WPS8359

Policy Research Working Paper 8359

The Reallocation of District-Level Spending and Natural Disasters

Evidence from Indonesia

Emmanuel Skoufias
Eric Strobl
Thomas Tveit

WORLD BANK GROUP
Poverty and Equity Global Practice
March 2018

Abstract

This paper combines district-level government spending data from Indonesia and natural disaster damage indices to analyze the extent to which districts are forced to reallocate their expenditures across categories after the incidence of floods, earthquakes, and volcanic eruptions. The results reveal that district government spending is quite sensitive to the incidence of natural disasters at the local level. In the case of floods, districts reallocate spending away from the category of general administration to sectors such as health and infrastructure. Moreover, volcanic eruptions seem to lead to less investment in durable assets both in the year of the disaster as well as the following year. Overall, these results highlight the potentially useful role of a national disaster risk financing insurance program toward maintaining a relatively stable level of district-level spending in different sectors.

This paper is a product of the Poverty and Equity Global Practice. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The authors may be contacted at eskoufias@worldbank.org.

The Reallocation of District-Level Spending and Natural Disasters: Evidence from Indonesia*

Emmanuel Skoufias (World Bank)

Eric Strobl (University of Bern)

Thomas Tveit (University of Bern)

JEL Classification: R5, C33, Q54, C63, R11, H12, H72

Keywords: Natural Disasters, Damage Index, Public Finances, Budget Redistribution

*This paper was financed in part by the Disaster Risk Finance Impact Analytics project of the Disaster Risk Financing and Insurance Program of The World Bank Group

1 Introduction

During the period 2003 through 2013 natural disasters have been estimated to have caused damages of up to US$1.5 trillion (Food and Agriculture Organization of the United Nations, 2015), arguably leading to stagnating GDP growth and funding issues for impacted countries. These disasters affect public finances through losses in revenues from lower tax income from less production output and increased spending for aid and rebuilding (Hofman *et al.*, 2006). In Indonesia, specifically, it was estimated that the annual impact of natural disasters is around 0.3 percent of GDP, potentially rising to up to 3 percent in the case of a major earthquake (The Global Facility for Disaster Reduction and Recovery, 2011).[1] There are a number of studies that have examined how natural disasters have impacted the fiscal sector of affected countries. For a large set of countries and different natural disaster events grouped together, Lis & Nickel (2010), for example, estimate that the negative budgetary impact of extreme weather events can be up to 1.1 percent of GDP. Melecky & Raddatz's (2014) analysis shows that government expenditure increases, whereas revenue does not respond to climate shocks. Looking at tropical storms in the Caribbean, Ouattara & Strobl (2013) demonstrate that hurricane strikes cause an increase in government spending and short term deficit financing. Lastly, Noy & Nualsri (2011) also note that the fiscal impact of natural disasters depends on the country-specific macroeconomic dynamics occurring in the aftermath of natural disaster shocks.

In most cases, the financial burden of rebuilding and recovering after these disasters falls on local and central governments. The funding of these financial shortfalls could be done

[1]Major earthquake is defined as an earthquake that occurs once every 250 years.

through both ex-ante strategies, such as insurance as well as ex-post financing, for example through loans. However, for developing countries, it can often be difficult to get access to external loans through private markets, leaving only insurance, external aid, tax increases or internal redistribution of finances as potential sources of funding (Bevan *et al.*, 2016; Mahul & Ghesquiere, 2010). With insurance still uncommon in most developing countries[2], foreign aid is usually available only after large disasters, and tax increases politically unpalatable, redistribution of spending across different budget categories is perhaps the only remaining or default alternative for post-disaster financing for many governments. A key question - that will be addressed in this paper - is which sectors receive less funding to finance the disaster relief. This is an insight that can potentially help policy makers detect any sectors that experience shortfalls following disasters.

Budget reallocation as a response to post-disaster financing has received only scarce attention in the literature. For example, papers such as Bevan *et al.* (2016) focus on the redistribution at a sovereign level, and only as a theoretical exercise. In this paper we will use detailed budget expenditure data for Indonesian districts for the period 2005 through 2012, and combine these with spatially disaggregated damage indices for floods, earthquakes, volcanic eruptions and the 2004 tsunami to construct a unique spatial panel data set. This will allow us to obtain a first empirical estimate of how local governments change their spending following natural disasters.

The district level budget data contain revenues and expenditures provided every year to

[2]Rauch & Neuthor (2013), for example, claim that for the years 1980-2012, low income countries constituted 10 percent of disaster losses, but only 1 percent of the insured losses.

the Regional Financial Information (SIKD) and are broken down across 12 different economic sectors such as health, education, agriculture and infrastructure. In addition to the sectoral breakdown, local government spending is also classified into four categories; namely, capital expenditure, goods and services, personnel and other, providing an alternative for analyzing any changes among these categories.

To answer how disaster relief is financed, one needs a proxy for local damages. In Skoufias *et al.* (2017), the authors have constructed damage indices for different disaster types, and this paper will see how well these can be used to identify potential district budget reallocations due to natural disasters. An added benefit of the indices is that they are constructed from freely available data, implying that they can be a cost efficient resource for identifying local economic activity. The natural disaster damage indices in Skoufias *et al.* (2017) are constructed by modeling the local strength of each disaster using its physical characteristics and taking account of local exposure to these aspects using nightlight intensity derived from satellite imagery. The disasters examined are floods, earthquakes, volcanic eruptions and the 2004 tsunami, all of which are modeled using different remote sensing data that are aggregated up to district level.

The remainder of this paper consists of four parts. First, there is a brief section on the construction of the damage indices. Then a part presenting the budget data, followed by the main part with the methodology and results, before finishing with a conclusion.

2 Natural Disaster Damage Indices

The methodology and data sources used to make damage indices for natural disasters are extensively covered in Skoufias *et al.* (2017), and there are also additional details in Appendix A. Generally, the paper uses remote sensing data for the different disaster types - floods, earthquakes, volcanic eruptions and the 2004 tsunami - that are combined with nightlight data - used as a proxy for economic activity - to construct an index that estimates the impact on districts and provinces.

More specifically, the nightlight data used provide a normalized annual light value ranging from 0 (no light) to 63 (maximum light) and are from the Defense Meteorological Satellite Program (DMSP) satellites. Using these data as a proxy for economic activity - when no other data exist - has been employed in papers such as Henderson *et al.* (2012), Hodler & Raschky (2014) and Michalopoulos & Papaioannou (2014). In our case, the nightlight data have been employed as a weight for the economic impact of disasters.

Floods are modeled through a combination of remote sensing images and GIS-modeling using the Geospatial Stream Flow Model (GeoSFM). The remote sensing inputs comprise weather data, such as rain and temperature, as well as soil and terrain data. These sources are then used by GeoSFM to model basins across Indonesia and the stream flow in each of these. The final steps consist of setting a threshold for when a stream flow is strong enough to flood the basin and then weighting this with the nightlight data and aggregating up to a district level.

The earthquake index is constructed from computer generated contour maps by the US Geological Survey (USGS) of earthquake intensity data, commonly used as potential damage proxy (De Groeve *et al.*, 2008; GeoHazards International and United Nations Centre for Regional Development, 2001; Federal Emergency Management Agency, 2006). Utilizing the contour maps as a base for damage infliction, we combine them with the nightlight and building type data from the USGS building inventory for earthquake assessment to create fragility curves by building type; see Jaiswal & Wald (2008) and GeoHazards International and United Nations Centre for Regional Development (2001). Finally, the data are aggregated up to a district level set.

To model volcanic eruption intensity, we utilized a two-fold process. First, volcanic ash advisory data from Volcanic Ash Advisory Centers (VAAC) are used to detect eruptions. The advisories are produced for the airline industry to warn airplanes about impending or ongoing eruptions through color coded messages. We use only the highest warning level of ongoing eruption as a threshold of when to include an eruption in the data set or not. Second, images containing sulphur dioxide data from the OMI/AURA satellite are used to model the intensity of the eruptions. These images provide SO_2 density data and have been utilized by Carn *et al.* (2009) and Ferguson *et al.* (2010) to model eruption intensity. The data are then combined with the nightlight data and aggregated up to district level.

Finally, the 2004 Christmas tsunami has been modeled following a method where Heger (2016) uses inundation maps to construct a district level damage index assuming uniform damage across all flooded areas. To construct an inundation map of the affected areas, a map based on MODIS satellite pictures from Anderson *et al.* (2004) is used with spatial algorithms to detect the difference in color between inundated and non-inundated areas. Once the map is constructed, it is weighted and aggregated just like the other indices.

As for the indices themselves, the actual coefficients for floods and volcanic eruptions are simple intensity measures that do not convey anything on their own apart from an intensity weighted by nightlights. For earthquakes and the tsunami, the numbers show the overall damage to buildings in the district.

Table 1 shows the descriptives of the damage indices, with floods striking districts 2,417 times over the 8 year time period, meaning that approximately 300 districts are affected by floods annually. The earthquakes struck 435 times, while the volcanic eruptions and the tsunami affected a limited number of districts, due to the limited number of big events. The strongest earthquake damaged almost 5 percent of the buildings in a district, while the district that was worst hit by the tsunami experienced damage to 23 percent of the building mass.

Table 1: Descriptives Damage Indices - 2005 - 2012

Disaster	N	Mean	SD	Min	Max
Flood	2417	27.94	22.25	0.01	175.08
Earthquake	435	2.54	4.94	0.01	45.07
Volcanic Eruption	61	32.25	42.58	0.03	184.67
Tsunami	6	0.14	0.08	0.06	0.23

Note: Earthquake mean, SD, min and max multiplied by 1,000

3 District Expenditure Data

The financial data used are the District budget data for the years from 2001 to 2012 (Fiscal Year of January-December every year). They were derived from the Regional Financial Information System (Sistem Informasi Keuangan Daerah, SIKD) of the Ministry of Finance. The district expenditures are available for 12 different sectors/functions (such as agriculture, health, education, etc.) and for four economic classifications (personnel, goods and services, capital, and other). The data are provided for 511 districts.[3]

The 12 sectors are presented in the top panel of Table 2, where nominal numbers are converted into yearly ratios, which eliminate inflationary issues as well as spending differences due to district size and wealth.[4] The three largest sectors are General Administration (GA), Education and Infrastructure. General Administration is - as the name suggests - a very general budget sector, which includes posts regarding planning, civil administration, governance, statistics and communication.[5] Most of the sectors have between 4,000 and 4,500 observations, but public law and order, housing and - in particular - religious affairs have much fewer observations, implying that the overall ratios might be skewed a bit by districts that report these sectors compared to districts that do not. However, on average the under-reported sectors constitute less than 5 percent of the total expenditures, making their overall impact small. The reason for the fewer observations[6] and the lack of completeness are unknown, but we will be treating missing data as missing and make ratios based on a

[3]Of these 511, we will be using 299 in our final dataset. Details on these are outlined in Section 4.

[4]Nominal data are shown in appendix B.

[5]Specifically the posts included are: Development Planning, Population and Civil Administration, General Governance and Public Administration, Apparatus, Village and Community Empowerment, Statistics, Archive, Communication and Information and finally Transmigration.

[6]Religious affairs are only reported for Aceh, implying that it is a province specific category.

total of reported sectors.

Table 2: Descriptives of ratios of Expenditure data by Economic Sectors and Categories

Sector	N	Mean	St. Dev.	Min	Max
General Administration	4,505	0.333	0.146	0.013	1.000
Public Law and Order	3,201	0.010	0.008	0.000	0.213
Economy	4,422	0.024	0.017	0.000	0.210
Environment	4,119	0.017	0.021	0.000	0.341
Housing and Public Facilities	3,401	0.023	0.041	0.000	0.345
Health	4,433	0.086	0.033	0.000	0.444
Tourism and Culture	3,997	0.006	0.012	0.000	0.372
Religious Affairs	717	0.006	0.008	0.0001	0.112
Education	4,440	0.328	0.125	0.000	1.000
Social Protection	3,972	0.009	0.008	0.000	0.127
Infrastructure	4,432	0.151	0.082	0.000	0.602
Agriculture	4,422	0.042	0.023	0.000	0.353
Category	N	Mean	St. Dev.	Min	Max
Capital Expenditures	4,770	0.236	0.112	0.000	0.976
Goods and Services	4,775	0.190	0.060	0.000	0.578
Other expenditures	4,747	0.085	0.058	0.000	1.000
Personnel Expenditures	4,790	0.493	0.138	0.000	1.000

The economic classifications ratios are in the bottom panel of Table 2.[7] The four categories are split partly by durability and partly by other criteria. Capital Expenditure is defined as expenditures on assets with durability of more than 12 months, whereas Goods and Services are on assets with a durability of less than 12 months. The former typically comprises purchase of land, buildings and large equipment, while the latter includes items such as work clothes, small repairs, stationaries and short term rental. Personnel Expenditures is mainly salaries to public servants, but also includes some other costs related to employees such as accident/death expenditures and expenditures related to tax income. Finally, the Other Expenditures include financial costs such as interests and subsidies as well as unforeseen costs related to for example natural disasters.

[7]Nominal data are shown in Appendix B.

Table 2 shows that Personnel Expenditures are the highest cost classification, with 49.3 percent of the costs being allocated to personnel. Overall the reporting seems to be more consistent for the four classifications since the number of observations is very similar for all four areas. That being said, some of the districts report that 100 percent of their costs for a year have been allocated to cover other or personnel, which seems unlikely.

4 Impact of Natural Disasters on District Spending

Despite the potentially large impact natural disasters can have on local finances, the literature analyzing the economic effects is practically non-existent. Our analysis will provide a simple framework that can be used for any natural disaster type and any type of local financial data.

For Indonesia, the local level that will be analyzed is districts. A caveat with that level, is that the number of districts has increased during the period due to administrative splitting. Out of 511 districts 167 of them have been part of a split, implying that the budget numbers would change sometime during our period. Any split districts will have to be disregarded as the nominal and relative size of the expenditures will change following a split.

Furthermore, not all of the 344 non-split districts have been affected by a disaster. The modeled damage indices have registered that 304 of the 344 districts have experienced at least one natural disaster large enough to be included.[8]

Finally, there are 488 districts that have reported at least one sector or classification for at least one year. Of these 488 there are 299 districts that are non-split and have experienced a natural disaster.

[8] 397 of the 511 total districts have been impacted by a natural disaster.

4.1 Methodology

Given that the data are structured as spatiotemporal panel data, a fixed-effect regression methodology could be used, with the expenditure ratios as the dependent variable and the damage indices as independent variables. That being said, the different ratios are necessarily related. We have therefore chosen to use the method for seemingly unrelated regression (SUR) as explained in Blackwell III *et al.* (2005).

Their methodology is based upon Baltagi (2001), Judge *et al.* (1988) and Wooldridge (2002). In short, they use a system of SUR with error components. It is assumed that all coefficients of constant terms are the same across the system and that all independent variables are quantitative and require restriction across the panels in their equations, while fixed-effect dummies vary by panel.

In our case this translates into a set of equations. The basis is:

$$\begin{aligned} B_{j,i,t} = \beta_{j0} + \beta_{j1} \cdot PD_{i,t} + \beta_{j2} \cdot ED_{i,t} + \beta_{j3} \cdot VD_{i,t} + \beta_{j4} \cdot TD_{j,t}, \qquad j = 1, \dots, J \\ + \sum_{k=1}^{K} \left(\beta_{j,4+k} \cdot PD_{i,t-k} + \beta_{j,5+k} \cdot ED_{i,t-k} + \beta_{j,6+k} \cdot VD_{i,t-k} \right) + \alpha_{j,i} + \mu_t + \lambda_{j,i,t} + \epsilon_{j,i,t} \end{aligned} \tag{1}$$

where the left hand side is defined as the ratio:

$$B_{j,i,t} \equiv \frac{C_{j,i,t}}{\sum_{j=1}^{J} C_{j,i,t}}, \qquad j = 1, \dots, J \tag{2}$$

where j are different economic sectors or classifications, i is the district, t is the year and C

is the expenditure. On the right hand side of Equation 1 we find the different damage indices by year and district. These are identical across the different economic sectors. Finally, there is a fixed effect term, $\alpha_{j,i}$, a yearly dummy term μ_t, a time trend term per district term $\lambda_{j,i,t}$ and an error term, $\epsilon_{j,i,t}$. Note that the above model has included a lag operator, i.e. allowed for disasters in the prior years.[9] The model can be used both with and without the lag terms.

4.2 Creating Panel Data

Equation 1 yields the best results if the input data are balanced. However, there are several years and sectors missing for many of the districts in our data set. Table 3 shows how the number of districts changes with how strict a criteria one sets for the data. Balanced means that a district has reported the specific sector for all years, whereas unbalanced means all observations regardless of how many years a district has reported. More precisely, unbalanced 1yr and 2yr means that a district has not reported for 1 or 2 years in a sector.

Comparing the results with the optimal case of all 299 districts having reported for all 8 years, we see that the number of districts reporting data for a sector across all years is very low. There is actually no district that has reported for all sectors in all years. Allowing for the expenditure data to be unbalanced adds many more districts. However, leaving the sectors fully unbalanced, i.e. a district would be included even if a sector is only reported once, would potentially skew the data. By including districts that did not report a sector expenditure in one or two of the years, we increase the number of observations and avoid the

[9] Due to the limited time period, we only lagged for one period. Hence, the tsunami index is not included in the lag operator.

districts that rarely report a sector. The assumption is that districts that regularly file their expenditures are more likely to report correct numbers. The difference between allowing 1 and 2 years of missing reporting is fairly significant, most likely due to some years generally having fewer reports. For example, the years 2007 and 2011 had fewer than 200 districts reporting across all sectors[10], the reasons for which are unknown.

Table 3: Comparison of Data depending on Balanced vs Unbalanced

	Balanced		Unbalanced		Unbalanced 1yr		Unbalanced 2yr	
Sector	Mean	Total	Mean	Total	Mean	Total	Mean	Total
Agriculture	90	720	228	1,827	168	1,343	205	1,643
Economy	92	736	230	1,838	170	1,359	207	1,653
Education	92	736	230	1,841	171	1,366	207	1,654
Environment	71	568	212	1,694	129	1,030	171	1,366
General Administration	107	856	234	1,873	176	1,409	213	1,703
Health	92	736	230	1,840	171	1,366	207	1,654
Housing and Public Facilities	10	80	105	841	38	304	71	568
Infrastructure	91	728	230	1,836	168	1,344	206	1,650
Social Protection	53	424	203	1,622	119	949	158	1,267
Tourism and Culture	59	472	190	1,518	115	920	157	1,256
Public Law and Order[a]			231	1,386			123	738
Total		6,056		18,116		11,390		15,152

Given how the expenditure data are distributed, the unbalanced panel that allows for 2 missing years of reporting is the best compromise between a balanced panel and retaining enough observations across the sectors. To make sure that this does not affect our damage indices too much, we have shown how the disaster descriptives change in Table 4.

Compared with the full set of disasters shown in Table 1, the mean and standard deviation for floods and earthquakes fall. The main reason for the earthquake coefficients to move down is that some big earthquakes hit districts that were later split. One of the more active earthquake areas is the province of Aceh, which has experienced many district splits. This is

[10] General Administration had 202 reports in 2011.

also why the number of tsunami districts is just 1 or 2 instead of the 6, which is all affected districts. Volcanic eruptions see a slight increase in mean, whereas the standard deviations are close to what they are for the full sample.

Some sectors with fewer observations, such as Public Law and Order, Housing and Social Protection deviate more from the norm than the more robust sectors with more observations. However, importantly, most sectors stay within a fairly tight band both for mean and standard deviation, implying that the sectors experience similar disaster impact. Overall, we believe the number of observations for floods and earthquakes is high enough to provide fairly robust results, and even volcanic eruptions can be useful as a guidance. The tsunami index however is suffering from having only one or two districts in our sample.

Table 4: Damage Indice Descriptives when Unbalanced 2 years

	Flood			Earthquake[a]			Volcanic Eruption			Tsunami		
Sector	Obs	Mean	SD	Obs	Mean	SD	Obs	Mean	SD	Obs	Mean	SD
General Administration	1,691	25.86	22.01	222	1.66	3.34	44	34.87	42.58	1	0.23	
Agriculture	1,631	25.99	22.12	220	1.81	3.54	43	35.13	43.05	2	0.15	0.11
Public Law and Order	738	27.41	22.80	81	2.12	3.59	33	40.10	46.52			
Economy	1,641	26.01	22.09	220	1.81	3.54	44	34.87	42.58	2	0.15	0.11
Environment	1,360	25.74	21.34	183	1.87	3.63	41	36.51	43.56	2	0.15	0.11
Housing and Public Facilities	568	26.54	20.97	66	2.04	4.10	16	35.07	42.57	1	0.23	
Health	1,642	26.03	22.09	220	1.81	3.54	44	34.87	42.58	2	0.15	0.11
Tourism and Culture	1,244	26.59	22.49	176	1.87	3.55	39	34.08	43.78	2	0.15	0.11
Education	1,642	26.03	22.09	220	1.81	3.54	44	34.87	42.58	2	0.15	0.11
Social Protection	1,255	25.15	21.66	172	2.01	3.81	30	28.72	38.29	2	0.15	0.11
Infrastructure	1,638	26.01	22.10	219	1.80	3.55	44	34.87	42.58	2	0.15	0.11
Category	Obs	Mean	SD	Obs	Mean	SD	Obs	Mean	SD	Obs	Mean	SD
Capital Expenditures	1,740	27.28	21.89	207	2.15	3.73	47	33.41	41.67	2	0.15	0.11
Goods and Services	1,739	27.27	21.90	207	2.14	3.74	47	33.41	41.67	2	0.15	0.11
Other Expenditures	1,733	27.24	21.85	210	2.16	3.71	47	33.41	41.67	2	0.15	0.11
Personnel Expenditures	1,752	27.22	21.87	210	2.11	3.72	47	33.41	41.67	2	0.15	0.11

[a] Mean and standard deviation numbers multiplied by 1,000

For the economic categories, the overall data look better, as seen in the lower panel of Table 4. The flood and earthquake districts are well covered, and for volcanic eruptions it is the same districts that have reported for all categories. Finally, the tsunami data are covered through two districts. Overall, the data are more complete than for sectors.

4.3 Results

Having decided on the methodology and datasets we ran the regressions based on Equation 1, both with and without lags. There were two different sets of regressions, one with the 12 sectors as dependent variables and another one with the four categories being the dependent variables. In both cases, the damage indices were independent variables. In addition we controlled for the fixed effects, potential time trends and potential regional time trends. The datasets used were the panels missing no more than 2 years of reporting.[11]

Note that lags have not been included for the tsunami data. The reason for this is that the tsunami data are already lagged. The tsunami happened on 26 December 2004, hence a lot of the expenses incurred and any shifts in spending are likely to not be realized until the fiscal year of 2005. As mentioned in the report by The Global Facility for Disaster Reduction and Recovery (2011) the budget allocation for 2005 had already been approved, so major changes were needed during the mid-year budget revision of 2005. Furthermore, the earthquake data does not start until 2005, so to be able to control for all disasters at the same time, the starting year is 2005. As for the other lags, they are added to check whether any spending patterns or redistribution of expenses occur the year after the disaster has struck.

To better understand the results and the timing, it is worth noting how disaster relief is financed in Indonesia. In short, from the report by The Global Facility for Disaster Reduction

[11]We also ran the regressions based on balanced data and 1 year of reporting missing. Overall the results were quite similar, but for some of the lesser reported sectors they differed more.

and Recovery (2011), Law 24/2007 provides the framework for how disasters are handled and the responsibilities of central and local governments. In general, minor disasters are handled by local governments through their budgets, whereas any disaster deemed a national disaster or a disaster of national importance will be financed by the central government. In terms of timing and budget appropriation, The Global Facility for Disaster Reduction and Recovery (2011) points to problems arising when disasters happen "outside" of season. It is our understanding that additional resources cannot be allocated outside of year-end and mid-year budget reviews. This can lead to situations as mentioned above, when the tsunami struck after the 2005 budget had already been approved, and hence changes to the budget could not happen till mid-year.[12] The disaster funding is split into three phases: the response phase immediately after the disaster, then the recovery phase typically being the period three to six months post-disaster and finally the reconstruction phase. The central government assists in all three phases when a disaster is deemed a national disaster or when the costs go higher than what the local governments can afford. It is noted that what constitutes a national disaster and not is not clearly defined. For example the Merapi eruption in 2010 was not declared a national disaster, but the central government did support local governments in both response and recovery phases.

4.3.1 Sector Results

The first sector results are presented in the left panel of Table 5, which shows the coefficients for the sector regressions.[13] Each column presents the coefficient for each disaster by sector.

[12] This seems to clearly be the case for the central government, but it is not clear if this holds all the way down to local districts.

[13] Only main sectors are shown. For full results, see Appendix C.

Since SUR has been used, the table shows the results for one regression, i.e. all coefficients are part of the same regression.

For floods, several of the districts have changed their sector expenditures. The four large sectors - Education, GA, Health and Infrastructure - all have changes that are significant, with GA and Infrastructure being so at a 1 percent level, while Health and Education are significant at 5 and 10 percent levels, respectively. Also Agriculture shows a 1 percent significance, while Economy, Public Law and Order and Tourism and Culture also show significance. Overall, we find that the key variables show a strong significance.

There is a strong negative effect on GA and Education, whereas Health and Infrastructure expenditure goes up. For a disaster type such as flooding it makes sense that health and infrastructure spending goes up since there will be an increased need for medical attention and roads and other infrastructure might be swept away.

Regarding the other sectors, Agriculture is highly significant and spending goes up, potentially due to fields and other arable land being washed away or flooded. Agriculture is a sector that is often close to water sources and hence might be more prone to be hit by floods. The rather general sector of Economy also experiences a statistically significant increase in spending, a pattern it shares with Tourism and Culture. It has to be mentioned that these are rather small sectors with Tourism and Culture constituting 0.6 percent of the total budget on average.

In terms of what this translates into, the left panel of Table 6 shows percentage point changes for the four largest sectors for the different disaster types given a mean and max disaster. GA would decrease almost 1 percentage point from 33.3 to 32.4. Assuming a mean budget of 441,703RP million[14] that translates into 4,036 RP million (US$300,000) less being spent on GA. For Education the decrease is 0.7 percentage points from 32.8 percent to 32.1 percent. Health goes up 0.3 percentage points to just about 9 percent and Infrastructure goes up 0.9 percentage point to 16 percent, a change of almost 6.5 percent. Overall, we do find significant shifts in the districts spending patterns once a flood hits. Given that floods are usually relatively small in scale, it is plausible that they have an immediate effect on the local districts' budgets since they are expected to be able to cover these minor events on their own.

If the worst flood hits the mean district, GA will constitute 5.7 percent less of the total, and Education 4.4 percent less. Health and Infrastructure will see an increase of 2.2 percent and 5.8 percent respectively. Any 5 percent shift in the mean budget equals 22,000 RP million (US$1,650,000), showing that the shifts here are very large. Only the four key sectors make up a larger share of the budget than 5 percent.

Continuing with the earthquake results in the next column in Table 5, there is no significance apart from for Tourism and Culture and Public Law and Order, which are significant at the 10 and 5 percent level, respectively. The reason for the lack of significance might be due to earthquakes being more likely to be declared national disasters and/or recovery costs exceeding what local governments are capable of covering, one might expect to find a limited

[14] As found in the nominal tables in Appendix B.

effect during the year of the disaster.

For volcanic eruptions, the results show the same strong negative effect as floods for GA and positive effect for Health. At the same time it shows strongly significant and decreased spending for Infrastructure and increased spending for Education. The latter two are somewhat counterintuitive, but one could expect limited damage on infrastructure due to volcanic eruptions, given that many of the districts are not in the immediate proximity of the volcano and that the SO_2-proxy will not capture lava and pyroclastic flows that are more likely to cause damage on infrastructure. The increase in Education is harder to explain, but it could be due to the somewhat limited amount of observations for the volcanic events. Another reason can be that response and recovery financing after the (by far) biggest event - the Merapi Eruption in 2010 - came from the central government, meaning that any effect on local spending might be skewed or incorrect.

The key sectors' change for volcanic eruptions show that a mean eruption would lead to Education spending taking up 1.9 percent more of the total, GA 0.4 less, Health 0.5 more and Infrastructure 1.2 less. The worst eruption would lead to increases of 10.7 and 2.8 percent for Education and Health and decreases of 2.5 and 7 percent for GA and Infrastructure. This seems to be too high, and these changes could be due to some other transfers to the districts.

The fourth column shows the tsunami results. Agriculture and Economy expenditure are strongly negative. In addition, Education spending is strongly significant and positive. Finally there is a decrease in GA, which is 10 percent significant. The changes translate into a

10.1 increase in Education spending and a 7.4 percent decrease in GA. However, these results might not be very robust, given the very limited number of districts in our dataset and the fact that funding for response, recovery and reconstruction came from a plethora of sources including international donors and governments as well as the Indonesian government.

Continuing with columns 5 through 9 in Table 5 - the same model with the addition of variables lagged a year - the same pattern shows itself across the sectors for flood. With the addition of the lags, the significance decreases for some of the sectors. For instance, the Health sectors shows no effect the year after a flood has hit. However, there is still a decrease in GA and Education. Agriculture still experiences an increase in spending the year after, while Infrastructure is not significant. Potential reasons for the other shifts can be that Health spending consists of an increase in short term spending, while the medium term health effects after a flood are not as pronounced. The same can be said for infrastructure, i.e., washed out roads and railroads are fixed as soon as possible and hence the sector is not as affected the next year. It should be noted that there is an overall effect on the budget the year after, though, although it is less than for the year the disaster strikes. For agriculture it might be harder to fully assess the damage and some of the repair costs will come in the form of help the year after. Any shortcomings seem to be taken from General Administration and Education. The changes for Law and Order are hard to explain, but that sector is very small in general.

The final four columns of Table 6 show the percentage changes for the four key sectors with the lagged variables. GA and Education decreases by 1.1 and 0.9 percent, while Health and Infrastructure increases by 0.4 and 1 percent. These changes are in line with the results

Table 5: Regression results for Unbalanced 2 year Sector Data with lags

	Without Lag				With Lag			
Sector	Flood[a]	Earthquake	Volcanic Eruptions[a]	Tsunami	Flood[a]	Earthquake	Volcanic Eruptions[a]	Tsunami
Agriculture	0.094***	0.092	-0.038	-0.285***	0.108***	0.083	-0.049	-0.173***
	(0.033)	(0.170)	(0.047)	(0.051)	(0.030)	(0.193)	(0.041)	(0.027)
Education	-0.253*	0.514	0.581***	0.726***	-0.307**	0.154	0.671***	0.607*
	(0.136)	(1.423)	(0.178)	(0.280)	(0.131)	(1.543)	(0.156)	(0.312)
General Administration	-0.327***	1.624	-0.134**	-0.529*	-0.381***	2.400*	-0.186**	-0.555**
	(0.117)	(1.418)	(0.064)	(0.290)	(0.105)	(1.411)	(0.090)	(0.273)
Health	0.124**	0.208	0.151***	-0.045	0.127**	0.245	0.144***	-0.025
	(0.060)	(0.221)	(0.033)	(0.074)	(0.059)	(0.220)	(0.027)	(0.076)
Infrastructure	0.331***	-0.033	-0.380**	-0.119	0.374***	0.010	-0.404**	-0.037
	(0.093)	(0.869)	(0.179)	(0.154)	(0.095)	(0.911)	(0.162)	(0.157)
Agriculture Lag					0.104***	0.546**	-0.032	
					(0.038)	(0.254)	(0.036)	
Education Lag					-0.426**	-4.006**	0.529***	
					(0.206)	(1.832)	(0.196)	
General Administration Lag					-0.316**	5.058**	-0.180*	
					(0.154)	(2.003)	(0.100)	
Health Lag					0.048	0.473***	-0.030	
					(0.042)	(0.198)	(0.034)	
Infrastructure Lag					0.270	1.810*	-0.141	
					(0.171)	(0.998)	(0.175)	
Observations	15,152	15,152	15,152	15,152	15,152	15,152	15,152	15,152

Notes:
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.
[a] Coefficients and standard errors multiplied by 1,000.

Table 6: Percentage change of Total Budget by Key Sectors

	Without Lag				With Lag			
Sector	Flood[a]	Earthquake	Volcanic Eruptions[a]	Tsunami	Flood[a]	Earthquake	Volcanic Eruptions[a]	Tsunami
Mean disaster								
Education	-0.71*	0.13	1.87***	10.16***	-0.86**	0.04	2.16***	8.50*
General Administration	-0.91***	0.41	-0.43**	-7.41*	-1.06***	0.61*	-0.60**	-7.77**
Health	0.35**	0.05	0.49***	-0.63	0.35**	0.06	0.46***	-0.35
Infrastructure	0.92***	-0.01	-1.23**	-1.67	1.04***	0.00	-1.30**	-0.52
Education Lag					-1.19**	-1.02**	1.71***	
General Administration Lag					-0.88**	1.28**	-0.58*	
Health Lag					0.13	0.12***	-0.10	
Infrastructure Lag					0.75	0.46*	-0.45	
Max Disasters								
Education	-4.43*	2.32	10.73***	16.7***	-5.37**	0.69	12.39***	13.96*
General Administration	-5.73***	7.32	-2.47**	-12.17*	-6.67***	10.82*	-3.43**	-12.77**
Health	2.17**	0.94	2.79***	-1.04	2.22**	1.10	2.66***	-0.58
Infrastructure	5.80***	-0.15	-7.02**	-2.74	6.55***	0.05	-7.46**	-0.85
Education Lag					-7.46**	-18.06**	9.77***	
General Administration Lag					-5.53**	22.80**	-3.32*	
Health Lag					0.84	2.13***	-0.55	
Infrastructure Lag					4.73	8.16*	-2.60	

Notes:

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

without the lags, potentially showing that the effects of floods can affect next year's budget as well. For the year after the disaster, GA and Education still show significant decreases, with spending 0.9 and 1.2 percent lower. The total effect on GA and Education on the budget for the year after the disaster is negative 1.9 and 2 percent. If one assumes that the max flood strikes a district, the changes are in excess of minus 5 percent for GA and Education and plus 5 percent for Infrastructure. Overall, there is some evidence that districts tend to redistribute costs not just for the year of the disaster, but also for the year after.

For earthquakes, most of the sectors are significant the year after the disaster. As mentioned, earthquakes are more likely to be declared national disasters and/or recovery costs exceeding what local governments are capable of covering, which might limit the local costs during the year of the disaster, while one might see a stronger effect the year after, once the true reconstruction phase starts. For the year after the disaster, Education is strongly negatively affected. In terms of Health and GA there is a strong positive effect, and Health is 1 percent significant. For two sectors that one might expect a large change in, Infrastructure is just 10 percent significant and Housing not significant at all. It is not clear why this would be the case, but potentially it is easier to get central government funding for infrastructure and housing reconstruction. This is supported by the findings in a follow-up mission to the The Global Facility for Disaster Reduction and Recovery (2011) report, which found that local governments have incentives to inflate loss estimates since they are not required to contribute toward reconstruction costs.[15] One sees a strong significant increase in most other sectors, with Agriculture, Economy, Environment, Public Law and Order, Social Protection

[15]Findings presented in an Aide Memoire in Jakarta 13-17 April 2015. The mission was a joint effort between the World Bank and the Government of Indonesia represented by BNPB and the Ministry of Finance.

and Tourism all being positive and significant the year after. A potential reason for this can be transfers from the central government somehow being included in the local budgets.

In terms of actual change, the year after the earthquake one would see a decrease of 1 percentage points for Education and a 1.3 percentage points increase in GA, whereas the other sectors will see minor changes. However, assuming that the worst earthquake struck a district, the changes would be negative 18 percent for Education and positive 22.8 percent for GA. As for the floods, earthquakes show some evidence of redistribution happening in the year after the disasters.

The volcanic eruptions' coefficients are very similar as the model with no lags, with GA, Education, Health, Infrastructure and Environment being significant in the disaster year. For the year after the disaster, GA, Education and Environment stay significant, while Economy and Public Law and Order become significant. The largest effect is seen on Education, which changes 2.2 percent with the disaster year and 1.7 percent the year after, for a total effect of 3.9 percent. At the same time, GA decreases 1.2 percent in total.

Finally, there are no lag variables for the tsunami, as the original coefficients have already been lagged one year. However, the regular variables are included in the SUR with the other indices and their lagged variables. The results stay the same as for the model with no lags both in terms of significance and the coefficient sizes, with just minor changes.

Overall, our models seems to have performed well with fairly consistent results across both models. Generally speaking, these types of disasters do seem to lead to a reallocation of resources, both for budgets in the disaster year as well as for the budget the year after a disaster.

4.3.2 Category Results

Table 7 shows the results for the four economic categories, with columns 2-5 presenting the results for the model without lag. Floods cause a 1 percent significant decrease in spending on Goods and Services, which is partly offset by a 10 percent significant gain in Other Expenditures. This seems plausible, Other Expenditures have been known to be used to fund natural disaster repairs and short term goods and services consists of many small and flexible line items where purchase can be postponed or canceled.

The percentage changes to the expenditures are shown in Table 8, with four panels where the top one shows the changes for a mean disaster and the bottom one shows for a maximum damage disaster. Furthermore, each panel is split into two with the model without lag being on the left side and the model with lag is on the right side. The changes are relatively speaking fairly small compared to what was found for the sectors. Goods and Services is down 0.9 percent, while Other Expenditures increase by 0.3 percent for a mean disaster. With the strongest possible flood, Goods see a decrease of 5.7 percent, while Other increases by 2.1 percent. This might be due to each of the categories including a wide variety of costs from different sectors, leading to a smoothing effect. Potentially it can also be that the more balanced number of observations leads to better estimates and that changes overall are less pronounced than what it could seem like for the sectors.

Earthquakes see no immediate expenditure effects across the categories, similar to the sectors. Volcanic eruptions experience strongly significant changes in Capital and Personnel Expenditures, with the former being negative and the latter being positive. The same coefficient change holds for the tsunami. The reason for this might be that investment into durable long term items is not a priority shortly after big disasters as the eruptions and tsunami were. Another possibility is that repairs and investment for the larger items are being covered by the central government or other sources when the disasters are big and that the districts prefer to change costs to personnel that can be of immediate assistance. For Volcanic Eruptions the change after a mean disaster is positive 2.7 percent into Personnel and negative 2.2 for Capital, while the tsunami saw a close to 12 percent increase for Personnel and a similar decrease for Capital.

The results for the lagged model are very similar for the disaster year, as seen in Table 7. The main difference is for the earthquake coefficients, that see 5 percent and 1 percent significance for Capital and Personnel expenses for the year following the disaster. The capital being positive and the personnel change being negative. This can possibly be due to the recovery phase having started and the local districts taking on more of the disaster costs, with preference being given to the repairs of long term assets over hiring people. However, for volcanic eruptions the picture is the opposite, with Capital being negatively affected and Personnel being positive. This can - as mentioned earlier - be due to our SO_2 model not being a good proxy for damage to durable assets.

The changes for the different disaster types are summarized in the rightmost columns of

Table 7: Regression results for Unbalanced 2 year Category Data

	Without Lag				With Lag			
Category	Flood[a]	Earthquake	Volcanic Eruptions[a]	Tsunami	Flood[a]	Earthquake	Volcanic Eruptions[a]	Tsunami
Capital Expenditure	0.191	0.416	-0.696***	-0.846***	0.241	0.910	-0.794***	-0.675***
	(0.172)	(1.086)	(0.266)	(0.157)	(0.194)	(0.974)	(0.253)	(0.172)
Goods and Services	-0.323***	-0.110	-0.186	-0.003	-0.345***	-0.006	-0.105	-0.027
	(0.097)	(0.682)	(0.184)	(0.326)	(0.102)	(0.733)	(0.182)	(0.310)
Other Expenditures	0.119*	-0.490	0.024	-0.010	0.125**	-0.426	0.000	0.001
	(0.068)	(0.880)	(0.196)	(0.101)	(0.062)	(0.837)	(0.187)	(0.077)
Personnel Expenditures	-0.144	-0.666	0.842***	0.856***	-0.183	-1.122	0.902***	0.721***
	(0.134)	(0.706)	(0.149)	(0.195)	(0.135)	(0.702)	(0.153)	(0.186)
Capital Expenditure Lag					0.375	3.262**	-0.539*	
					(0.284)	(1.430)	(0.284)	
Goods and Services Lag					-0.145	0.660	0.338	
					(0.142)	(0.924)	(0.209)	
Other Expenditures Lag					0.085	1.169	-0.148	
					(0.102)	(1.290)	(0.206)	
Personnel Expenditures Lag					-0.353*	-4.158***	0.332*	
					(0.201)	(1.257)	(0.172)	
Observations	7,540	7,540	7,540	7,540	7,540	7,540	7,540	7,540

Notes:
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.
[a] Coefficients and standard errors multiplied by 1,000.

Table 8: Percentage change of Total Budget by Category

	Without Lag				With Lag			
Category	Flood[a]	Earthquake	Volcanic Eruptions[a]	Tsunami	Flood[a]	Earthquake	Volcanic Eruptions[a]	Tsunami
Mean disaster								
Capital Expenditures	0.53	0.11	-2.24***	-11.84***	0.67	0.23	-2.56***	-9.45***
Goods and Services	-0.90***	-0.03	-0.60	-0.04	-0.96***	0.00	-0.34	-0.38
Other Expenditures	0.33*	-0.12	0.08	-0.14	0.35**	-0.11	0.00	0.01
Personnel Expenditures	-0.40	-0.17	2.72***	11.98***	-0.51	-0.28	2.91***	10.09***
Capital Expenditures Lag					1.05	0.83**	-1.74*	
Goods and Services Lag					-0.41	0.17	1.09	
Other Expenditures Lag					0.24	0.30	-0.48	
Personnel Expenditures Lag					-0.99*	-1.06***	1.07*	
Max Disasters								
Capital Expenditures	3.34	1.87	-12.85***	-19.46***	4.22	4.10	-14.66***	-15.53***
Goods and Services	-5.66***	-0.50	-3.43	-0.07	-6.04***	-0.03	-1.94	-0.62
Other Expenditures	2.08*	-2.21	0.44	-0.23	2.19**	-1.92	0.00	0.02
Personnel Expenditures	-2.52	-3.00	15.55***	19.69***	-3.20	-5.06	16.66***	16.58***
Capital Expenditures Lag					6.57	14.69**	-9.95*	
Goods and Services Lag					-2.54	2.97	6.24	
Other Expenditures Lag					1.49	5.27	-2.73	
Personnel Expenditures Lag					-6.18*	-18.74***	6.13*	

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 8, with the main difference compared to the lag free budgets are that earthquakes now cause a 0.8 percent increase to Capital costs in the year after the disaster combined with a 1.1 percent decrease in Personnel Expenditures. Furthermore, Volcanic Eruptions lead to a total decrease of 4.3 percent to Capital Expenditures across the disaster year and the lag year, while at the same time Personnel increases by 4 percent. However, for the year after the disaster, the coefficients are only 10 percent significant.

The overall results for the four categories show - like the sector results - that some redistribution seems to occur in the districts following disasters. The level of change depends on the strength of the disaster, but there might be an issue arising from some disasters being large enough to cause the central government or other sources to come in and provide funding.

5 Conclusion

Using damage indices from Skoufias *et al.* (2017) for floods, earthquakes, volcanic eruptions and the 2004 tsunami, this paper combines these indices with district-level expenditure data to investigate how districts might redistribute their spending depending on the type of disaster that strikes. The analysis yields evidence that redistribution is taking place across economic sectors and by category, irrespective of the disaster type, with the direction and the size of the redistribution differing with the type and strength of disaster. For example, floods show a strong decrease in spending on General Administration both in the year of the disaster as well as in the spending of the following year. At the same time, there is a sizable increase in spending on infrastructure and health for the same period.

These results demonstrate how remotely sensed and freely available data can be used to analyze local economic data. Unless one has access to more complete data and local level damage data that allow better calibration of the damage indices, the methodology presented here can be used to get an overview of damages shortly after the incidence of an actual disaster. Moreover, with data available on the budget of last year, one can quickly assess which budget categories at the district-level might need extra funding.

Overall this is an area that has received little attention in the literature, and future research can shed more light on how local level authorities deal with disasters by comparing the results of this study in Indonesia with other emerging countries or middle income countries. Another potential avenue for future research could be assessing policy impact. More specifically, Indonesia has a strong focus on strategies and policies for dealing with natural disasters[16], where key areas of improvement are outlined[17]. We believe that while the current dataset can only be used to find how budgets are allocated ex-post, the methodology outlined could very well be used for analyzing the impact of the Indonesian policies given further improvement in reporting of disaster related costs.

[16]These are outlined across the National Disaster Management Plan 2015-19 (NDMP), Indonesia Disaster Risk Index 2013 (IRBI), and National Medium-Term Development Plan (RPJMN) 2015-19.

[17]The addressed areas are (i) mainstream disaster risk reduction within the framework of sustainable development planning and policy making at central and regional levels; (ii) decrease vulnerability levels through improved knowledge dissemination and community awareness; and (iii) strengthen capacity of governments and communities to manage disasters.

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A Constructing the Damage Indices

This appendix provides more details from Skoufias *et al.* (2017) on the construction and aggregation of the disaster indices in the main paper. To weight the indices, nightlight data are used as a proxy for economic activity.

A.1 Flood Index

The flood index is made from stream flow modeled in GeoSFM, a software that uses remotely sensed data as inputs, which are weather and soil and terrain based. GeoSFM models basins and the volume of water running through each basin. Once the stream flows have been modeled, we apply the following formula to decide whether a flood has occurred or not:

$$Q > P_{95} + \sigma \qquad and \qquad Q > 10m^3/s \tag{3}$$

where Q is the stream flow in cubic meters, P_{95} is the 95th percentile value and σ is the standard deviation of the stream flow.

The next step is to define the flood intensity through the formula:

$$I_{b,t} \equiv \begin{cases} 0, & \text{if } Flood = 0 \\ \frac{Q_{b,t} - \bar{Q}_b}{\sigma_b}, & \text{otherwise} \end{cases} \tag{4}$$

where $I_{b,t}$ is the intensity of the flood in basin b at date t, $Q_{b,t}$ is the stream flow in the same basin at the same time and $\bar{Q}_b$ and σ_b are mean and standard deviation of stream flow in b. The intensity is set to zero if the flood threshold - 95th percentile plus 1 standard deviation above the average - has not been exceeded.

To aggregate the flood impact each basin is weighted based on the nightlights in it. The weights per basin, b, in province p, $W_{b,p,t-1}$, are defined as:

$$W_{b,p,t-1} \equiv \frac{\sum_i^I L_{b,i,t-1}}{\sum_j^J L_{p,j,t-1}}, \qquad b = 1, \ldots, B, \qquad p = 1, \ldots, P \tag{5}$$

where $\sum_i^I L_{b,i,t-1}$ is the sum of lights, i, in basin b one year, $t-1$, before the flood year and $\sum_j^J L_{p,j,t-1}$ is the same at a province or district level.

Furthermore, the weights from (5) are multiplied with the intensity from (4) to get the overall flood impact, $FI_{b,p,t}$ in basin b on the province p at time t:

$$FI_{b,p,t} \equiv W_{b,p,t-1} \cdot I_{b,t}, \qquad b = 1, \ldots, B \qquad p = 1, \ldots, P \tag{6}$$

Then, to aggregate up to a district or province level, we have used a simple method for the total damage experienced per year:

$$PD_{p,y} = \sum_t^T \sum_b^B FI_{b,p,t}, \qquad p = 1, \ldots, P, \qquad y = 2001, \ldots, 2014 \tag{7}$$

where p is the province or district, sum of t is all the days in year y, sum of b are all the basins in the province or district and $FI_{b,p,t}$ is the flood impact from Equation 6 for province or district p.

A.2 Earthquake Index

To model earthquake damage, contour maps - known as ShakeMaps - from USGS are used. These provide intensity data such as peak ground acceleration (PGA), peak ground velocity (PGV) and modified Mercalli intensity (MMI). The PGA is a measure of the maximum horizontal ground acceleration as a percentage of gravity, PGV is the maximum horizontal ground speed in centimeters per second and MMI is the perceived intensity of the earthquake, a subjective measure.

To construct the damage index, two types of data will be used; the intensity data - expressed as PGA - and building inventory data, to assess what damage one could expect for different intensities. In order to take account of the building types in Indonesia we use information from the USGS building inventory for earthquake assessment, which provides estimates of the fractions of building types observed by country; see Jaiswal & Wald (2008). The data provides the share of 99 different building types within a country separately for urban and rural areas, where - due to lack of other information - a homogenous distribution of buildings is assumed.

Then fragility curves by building type are derived from the curves constructed by the Global Earthquake Safety Initiative project; see GeoHazards International and United Nations Centre for Regional Development (2001). More specifically, buildings are first divided into 9 different types. 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 which provides estimates of the percentage of building damage for a set of 28 peak ground acceleration intervals.

In order to use these vulnerability curves for Indonesia we first allocated each of the 99 building types given in the USGS building inventory to one of the 9 more aggregate categories of the GESI building classification. However, in order to assign a building type its quality specific vulnerability curve we would further need to be able to determine its quality in terms of design, construction, and materials, an aspect for which we unfortunately have no further information. We instead assume that building quality is homogenous across building type in Indonesia and use a median quality of 4 for our model.[18]

To model estimated damage due to a particular earthquake event the data from the ShakeMaps and GESI are used. Then, one identifies the value of peak ground acceleration that each nightlight cell in Indonesia experiences by matching each earthquake point with its nearest nightlight cell. If the cell is further away than 1.5 kilometers or if it experiences shaking (PGA) of less than 0.05 the value is set to 0. In order to derive a cell i specific earthquake damage index, ED, the following equation is applied:

$$ED_{i,q,p,t} = W_{i,p,t-1} \cdot DR_{i,p,k,t,pga_{k,q}}, \qquad p = 1, \ldots, P, \qquad k = U, R, \qquad q = 0, \ldots, 7 \qquad (8)$$

[18] We ran the model for all building qualities from 0 through 7, without it changing the results materially.

where DR is the damage ratio according to the peak ground acceleration, pga, and the urban (U) or rural (R) qualification, k, of cell i, defined for a set of 8 different building quality q categories. t is the year of the event and p is the province or district.[19] The weight $W_{i,p,t-1}$ is similar to before, being defined as:

$$W_{i,p,t-1} \equiv \frac{L_{i,p,t-1}}{\sum_j^J L_{j,p,t-1}}, \qquad i = 1, \ldots, I, \qquad p = 1, \ldots, P \tag{9}$$

which translates to the weight of the light from nightlight cell i in year $t-1$ over the total amount of nightlight cell light, $\sum_j^J L_{p,j,t-1}$, in province p in year $t-1$.

Finally, when aggregating, a similar method as for floods is used, but now the aggregation is done directly by nightlight cells instead of by basin. The equation is:

$$ED_{p,q,y} = \sum_i^I \sum_t^T ED_{i,q,p,t}, \qquad p = 1, \ldots, P, \qquad q = 0, \ldots, 7 \qquad y = 2004, \ldots, 2014 \tag{10}$$

where sum of t is the sum of all days in the year y, i is all nightlight cells in the province or district p and ED is the damage from Equation 8.

A.3 Volcanic Eruption Index

The construction of the volcanic eruption index utilizes ash advisory data and satellite data to model sulphur dioxide concentration in the atmosphere, and the SO_2 value is used as a proxy for eruption intensity as the strength of an eruption is closely correlated with the

[19] In our case the value of p in DR is irrelevant as all provinces have the same fragility curves. However, if one looks at different countries or have access to local data, it would affect the results.

amount of SO_2 that is emitted into the atmosphere.

First, ash advisories from the Darwin VAAC, which are ash cloud warnings for airplanes, are used to determine whether an eruption is happening. The warnings show relevant data such as volcano name, position, summit height, height of clouds and a color code that reflects the condition of the air/volcano. There are 4 different codes ranking from the normal state, green, to imminent danger of or ongoing volcanic eruption, red. Data on advisories from code orange or below were not used, due to eruptions of this scale not being large enough to be properly captured by the SO_2-data.

Second, to measure the intensity of an eruption, data from the Sulphur Dioxide images of the OMI/Aura project (Krotkov & Li, 2006) are used. The data have been used to model ash cloud intensity and movement in several publications such as Carn *et al.* (2009) and Ferguson *et al.* (2010).

The satellite images have a spatial resolution of $13 * 24$km and are taken from 80km above ground. The spectral imaging shows the SO_2 vertical column density in Dobson Units and there are 14 or 15 orbits per day, where one orbit covers an area that is approximately 2,600km wide. A dobson unit is a measure of density.

When constructing a damage index based on SO_2-values from ash clouds, one has to set thresholds for distance from the event and from the centroid of the nightlight cell and also a lower sulphur dioxide-threshold. There are no papers or literature that have estimated any parameter values and there are no usable local data, so the thresholds have been set somewhat arbitrarily.

For event distance, we set a very relaxed condition with any point closer than 10 degrees of latitude and longitude included. Secondly, for nightlight matching, a maximum distance between a nightlight point and the nearest SO_2-point is set at 50km. Finally, a minimum SO_2-value in Dobson Units is chosen. According to the Belgian Institute for Space Aeronomy, a typical normal level in air is 0.1DU and a strong eruption is above 10, which is the threshold value chosen.

Once the thresholds have been set, the same nightlight weighting method as for our other indices is applied and then the weights are multiplied with the SO_2 value to get an intensity value. The equation is:

$$VD_{i,t} \equiv \begin{cases} 0, & \text{if } VSO2_t < 10 \\ W_{i,p,t-1} \cdot VSO2_t, & \text{otherwise} \end{cases} \tag{11}$$

where i is the nightlight cell on date t, and $W_{i,p,t-1}$ is the previously used weight where i is the nightlight cell, $t-1$ is the nightlight strength from the prior year and it is divided by the sum of total nightlights in the province or district. $VSO2_t$ is the SO_2 value on date t.

Finally, to aggregate the data, the same method as before is applied, with:

$$VD_{p,y} = \sum_t^T \sum_i^I VD_{p,i,t}, \qquad p = 1, \ldots, P, \qquad y = 2004, \ldots, 2014 \tag{12}$$

where all days t of a year and all nightlight cells i in province or district p are aggregated.

A.4 Tsunami Index

The final disaster damage index constructed is for the 2004 Christmas tsunami. There is little local district level damage data available, so it was decided to use the methodology from Heger (2016), whereby inundation maps are used to construct a district level damage index assuming uniform damage across all flooded areas.

To construct an inundation map of the affected areas, a map based on MODIS satellite pictures from Anderson *et al.* (2004) is used. In terms of the intensity of the flood, there is no existing data on that, but a uniform flood intensity across all flooded areas is assumed, just as in Heger (2016). Using a base map from DFO, spatial algorithms were used to detect the difference in color between inundated and non-inundated areas. This process started with overlying the base map on a regular shapefile of Indonesia, then detecting the specific color of inundated areas, before constructing a new shapefile where all inundated areas (areas with the same color) have value 1 and all other areas have value 0.

Finally, the weights are - again - defined as nightlight in the cell over total nightlight in the province. Assuming a damage of 75 percent in the inundated cells, yields a final damage index formula:

$$TD_i = W_{i,p,t} \cdot D, \qquad i = 1, \ldots, I \tag{13}$$

where TD_i is the province weighted damage from nightlight cell i, $W_{i,p,t}$ is the same weight as for earthquakes and D is the flat damage number of 0.75.

Aggregating up the data is done using the same method as in all previous sections, where the nightlight cells across the district are summed up:

$$TD_p = \sum_{i}^{I} TD_{p,i} \tag{14}$$

where all nightlight cells i in province or district p are aggregated.

B Nominal Expenditure Data

Table B1: Descriptives of Expenditure data by Economic Sectors

Statistic	N	Mean	St. Dev.	Max
General Administration	4,762	151,816	144,886	3,584,915
Public Law and Order	3,458	5,286	5,656	107,046
Economy	4,679	11,088	12,844	221,310
Environment	4,376	9,821	27,006	898,914
Housing and Public Facilities	3,658	8,618	19,250	286,751
Health	4,690	44,489	50,860	1,777,818
Tourism and Culture	4,254	2,976	6,118	204,020
Religious Affairs	717	1,660	3,684	50,718
Education	4,697	167,218	170,056	3,298,403
Social Protection	4,229	4,195	5,697	127,606
Infrastructure	4,689	76,533	99,461	3,145,709
Agriculture	4,679	19,469	22,635	1,061,025
Total	5,305	441,703	447,503	13,328,544

In RP million

Table B2: Descriptives of Expenditure data by Economic Categories

Statistic	N	Mean	St. Dev.	Max
Capital Expenditures	4,770	124,863	127,322	1,817,070
Goods and Services	4,775	97,234	83,776	1,210,640
Other expenditures	4,747	46,846	53,648	731,533
Personnel Expenditures	4,790	262,931	216,098	1,908,810
Total	5,305	479,115	423,606	4,942,255

In RP million

C Regression Results

Table C1: Regression results for Unbalanced 2 year Sector Data

Sector	Flood[a]	Earthquake	Volcanic Eruptions[a]	Tsunami
Agriculture	0.094***	0.092	-0.038	-0.285***
	(0.033)	(0.170)	(0.047)	(0.051)
Economy	0.069**	-0.120	-0.023	-0.094***
	(0.029)	(0.153)	(0.056)	(0.031)
Education	-0.253*	0.514	0.581***	0.726***
	(0.136)	(1.423)	(0.178)	(0.280)
Environment	-0.027	-0.401	-0.026	-0.015
	(0.024)	(0.339)	(0.021)	(0.062)
General Administration	-0.327***	1.624	-0.134**	-0.529*
	(0.117)	(1.418)	(0.064)	(0.290)
Health	0.124**	0.208	0.151***	-0.045
	(0.060)	(0.221)	(0.033)	(0.074)
Housing and Public Facilities	-0.096	-0.036	-0.072	0.007
	(0.068)	(0.216)	(0.162)	(0.028)
Infrastructure	0.331***	-0.033	-0.380**	-0.119
	(0.093)	(0.869)	(0.179)	(0.154)
Public Law and Order	-0.028*	-0.238**	0.006	
	(0.015)	(0.119)	(0.026)	
Social Protection	0.034	0.010	0.014	-0.003
	(0.021)	(0.119)	(0.048)	(0.044)
Tourism and Culture	0.073**	-0.287*	-0.003	0.009
	(0.035)	(0.151)	(0.045)	(0.026)
Observations	15,152	15,152	15,152	15,152

Notes:
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.
[a] Coefficients and standard errors multiplied by 1,000.

Table C2: Regression results for Unbalanced 2 year Sector Data with lags

Sector	Flood[a]	Earthquake	Volcanic Eruptions[a]	Tsunami
Agriculture	0.108***	0.083	-0.049	-0.173***
	(0.030)	(0.193)	(0.041)	(0.027)
Economy	0.070***	-0.132	-0.038	-0.073***
	(0.027)	(0.127)	(0.043)	(0.026)
Education	-0.307**	0.154	0.671***	0.607*
	(0.131)	(1.543)	(0.156)	(0.312)
Environment	-0.028	-0.377	-0.037*	0.004
	(0.026)	(0.329)	(0.019)	(0.060)
General Administration	-0.381***	2.400*	-0.186**	-0.555**
	(0.105)	(1.411)	(0.090)	(0.273)
Health	0.127**	0.245	0.144***	-0.025
	(0.059)	(0.220)	(0.027)	(0.076)
Housing and Public Facilities	-0.086	-0.109	-0.070	0.019
	(0.069)	(0.195)	(0.172)	(0.049)
Infrastructure	0.374***	0.010	-0.404**	-0.037
	(0.095)	(0.911)	(0.162)	(0.157)
Public Law and Order	-0.023	0.003	-0.001	
	(0.018)	(0.128)	(0.021)	
Social Protection	0.032	0.011	0.008	0.009
	(0.019)	(0.091)	(0.045)	(0.039)
Tourism and Culture	0.073**	-0.341***	-0.009	0.028
	(0.034)	(0.124)	(0.043)	(0.025)
Agriculture Lag	0.104***	0.546**	-0.032	
	(0.038)	(0.254)	(0.036)	
Economy Lag	0.045*	0.617***	-0.091*	
	(0.027)	(0.170)	(0.051)	
Education Lag	-0.426**	-4.006**	0.529***	
	(0.206)	(1.832)	(0.196)	
Environment Lag	0.017	0.721***	-0.072**	
	(0.028)	(0.259)	(0.030)	
General Administration Lag	-0.316**	5.058**	-0.180*	
	(0.154)	(2.003)	(0.100)	
Health Lag	0.048	0.473***	-0.030	
	(0.042)	(0.198)	(0.034)	
Housing and Public Facilities Lag	0.063	-0.268	0.009	
	(0.161)	(0.374)	(0.203)	
Infrastructure Lag	0.270	1.810*	-0.141	
	(0.171)	(0.998)	(0.175)	
Public Law and Order Lag	0.048**	0.237**	-0.038*	
	(0.020)	(0.119)	(0.023)	
Social Protection Lag	0.014	0.384***	-0.024	
	(0.020)	(0.137)	(0.045)	
Tourism and Culture Lag	0.028	0.516***	-0.030	
	(0.036)	(0.121)	(0.045)	
Observations	15,152	15,152	15,152	15,152

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.
[a] Coefficients and standard errors multiplied by 1,000.