were less developed at the time of the earthquake do not receive more aid. Turning to our distance variables, the insignificant marginal effect of *distance to airport (ln)* suggests that municipalities closer to an airport are not attracting more proposed projects. However, we find that municipalities closer to the capital receive more proposed projects in the Flash Appeal, as indicated by the highly significant negative marginal effect of *distance to Kathmandu (ln)*. If decision-makers allocate aid dollars where they see the biggest bang-for-the-buck, they naturally disadvantage more distant, hard-to-reach locations.

Summarizing our results so far, it thus appears that socio-economic and physical vulnerabilities are not sufficiently taken into consideration when the locations of proposed projects are assembled in the Flash Appeal. These results qualify our earlier interpretation of a need-based allocation of aid.

Next, we find evidence for aid inertia. Municipalities that have benefitted from general development aid in the past are more likely to be included in the Flash Appeal. The marginal effect of *general aid probability* is statistically significant at the ten-percent level and suggests that a municipality that received an aid project on an annual basis obtains 3.6 additional Flash Appeal projects compared to a municipality that never received general development aid over the 2002-2014 period.

In Column 2 of Table 3, we find some evidence suggesting that ethnic and political distortions play a role. Specifically, regions with a higher share of privileged castes receive significantly more projects at the design stage. According to the marginal effect of *privileged castes (%)*, a municipality that is entirely populated by Brahman, Chhetree, and Newari receives 1.4 additional proposed projects compared to a municipality without high-caste people. There is weak evidence that municipalities with a higher share of Hindus receive fewer proposed projects. Since the effect of *Hindu (%)* loses statistical significance once we exclude Kathmandu in Appendix 8, we suggest interpreting this effect as a "capital effect" rather than the outcome of religious biases.

Finally, there is evidence that typical strongholds of the *Nepali Congress Party* receive a favorable treatment at the design stage. Municipalities with a ten percent higher vote share receive one additional aid project. We present the importance of the factors associated with the number of proposed projects in Figure 5. The figure displays the effect of a one-standard-deviation increase in the number of proposed projects per municipality for each of the statistically significant variables.

We repeat our analysis with logged proposed financial amounts rather than project numbers as the dependent variable. The results in columns 3 and 4 largely support our earlier findings. We again discover a strong response to municipalities' damage following the major shock and—albeit less robust—the aftershock.[22]

From a humanitarian perspective, it is worrisome that we again find that municipalities closer to Kathmandu obtain more aid and that the design is also not responsive to the level of development of VDCs, as measured by nighttime light emissions. The negative coefficient on *population (ln)* even suggests that larger municipalities receive smaller financial amounts of aid rather than more support for the larger amount of needy people. There is however also some good news. Less urban parts of the country, arguably those with a higher self-aid capacity, receive more aid. Moreover, while we did not detect responsiveness of project numbers to monsoon rain, there is at least weak evidence that municipalities suffering from rain obtain larger financial amounts of aid.

We again find some evidence suggesting that political favoritism or patronage plays a role. More specifically, we find that larger financial amounts flow into strongholds of the Nepali Congress Party, the party that was in power at the time of the design of the Flash Appeal. The same is true for the Communist party. While it appears counterintuitive at first sight that the strongholds of the major opposition party were similarly favored, the Nepali government had a large interest in buying support for the upcoming referendum on the Nepali constitution (Sharma and Ellen, 2015). All remaining variables show no significant marginal effects in the full specification in column 4.[23]

[22] Note that the coefficient on *aftershock damage* loses its statistical significance when we control for potential ethnic, religious, and political distortions in column 4, but regains statistical significance when we run regressions with binary indicators for each zone (ADM2 region) to account for unobserved regional characteristics zone dummies (see Appendix 8).

[23] Our major findings are largely robust when we exclude Nepal's capital from the sample. We provide detailed regression results in Appendix 8.

(b) Funding stage: Committed projects

Table 4 analyzes the funding stage. Columns 1 and 3 display the results with the number of funded projects and columns 2 and 4 show those with the funded financial amount as the dependent variable, respectively. Qualitatively, the results in the first two columns largely mimic those for the design stage in Table 3.[24] Quantitatively, the marginal effects tend to be smaller, which partly reflects the fact that the 2015 Nepal Earthquake Flash Appeal has been underfunded.

To understand the mechanisms at the funding stage, we need to disentangle it from the design stage. Therefore, columns 3 and 4 include the number of proposed projects and the proposed financial amount, respectively, as additional covariates. By conditioning on proposed aid, we can analyze the factors that are associated with deviations from the initial proposal.

It appears that the funding decisions of donors aggravate some of the distortions in aid allocation. First, donors are more likely to support and provide more funding to projects closer to Kathmandu, which likely reflects accessibility for aid delivery. Logistical convenience matters, which is in line with the findings for Pakistan in Benini et al. (2009). Second, we find some evidence for aid inertia; municipalities that were popular aid locations in the past are more likely to get their projects funded. Thus, rather than sticking to the plans outlined in the Flash Appeal, donors appear to cuddle their aid darlings. If a municipality's propensity of past aid receipt increases from 0 (never received general development aid) to 1 (received aid each year), the number of funded projects increases by almost 2. Finally, since there is no evidence that the share of the privileged castes plays a role for the number of funded projects once we control for proposed aid, the bias from the design stage seems to persist. The bias based on a municipality's electoral record even seems to aggravate as suggested by the positive and highly significant marginal effect of *Nepali Congress Party (%)*.

There are a few positive aspects to highlight. First, donors put more emphasis on the aftershock damage, which was undervalued at the design stage (column 4). Second, donors fund more projects in less urban municipalities and channel higher amounts to larger munic-

[24] The only noteworthy exception is the negative and now weakly significant marginal effect of *pre-earthquake nightlight (ln)* in column 1.

ipalities as suggested by the significant marginal effects on *solid house foundation (%)* and *population (ln)* in column 3 and 4, respectively. It is, however, worrisome that most of the weaknesses of the design stage are not corrected at the funding stage. For example, we find no robust evidence that municipalities with heavy monsoon rain or those with a large share of low-caste people obtain more funding since the corresponding coefficients on *mean rainfall* and *privileged castes (%)* are not statistically significant at conventional levels in columns 3 and 4.

In Column 5 of Table 4, the dependent variable is the ratio of the received funding from international donors to the requested aid amount. We confirm that donors are more likely to fund VDCs suffering from the aftershock than originally planned according to the Flash Appeal. In line with our earlier findings, there is no evidence that funding decisions respond to the specific socio-economic and physical vulnerabilities. The results rather suggest that projects in municipalities closer to Kathmandu and those that are populated by privileged castes obtain a larger share of funding. Again, we find that donors support their aid darlings by channeling more funds to previous aid beneficiaries. Finally, we observe that donors favor municipalities populated by higher castes also in the funding stage, which strengthens the ethnic bias from the design stage. A municipality that is entirely inhabited by privileged castes obtains an additional funding share of ten percentage points compared to a municipality without high-caste people.[25]

Taken together, our results suggest that the need orientation of the spatial project selection and funding should be strengthened at all levels of decision-making: during the design of flash appeals by UNOCHA and the OHC, as well as in the coordination and funding phase of donor countries and non-state donors.

[25] We also checked for the impact of an exclusion of Kathmandu from our sample and run regressions with binary indicators for each zone (ADM2 region). We provide detailed regression results in Appendix 9. While some variables lose statistical significance in some specifications, our major conclusions are unaffected.

5 Conclusions

Four days after the 2015 Nepal earthquake, when the United Nations issued its Flash Appeal, the death toll already stood at 5,006 and the number of injured people was at five-figure levels (UNOCHA 2015a). At that point in time, national and international relief efforts were already underway but were far from meeting the needs on the ground. To scale up such efforts, the Flash Appeal called upon the international community to provide an additional US$ 422 million in response to the most urgent humanitarian needs over a period of three months. From the inception of UN flash appeals in 2003 until 2015, a total of 78 such appeals have been launched to quickly respond to the severe fast-onset humanitarian disasters worldwide. However, their design and implementation have been largely ignored by scholarly research. This paper attempts to fill this gap. More specifically, we analyzed the factors that drive the selection of proposed and funded project locations, as well as the size of the funds in the framework of the 2015 Nepal Earthquake Flash Appeal. By doing so, we have not only provided the first quantitative analysis of the design and implementation of UN flash appeals, but also contributed to the emerging literature on the subnational analysis of aid allocation (Findley et al., 2011; Briggs, 2014; Dreher et al., 2016; Briggs, 2017; Nunnenkamp et al., 2017; Öhler et al., 2017; Briggs, 2018).

Our results suggest that the allocation of proposed project locations is related to disaster destructiveness. However, other local need indicators, such as the population size and the level of development of municipalities, appear to not influence the design of flash appeals in the expected direction. There is also evidence that municipalities close to the Nepalese capital and those that have frequently received general development aid are more likely to attract projects. Even if this was the outcome of cost-benefit analyses, this finding highlights that individuals living in more distant, hard-to-reach locations which are not regular aid recipients are disadvantaged. Given that remote locations are also likely to be disadvantaged by national decision-makers, it is worrisome that international donors do not fill the void. Moreover, in some specifications, we find some evidence that the spatial distribution of privileged castes and the vote shares of Nepal's major political parties drive aid decisions. This is worrisome given the mandate of the UN. What is more, funding decisions counteract the need orientation of project proposals and show little regard for the specific socio-economic and physical vulnerabilities of the affected population. Although these results should be treated with caution because of the above discussed concerns about causality and remaining omitted-variable bias, one may carefully conclude that the need orientation of geographic project selection should be strengthened and that further measures are warranted to reduce the influence of ethnic and political distortions in the design and implementation of flash appeals. More precisely, UNOCHA and the OHC need to choose more carefully the proposed project locations in the design phase of the Flash Appeal, while international donors should improve the need orientation of their funding decisions.

Our study has some weaknesses that future research hopefully will be able to address. First, since the present paper focuses only on decisions made after a single disaster, it is an open question as to whether our findings can be generalized to other UN flash appeals. Future research should thus investigate other major catastrophes as more geo-referenced aid data become available to increase the external validity of our findings. Second, although previous research shows for other parts of the world that measures of disaster destructiveness based on physical features of the event and damage functions like ours were valid proxies (Antilla-Hughes and Hsiang, 2012), it remains only an estimate of actual destructions. Future research could endeavor to use daytime remote-sensing data on the state of physical infrastructure to obtain a more comprehensive picture of changes in local wealth in the aftermath of disasters. Third, we were not able to analyze gender as a form of exclusion since we focus on the geospatial allocation of aid. Future studies could look at this with individual-level data that allows one to detect discrimination between the two sexes. Fourth, while data availability restricted the focus of the present paper on the design and funding of flash appeal projects, research in the future could analyze whether such projects are indeed (successfully) carried out on the ground.

Finally, it would be interesting to analyze differences in aid allocation decisions between different types of funding organizations and different types of implementing organizations. Donors can be grouped into members of the OECD's Development Assistance Committee (DAC) and non-DAC bilateral donors, international organizations, non-governmental organizations (NGOs), and companies. More precisely, some donors might allocate aid to better use than others, as they select where and by whom aid projects are carried out. For example, regarding the decision to provide emergency aid, Fuchs and Klann (2013) find that non-DAC donor countries attach relatively more importance to political motives and that authoritarian donor countries favor countries rich in natural resources and disfavor democracies. Investigating differences in the extent to which different donors are more or less need-oriented than others would be a valuable addition to the literature on 'non-traditional' donors (Dreher et al., 2011; Nunnenkamp and Öhler, 2011; Fuchs and Vadlamannati, 2013; Acht et al., 2015; Semrau and Thiele, 2017).

These and other endeavors to carry out evidence-based research on UN flash appeals are highly warranted. Moreover, climate change is likely to make extreme weather events more frequent and lead to an increase in the incidence of climate-related catastrophes (Easterling, 2000). At the same time, the number of conflicts is on the rise over the past five years (Dupuy and Rustad, 2018). These developments will increase the frequency of UN flash appeals and will fuel demands to increase the transparency about the allocation of emergency aid, including the design, implementation, and effects of flash appeals.

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Figures and Tables

Table 1: List of 20 largest UN flash appeals (2005-2016)

Rank	Flash appeal	Year	Revised requirements (in mUS$)	Total resources available (in mUS$)	% Covered
1	PAKISTAN Floods July 2010	2010	1,963	1,371	69.9%
2	YEMEN 2015	2015	1,601	915	57.1%
3	HAITI Earthquakes January 2010	2010	1,502	1,101	73.3%
4	INDIAN OCEAN Earthquake/Tsunami December 2004	2005	1,409	1,248	88.5%
5	SOUTH ASIA Earthquake October 2005	2005	561	368	65.5%
6	MYANMAR Tropical Cyclone Nargis May 2008	2008	477	349	73.1%
7	**NEPAL Earthquake April 2015**	**2015**	**422**	**282**	**66.8%**
8	PAKISTAN Floods August 2011	2011	357	157	44.0%
9	LIBYA Unrest and Neighbouring Countries (Egypt, Niger and Tunisia) February 2011	2011	336	279	83.1%
10	IRAQ 2016	2016	284	276	97.4%
11	KENYA Post-Election Emergency January 2008	2008	208	137	66.0%
12	AFGHANISTAN 2016	2016	152	60	39.6%
13	PHILIPPINES Typhoon Ketsana September 2009	2009	144	63	43.7%
14	HAITI Hurricane Matthew October 2016	2016	139	86	62.2%
15	HAITI Hurricane Gustav and Tropical Storm Hanna September 2008	2008	121	73	60.5%
16	GEORGIA Crisis August 2008	2008	114	73	63.9%
17	LEBANON Crisis July 2006	2006	97	119	123.2%
18	KYRGYZSTAN Civil unrest June 2010	2010	94	69	72.8%
19	NIGER Drought/Locust Invasion Food Security Crisis 2005	2005	81	59	72.7%
20	INDONESIA Java Earthquake May 2006	2006	80	43	53.4%

Source: Own calculations with data from UNOCHA (2018).

Table 2: Descriptive statistics

	Count	Mean	Std. dev.	Min	Max
Dependent variables					
No. of proposed projects	2,816	11.56	19.78	0.00	75.00
No. of funded projects	2,816	6.49	10.76	0.00	40.00
Proposed financial amount (1,000 USD)	2,816	2,429.42	2,905.68	0.00	9,834.33
Funded financial amount (1,000 USD)	2,816	960.77	1,282.14	0.00	5,232.67
Share of funding obtained	2,816	0.18	0.22	0.00	0.60
Disaster impact variables					
Immediate damage	2,816	0.19	0.23	0.00	0.98
Aftershock damage	2,816	0.06	0.16	0.00	1.00
Socio-economic vulnerabilities					
Population	2,816	7,193.51	12,822.10	0.00	255,465.00
Solid house foundation (%)	2,816	10.55	13.53	0.00	77.86
Pre-earthquake nightlight	2,816	0.28	0.33	0.10	6.39
Physical vulnerabilities					
Admin 4 area	2,816	27.43	53.31	1.17	888.55
Mean rainfall	2,816	152.54	15.98	36.20	182.99
Distance to Kathmandu	2,816	128.30	64.45	0.00	271.28
Distance to airport	2,816	24.42	13.16	0.19	67.48
Ethnic, religious and political factors					
Hindu (%)	2,816	76.88	14.45	26.08	97.39
Privileged castes (%)	2,804	25.20	24.00	0.00	96.06
Nepal Communist Party (%)	2,816	24.29	8.93	6.95	39.82
Nepali Congress Party (%)	2,816	25.39	8.13	10.83	40.84
Existing aid networks					
General aid probability	2,797	0.12	0.07	0.08	0.62

Table 3: Proposed flash appeal projects after the 2015 Nepal earthquake

	(1) *No. of proposed projects*	(2) *No. of proposed projects*	(3) *Proposed financial amount (ln)*	(4) *Proposed financial amount (ln)*
Immediate damage	4.279**	3.537**	7.167**	7.183**
	[1.882]	[1.374]	[3.068]	[3.138]
Aftershock damage	2.702***	2.596***	4.436***	3.371
	[0.692]	[0.738]	[1.582]	[2.162]
Population (ln)	-0.120	0.008	-0.841***	-0.446*
	[0.137]	[0.088]	[0.285]	[0.237]
Solid house foundation (%)	-0.075***	-0.045**	-0.067**	-0.024
	[0.028]	[0.020]	[0.031]	[0.028]
Pre-earthquake nightlight (ln)	-1.192*	-0.673	-1.625	-0.409
	[0.638]	[0.412]	[1.028]	[0.799]
Admin 4 area (ln)	0.844***	0.657***	0.939*	0.594
	[0.284]	[0.225]	[0.469]	[0.457]
Mean rainfall	0.147	0.106	0.266	0.278*
	[0.134]	[0.088]	[0.184]	[0.152]
Mean rainfall squared	-0.001	0.000	-0.001	-0.001
	[0.000]	[0.000]	[0.001]	[0.001]
Distance to Kathmandu (ln)	-3.549***	-2.652***	-3.888***	-4.521***
	[0.910]	[0.597]	[0.912]	[0.840]
Distance to airport (ln)	-0.608	0.044	-1.464	-1.004
	[0.385]	[0.291]	[0.947]	[0.814]
General aid probability	3.565*	2.436*	2.248	6.163
	[2.137]	[1.440]	[5.061]	[4.109]
Privileged castes (%)		0.014**		-0.024
		[0.007]		[0.021]
Hindu (%)		-0.036*		-0.001
		[0.021]		[0.055]
Nepal Communist Party (%)		-0.025		0.219*
		[0.044]		[0.111]
Nepali Congress Party (%)		0.101**		0.186*
		[0.048]		[0.093]
Adjusted R-squared			0.520	0.603
N of observations	2796	2793	2796	2793
N of clusters	47	47	47	47

Notes: Results in columns 1 and 2 are estimated with NB regression and columns 3 and 4 with OLS. Columns 1 and 2 show marginal effects at the mean. Robust standard errors (in brackets) are clustered at the district level (ADM3). * (**, ***) indicates statistical significance at the ten-percent (five-percent, one-percent) level.

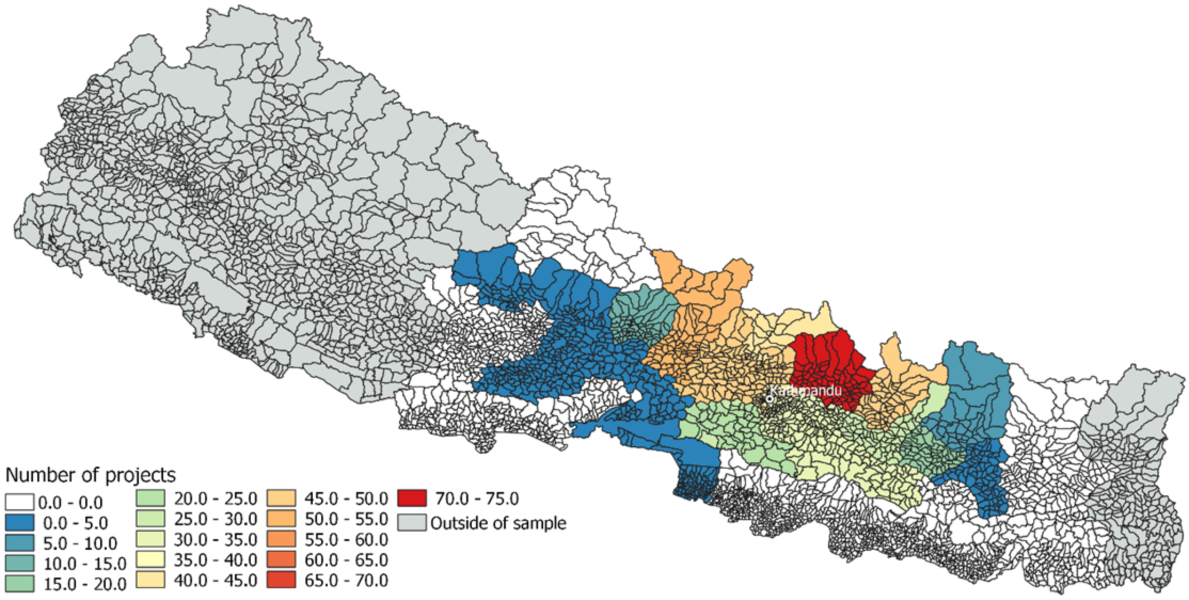
Table 4: Funded flash appeal projects after the 2015 Nepal earthquake

	(1) *No. of funded projects*	(2) *Funded financial amount (ln)*	(3) *No. of funded projects*	(4) *Funded financial amount (ln)*	(5) *Share of funding obtained*
Immediate damage	2.317**	6.724**	-0.825	0.178	-0.062
	[0.961]	[2.935]	[0.595]	[0.213]	[0.064]
Aftershock damage	1.898***	3.616*	-0.160	0.544**	0.147**
	[0.500]	[1.906]	[0.368]	[0.208]	[0.062]
Population (ln)	0.002	-0.390*	-0.021	0.017*	0.004
	[0.068]	[0.215]	[0.048]	[0.009]	[0.003]
Solid house foundation (%)	-0.034**	-0.024	-0.017**	-0.002	-0.001
	[0.015]	[0.026]	[0.008]	[0.001]	[0.001]
Pre-earthquake nightlight (ln)	-0.558*	-0.367	-0.076	0.006	-0.027
	[0.307]	[0.730]	[0.135]	[0.044]	[0.017]
Admin 4 area (ln)	0.478***	0.571	0.200**	0.03	0.018
	[0.164]	[0.421]	[0.082]	[0.020]	[0.011]
Mean rainfall	0.075	0.254*	0.041	0.001	-0.002
	[0.066]	[0.135]	[0.036]	[0.008]	[0.005]
Mean rainfall squared	0.000	-0.001	-0.000	0.000	0.000
	[0.000]	[0.001]	[0.000]	[0.000]	[0.000]
Distance to Kathmandu (ln)	-1.947***	-4.333***	-0.784***	-0.213***	-0.133***
	[0.417]	[0.782]	[0.245]	[0.047]	[0.023]
Distance to airport (ln)	-0.019	-0.882	-0.114	0.033	0.033
	[0.219]	[0.733]	[0.115]	[0.045]	[0.021]
General aid probability	2.135*	5.753	1.905*	0.136	0.226*
	[1.109]	[3.890]	[1.106]	[0.307]	[0.111]
Privileged castes (%)	0.011**	-0.021	0.002	0.001	0.001**
	[0.005]	[0.019]	[0.002]	[0.001]	[0.000]
Hindu (%)	-0.018	-0.004	-0.010	-0.003	-0.002
	[0.015]	[0.050]	[0.008]	[0.003]	[0.001]
Communist Party (%)	-0.010	0.194*	0.021	-0.006	-0.004
	[0.034]	[0.102]	[0.019]	[0.005]	[0.002]
Nepali Congress Party (%)	0.066*	0.178**	0.070***	0.008	0.004
	[0.036]	[0.087]	[0.023]	[0.007]	[0.003]
No. of proposed projects			0.073***		
			[0.018]		
Proposed financial amount (ln)				0.911***	
				[0.008]	
Adjusted R-squared		0.622		0.999	0.666
N of observations	2793	2793	2793	2793	1290
N of clusters	47	47	47	47	24

Notes: Results in columns 1 and 3 are estimated with NB regression and columns 2, 4, and 5 with OLS. Columns 1 and 3 show marginal effects at the mean. Robust standard errors (in brackets) are clustered at the district level (ADM3). * (**, ***) indicates statistical significance at the ten-percent (five-percent, one-percent) level.

Figure 1: Spatial distribution of aid projects of the 2015 UN Nepal Earthquake Flash Appeal across Nepalese VDCs

(a) Number of proposed humanitarian aid projects



(b) Number of (partly) funded humanitarian aid projects

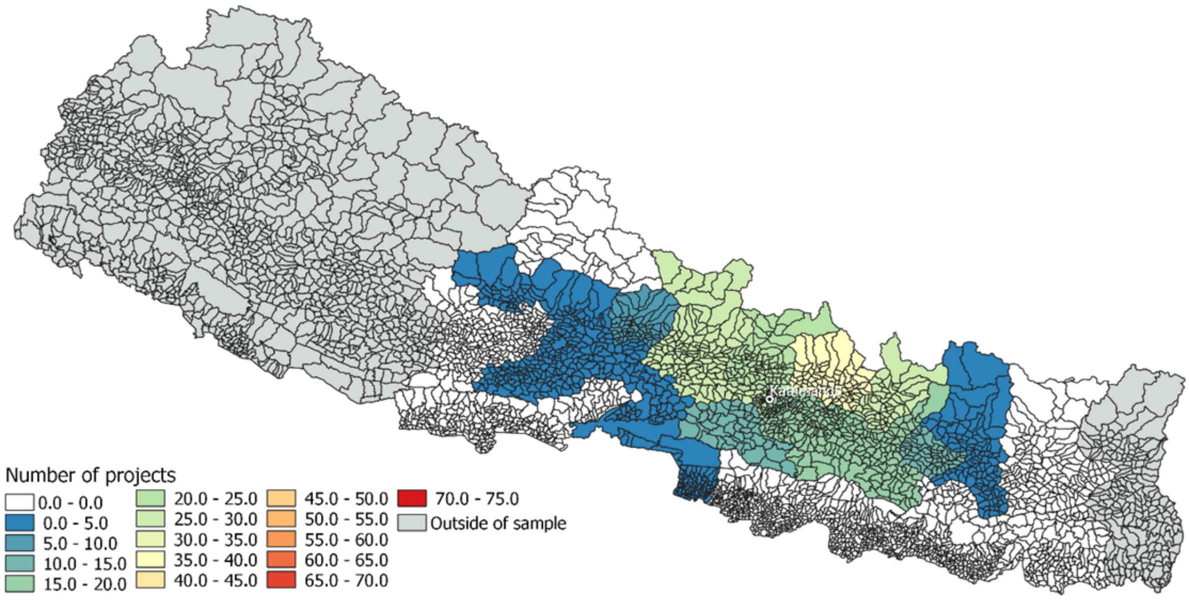
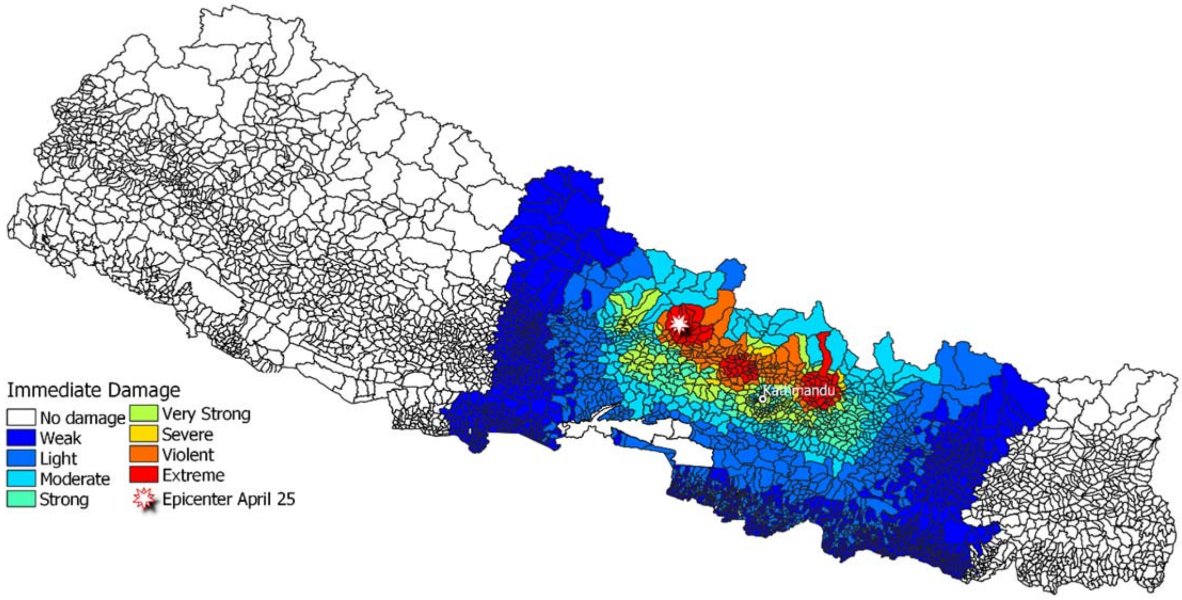
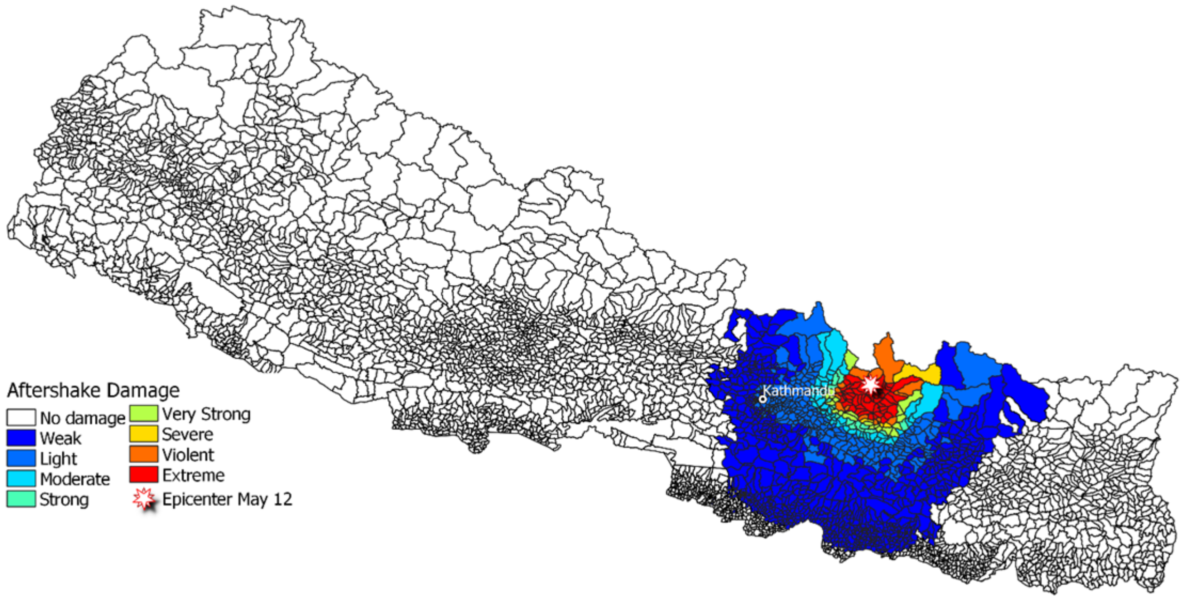


Figure 2: Spatial distribution of damages from the 2015 Nepal earthquake across Nepalese VDCs

(a) Damages of the immediate earthquake (April 25, 2015)



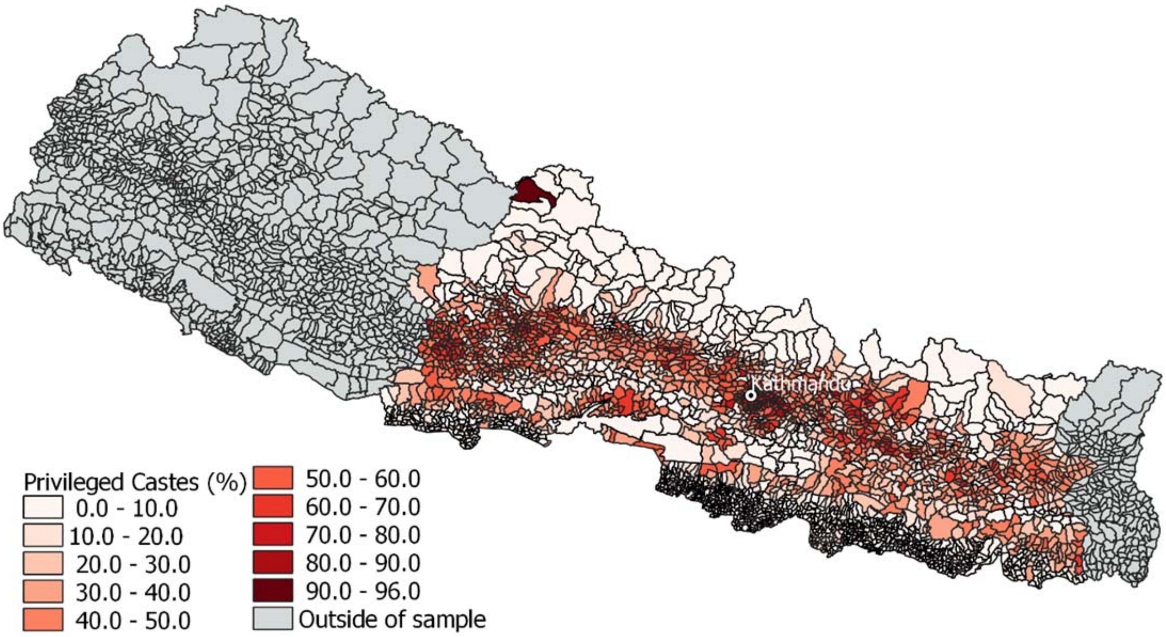
(b) Damages of the major aftershock (May 12, 2015)



Notes: The red stars mark the epicenter of the respective shake. Scale: Percentage of buildings destroyed per VDC: 0%-12.5% (weak), 12.5%-25% (light), 25%-37.5% (moderate) 37.5%-50% (strong), 50%-62.5% (very strong), 62.5%-75% (severe), 75%-87.5% (violent), 87.5%-100% (extreme).

Figure 3: Spatial distribution of Hinduism and privileged castes in Nepal across Nepalese VDCs

(a) Privileged castes (% of Brahman, Chhetree, Newari)



(b) Hindu (%)

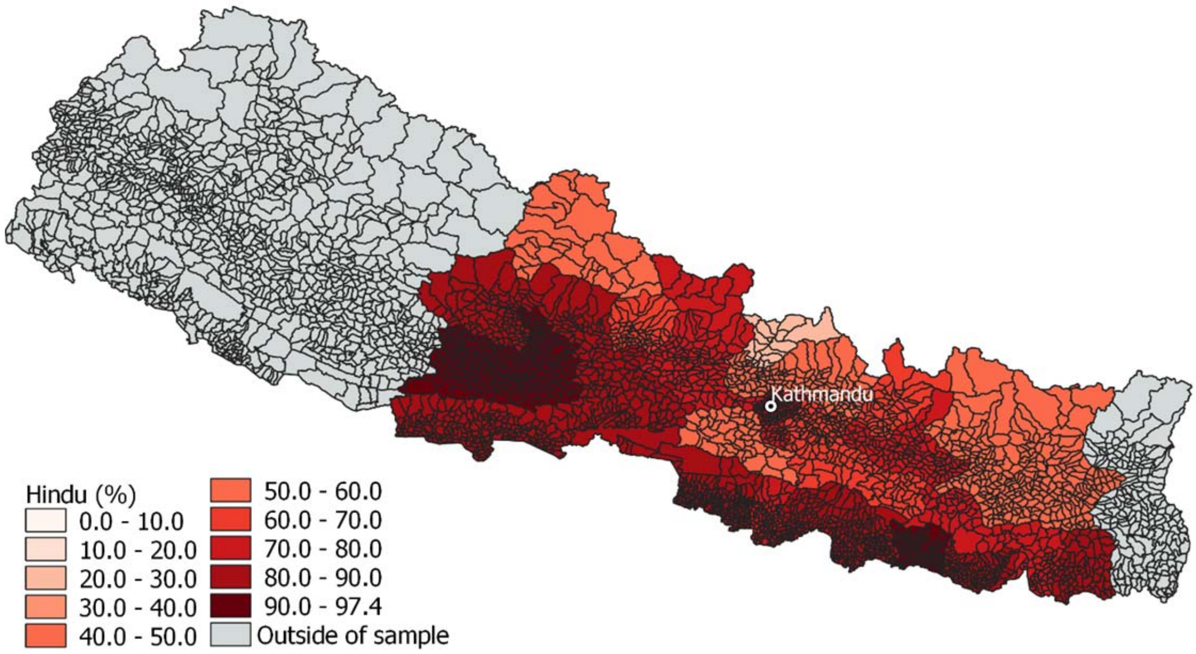
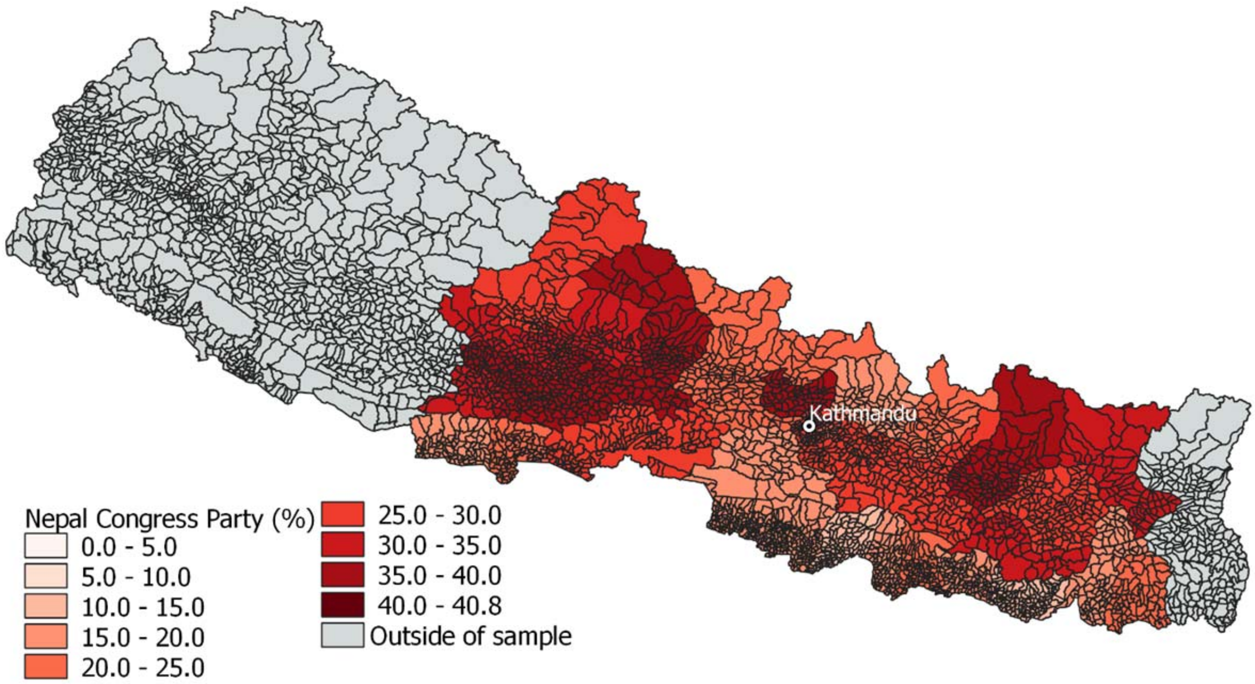


Figure 4: Spatial distribution of votes shares of dominant parties in Nepal across Nepalese VDCs

(a) Nepal Congress Party vote share in 2013 (%)



(b) Nepali Communist Party vote share in 2013 (%)

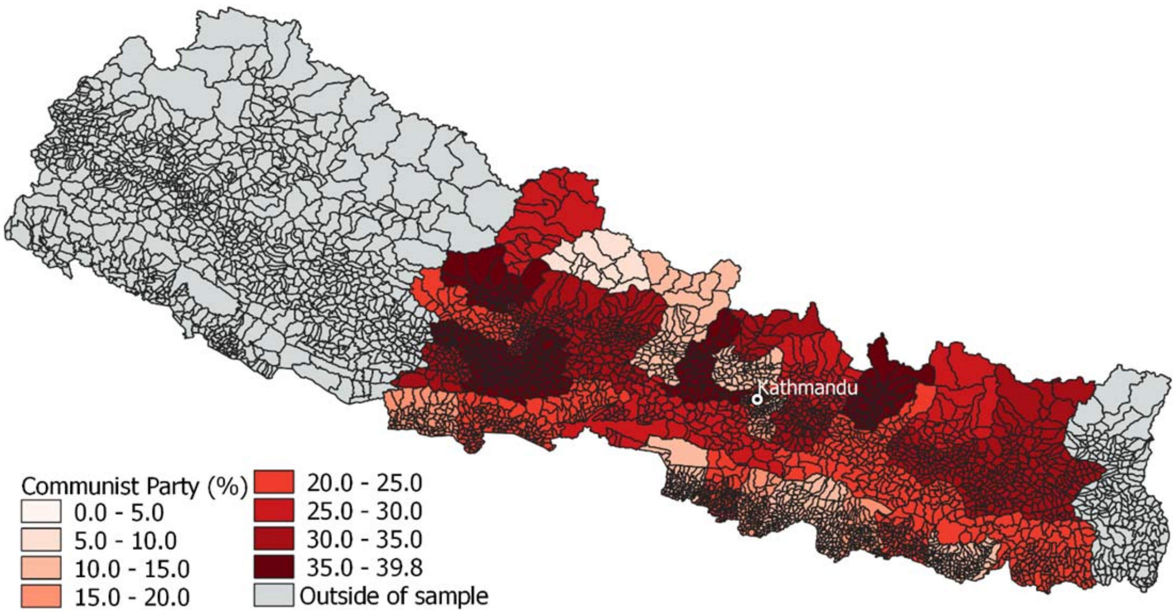
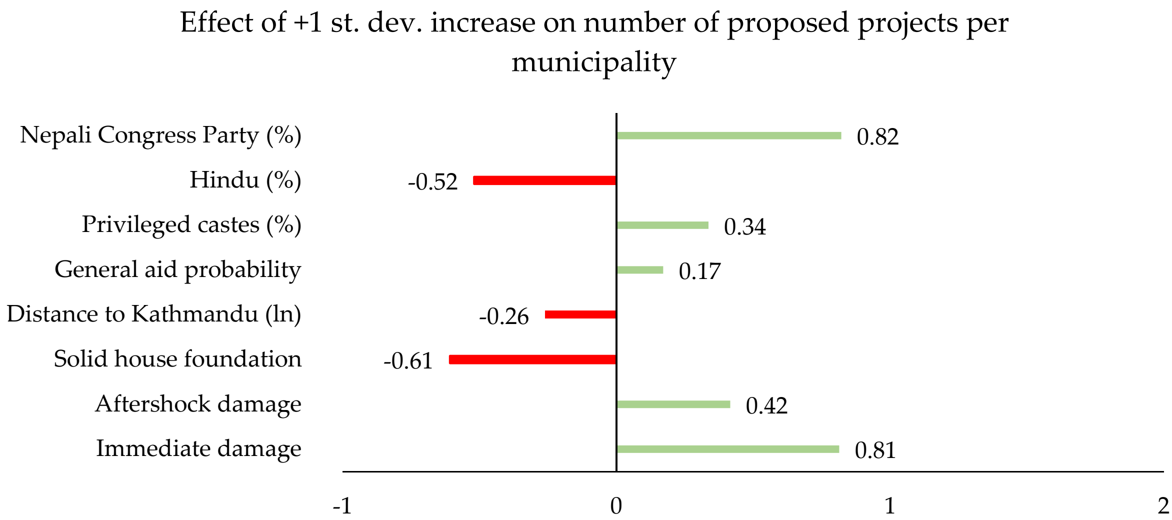


Figure 5: Significant correlates of the number of proposed projects



Source: Own illustration based on results in Table 3, column 2.

Appendix

Appendix 1: Timeline of the 2015 Nepal Earthquake Flash Appeal

Date	Event
2015-04-25	Earthquake (7.8 Magnitude) (major shake)
2015-04-25	Aftershock (6.6 Magnitude)
2015-04-25	Aftershock (6.7 Magnitude)
2015-04-26	Aftershock (6.7 Magnitude)
2015-04-29	Launch of initial Flash Appeal (April-July, US$ 415 million)
2015-04-29	First aid reaches Nepal
2015-05-04	Update of initial Flash Appeal document
2015-05-12	Earthquake (7.3 Magnitude) (major aftershock)
2015-05-29	Launch of revised Flash Appeal (April-September, US$ 422 million)
2015-06-13	Arrival of Monsoon season
2015-09-20	Constitution of Nepal came into effect
2015-09-30	End of revised relief phase (due to monsoon season)
2015-10-11	Change of government

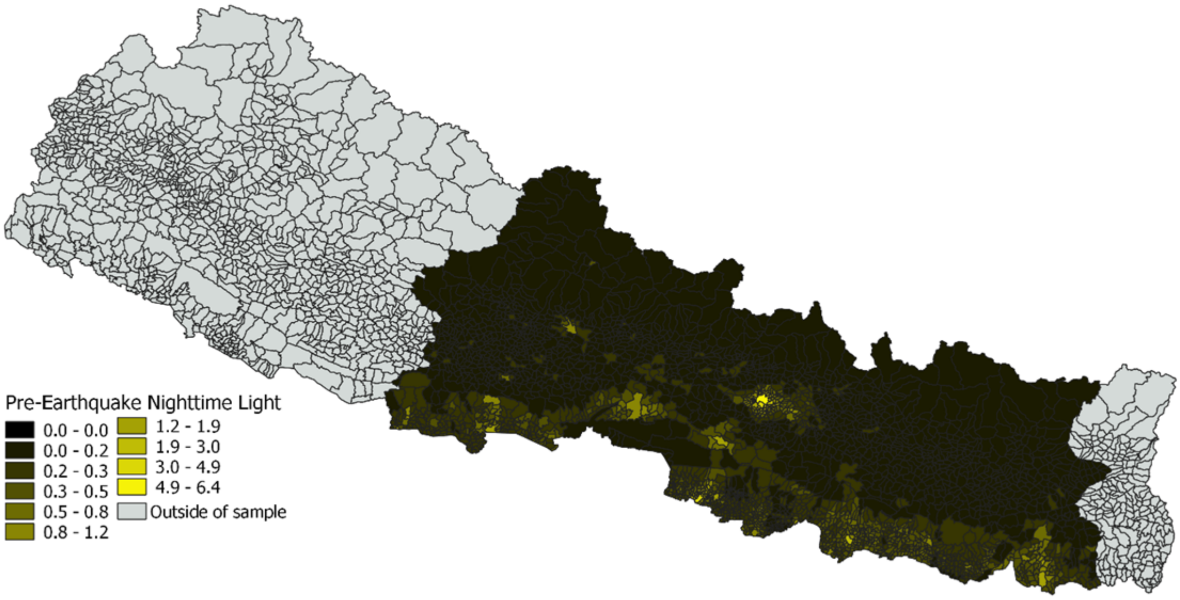
Source: UNOCHA (2015a, 2015b), Bhattacharjee (2016), internet research.

Appendix 2: List of the 20 largest funded 2015 Nepal earthquake flash appeal projects (in million USD)

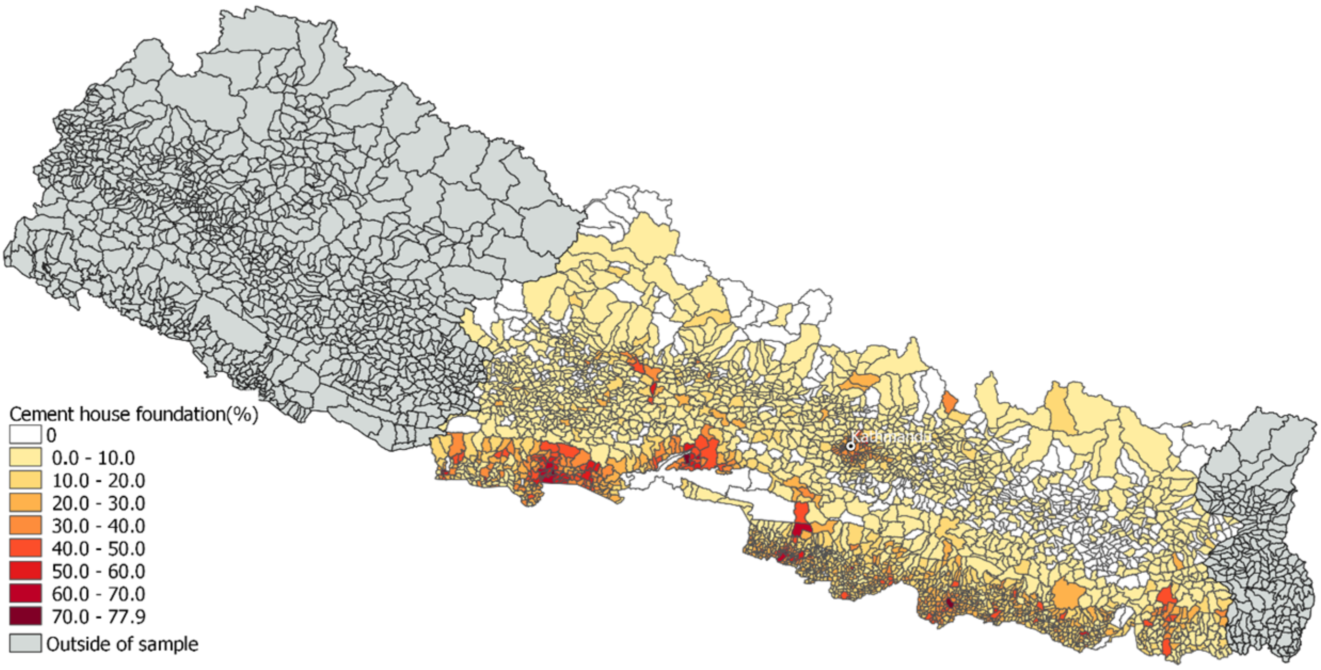
Emergency Food Assistance to Earthquake Affected Populations	23.1
Logistics Augmentation and Coordination in Response to the Earthquake in Nepal	14.8
Provide live saving emergency Water, Sanitation and Hygiene services for earthquake affected population, especially women and children in Nepal	14.0
Provision of Emergency Shelter, Non Food Items (NFI) and shelter support to self-recovery to Earthquake Affected Population in Nepal for 25,000 Vulnerable Households	12.8
Provision of Humanitarian Air Services in Nepal	11.2
Provision of Education in Emergencies to Earthquake-Affected Children in Nepal	10.4
Equitable emergency and lifesaving primary health care services for mothers, newborns and children	10.1
Shelter support through NFIs and training	8.7
Emergency Shelter	7.0
Addressing health needs in the earthquake affected population	6.6
Comprehensive Emergency Nutrition Response for Children and Mothers	5.6
Prevention and response to protect children in affected areas.	5.3
Emergency assistance to re-establish agricultural-based livelihoods of vulnerable earthquake-affected smallholder farmers in the six most affected districts in Nepal	5.2
Emergency and transitional shelter assistance to earthquake-affected populations	4.4
Protection monitoring, legal and psychosocial support to people affected by earthquake	4.0
Oxfam WASH Earthquake Response	3.6
Rehabilitation of community based infrastructure and emergency employment for immediate livelihoods support	3.5
Shelter assistance for 20,000 most vulnerable earthquake-affected families	3.4
Coordination response	3.3
To deliver a shelter response that supports appropriate, flexible, progressive solutions to affected, vulnerable populations that contributes to their own self recovery to provide a safer, more resilient and durable shelter	3.2

Data source: UNOCHA (2016).

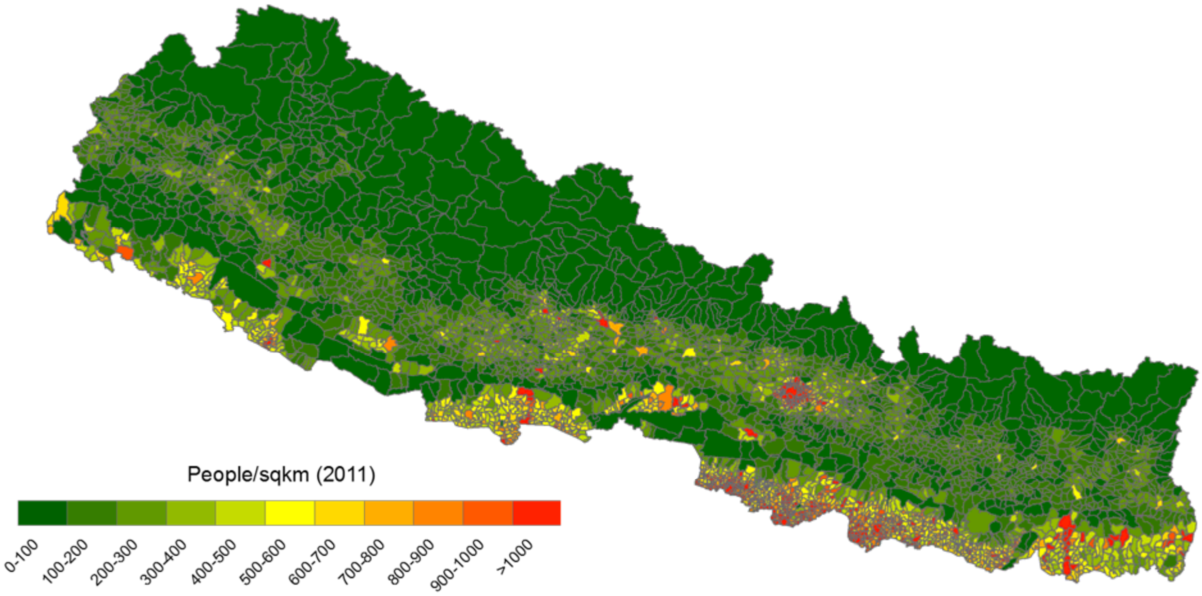
Appendix 3: Spatial distribution of nighttime light prior to 2015 Nepal earthquake across Nepalese VDCs



Appendix 4: Spatial distribution of households with solid house foundation (cement) across Nepalese VDCs



Appendix 5: Spatial distribution of Nepal's population density (people/square kilometer) as of 2011 across Nepalese VDCs



Appendix 6: Variable list with definitions and sources

	Definition	Data Source
Dependent variables		
No. of proposed projects	Number of proposed disaster aid projects in the VDC	AidData (2016a)
No. of funded projects	Number of funded disaster aid projects in the VDC	AidData (2016a)
Proposed financial amount (US$) (ln)	Financial value of all proposed disaster aid projects in the VDC (in 1000 US$)	AidData (2016a)
Funded financial amount (US$) (ln)	Financial value of all funded disaster aid projects in the VDC (in 1000 US$)	AidData (2016a)
Share of funding obtained	Ratio of funded to requested dinancial value of disaster aid projects in the VDC	AidData (2016a)
Disaster impact variables		
Immediate damage	Earthquake destruction index of the first earthquake (April 25, 2015) for the highest quality building type scenario	USGS (2017a)
Aftershock damage	Earthquake destruction index of the major aftershock earthquake (Mai 12, 2015) for the highest quality building type scenario	USGS (2017c)
Socio-economic vulnerabilities		
Population (ln)	Logarithm of the population size of the VDC	Central Bureau of Statistics (2011)
Solid house foundation (%)	Percentage of households with solid house foundation (cement) in the VDC in 2011	Central Bureau of Statistics (2011)
Pre-earthquake nightlight (ln)	Average nighttime light intensity in the VDC between January 2012 to March 2015	NOAA (2017)
Physical vulnerabilities		
Admin 4 area (ln)	Logarithm of the area (km2) of the VDC	Central Bureau of Statistics (2011)
Mean rainfall	Mean rainfall over the period 1998-2014 per VDC in mm	Own calculations based on Huffman et al. (2014)
Distance to Kathmandu (ln)	Logged distance from the VDC centroid to Kathmandu in kilometer	Own calculations
Distance to airport (ln)	Logged distance from the VDC centroid to the closest airport in kilometer	Own calculations
Ethnic, religious and political distortions		
Hindu (%)	Percentage of Hindus within the respective district (administrative level 3)	Central Bureau of Statistics (2011)
Privileged castes (%)	Percentage of people belonging to the Brahmin ("brahman-hill" and "brahmantarai"), Chetri ("chhetree"), and Newari ("newar") castes in the VDC	Central Bureau of Statistics (2011)
Nepali Communist Party (%)	Percentage of votes won by the Communist Party at the 2013 election within the respective district (administrative level 3)	Election Commission Nepal (2018)
Nepali Con-	Percentage of votes won by the Nepali Congress Party at the	Election Commissi-

gress Party (%)	2013 election within the respective district (administrative level 3)	on Nepal (2018)
Existing aid networks		
General aid probability	Probability to receive general aid over the period 2002-2014	AidData (2016b)

Appendix 7: Correlation matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1)	Immediate damage	100%													
(2)	Aftershock damage	35%	100%												
(3)	Population (ln)	-1%	-6%	100%											
(4)	Admin 4 area (ln)	5%	3%	-16%	100%										
(5)	Mean rainfall	23%	-2%	10%	7%	100%									
(6)	Pre-earthquake nightlight (ln)	3%	-1%	23%	-32%	3%	100%								
(7)	Solid house foundation (%)	-14%	-14%	22%	-36%	-8%	56%	100%							
(8)	Distance to Kathmandu (ln)	-74%	-34%	-7%	14%	-29%	-33%	-6%	100%						
(9)	Distance to airport (ln)	0%	-4%	4%	13%	-7%	-22%	-15%	9%	100%					
(10)	General aid probability	4%	14%	2%	10%	-4%	8%	6%	-7%	4%	100%				
(11)	Privileged castes (%)	26%	24%	-3%	1%	40%	4%	-17%	-29%	-21%	4%	100%			
(12)	Hindu (%)	-32%	-23%	17%	-37%	-9%	18%	36%	23%	11%	-4%	-7%	100%		
(13)	Nepal Communist Party (%)	-2%	17%	-22%	29%	27%	-27%	-44%	14%	1%	-9%	39%	-21%	100%	
(14)	Nepali Congress Party (%)	14%	-3%	-23%	29%	27%	-22%	-42%	1%	-16%	-11%	44%	-11%	61%	100%

Appendix 8: Robustness checks for design stage (based on Table 3)

	(1)	(2)	(3)	(4)	(5)	(6)
		Table 3, col. 2			*Table 3, col. 4*	
	Baseline	Exclude Kath-mandu	ADM2 FE	Baseline	Exclude Kath-mandu	ADM2 FE
Immediate damage	3.537**	3.105**	0.251**	7.183**	6.489*	3.588*
	[1.374]	[1.229]	[0.116]	[3.138]	[3.347]	[2.070]
Aftershock damage	2.596***	2.301***	0.228*	3.371	3.196	3.843*
	[0.738]	[0.680]	[0.117]	[2.162]	[2.189]	[2.163]
Population (ln)	0.008	0.011	-0.006	-0.446*	-0.432*	-0.162
	[0.088]	[0.084]	[0.010]	[0.237]	[0.234]	[0.176]
Solid house foundation (%)	-0.045**	-0.041**	-0.006**	-0.024	-0.023	-0.041
	[0.020]	[0.020]	[0.002]	[0.028]	[0.029]	[0.026]
Pre-earthquake nightlight (ln)	-0.673	-0.666	-0.080	-0.409	-0.292	0.627
	[0.412]	[0.431]	[0.055]	[0.799]	[0.875]	[0.789]
Admin 4 area (ln)	0.657***	0.610***	0.068***	0.594	0.626	0.546
	[0.225]	[0.208]	[0.022]	[0.457]	[0.457]	[0.365]
Mean rainfall	0.106	0.101	0.010	0.278*	0.282*	0.152
	[0.088]	[0.082]	[0.008]	[0.152]	[0.154]	[0.170]
Mean rainfall squared	0.000	0.000	0.000	-0.001	-0.001	0.000
	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]	[0.001]
Distance to Kathmandu (ln)	-2.652***	-2.502***	-0.388***	-4.521***	-4.991***	-1.984
	[0.597]	[0.623]	[0.097]	[0.840]	[1.044]	[1.310]
Distance to airport (ln)	0.044	0.021	0.011	-1.004	-1.066	-0.759
	[0.291]	[0.264]	[0.032]	[0.814]	[0.824]	[0.587]
General aid probability	2.436*	2.144*	0.270	6.163	5.613	1.750
	[1.440]	[1.302]	[0.174]	[4.109]	[4.218]	[4.106]
Privileged castes (%)	0.014**	0.013**	0.002***	-0.024	-0.022	-0.007
	[0.007]	[0.006]	[0.001]	[0.021]	[0.020]	[0.015]
Hindu (%)	-0.036*	-0.031	-0.006**	-0.001	0.002	-0.069
	[0.021]	[0.019]	[0.003]	[0.055]	[0.055]	[0.045]
Nepal Communist Party (%)	-0.025	-0.022	0.006	0.219*	0.225*	0.260**
	[0.044]	[0.040]	[0.004]	[0.111]	[0.112]	[0.104]
Nepali Congress Party (%)	0.101**	0.091**	0.005	0.186*	0.187*	0.102
	[0.048]	[0.045]	[0.006]	[0.093]	[0.095]	[0.082]
Adjusted R-squared	0.838		0.862	0.603	0.596	0.714
N of observations	2793	2735	2793	2793	2735	2793
N of clusters	47	46	47	47	46	47

Notes: The dependent variable is *no. of proposed projects* in columns 1-3 and *proposed financial amount (ln)* in columns 4-6. Results in columns 1-3 are estimated with NB regression and columns 4-6 with OLS. Columns 1-3 show marginal effects at the mean. Robust standard errors (in brackets) are clustered at the district level (ADM3). * (**, ***) indicates statistical significance at the ten-percent (five-percent, one-percent) level.

Appendix 9: Robustness checks for funding stage

	(1) Baseline (Table 4, col. 3)	(2) Exclude Kath-mandu	(3) ADM2 FE	(4) Baseline (Table 4, col. 4)	(5) Exclude Kath-mandu	(6) ADM2 FE	(7) Baseline (Table 4, col. 5)	(8) Exclude Kath-mandu	(9) ADM2 FE
Immediate damage	-0.825	-0.868	-0.080**	0.178	0.197	0.234	-0.062	-0.052	-0.013
	[0.595]	[0.570]	[0.035]	[0.213]	[0.214]	[0.156]	[0.064]	[0.061]	[0.048]
Aftershock damage	-0.160	-0.222	-0.096**	0.544**	0.552**	0.465**	0.147**	0.153**	0.071
	[0.368]	[0.347]	[0.040]	[0.208]	[0.209]	[0.223]	[0.062]	[0.063]	[0.060]
Population (ln)	-0.021	-0.018	-0.005	0.017*	0.017*	0.009	0.004	0.004	0.001
	[0.048]	[0.046]	[0.004]	[0.009]	[0.009]	[0.008]	[0.003]	[0.003]	[0.004]
Solid house foundation (%)	-0.017**	-0.014	-0.002**	-0.002	-0.002	-0.001	-0.001	-0.001	0.000
	[0.008]	[0.009]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Pre-earthquake nightlight (ln)	-0.076	-0.079	0.005	0.006	0.007	-0.003	-0.027	-0.025	-0.017
	[0.135]	[0.146]	[0.015]	[0.044]	[0.046]	[0.044]	[0.017]	[0.021]	[0.017]
Admin 4 area (ln)	0.200**	0.187**	0.011	0.03	0.030	0.023	0.018	0.019	0.01
	[0.082]	[0.076]	[0.007]	[0.020]	[0.021]	[0.019]	[0.011]	[0.011]	[0.009]
Mean rainfall	0.041	0.045	-0.001	0.001	0.001	0.000	-0.002	-0.002	-0.005
	[0.036]	[0.035]	[0.003]	[0.008]	[0.008]	[0.006]	[0.005]	[0.005]	[0.005]
Mean rainfall squared	-0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Distance to Kathmandu (ln)	-0.784***	-0.816***	-0.093***	-0.213***	-0.198***	-0.272***	-0.133***	-0.120***	-0.140***
	[0.245]	[0.250]	[0.021]	[0.047]	[0.056]	[0.074]	[0.023]	[0.031]	[0.031]
Distance to airport (ln)	-0.114	-0.124	0.001	0.033	0.034	0.036	0.033	0.035	0.045***
	[0.115]	[0.102]	[0.010]	[0.045]	[0.045]	[0.039]	[0.021]	[0.021]	[0.010]

General aid probability	1.905*	1.668	0.069	0.136	0.158	0.167	0.226*	0.236**	0.149
	[1.106]	[1.017]	[0.074]	[0.307]	[0.306]	[0.263]	[0.111]	[0.109]	[0.089]
Privileged castes (%)	0.002	0.001	0.000**	0.001	0.001	0.000	0.001**	0.001**	0.000**
	[0.002]	[0.002]	[0.000]	[0.001]	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]
Hindu (%)	-0.010	-0.007	-0.001*	-0.003	-0.003	-0.002	-0.002	-0.002	-0.002
	[0.008]	[0.008]	[0.001]	[0.003]	[0.003]	[0.004]	[0.001]	[0.001]	[0.001]
Communist Party (%)	0.021	0.021	0.005***	-0.006	-0.006	-0.008	-0.004	-0.004*	-0.003
	[0.019]	[0.018]	[0.002]	[0.005]	[0.005]	[0.005]	[0.002]	[0.002]	[0.002]
Nepali Congress Party (%)	0.070***	0.065***	0.007***	0.008	0.008	0.008	0.004	0.004	0.004
	[0.023]	[0.022]	[0.002]	[0.007]	[0.007]	[0.008]	[0.003]	[0.003]	[0.005]
No. of proposed projects	0.073***	0.068***	0.008***						
	[0.018]	[0.018]	[0.002]						
Proposed financial amount (ln)				0.911***	0.911***	0.918***			
				[0.008]	[0.008]	[0.007]			
Adjusted R-squared				0.999	0.999	0.999	0.666	0.647	0.706
N of observations	2793	2735	2793	2793	2735	2793	1290	1232	1290
N of clusters	47			47	46	47	24	23	24

Notes: The dependent variable is *no. of funded projects* in columns 1-3 and *funded financial amount (ln)* in columns 4-6. Results in columns 1-3 are estimated with NB regression and columns 4-9 with OLS. Columns 1-3 show marginal effects at the mean. Robust standard errors (in brackets) are clustered at the district level (ADM3). * (**, ***) indicates statistical significance at the ten-percent (five-percent, one-percent) level.