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**Shaking up Foreign Finance: FDI in  
a Post-Disaster World**

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# Shaking up Foreign Finance: FDI in a Post-Disaster World

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*September, 2023*

**Abstract:** This paper studies the effects earthquakes have on inward foreign direct investment (FDI) within a country. I use a dynamic difference-in-difference model to estimate the impact of geophysical disaster exposure in 416 Indonesian districts. The effects are only temporary: FDI inflows plummet by 90% on average in the first year after an earthquake before recovering to pre-earthquake levels. The effect is largely driven by shocks through affected upstream industries within local supply chains, and centered within the manufacturing sector. This highlights the importance to also consider indirect earthquake effects through spatial and production networks, besides the direct effects on labor and capital.<sup>†</sup>

**Keywords:** Foreign Direct Investment, Disasters, Risk, Input-Output

**JEL:** F21, O12, Q54, C67

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# 1 Introduction

The literature of disaster adaptation, particularly within the context of climate change, has seen a growing body of research. However, little research exists on the exploration of the impact of multinational corporations in the post-disaster landscape. This gap is particularly striking given the significant contributions of foreign firms to economic development and their key position in domestic supply chains. It also provides motivation to analyze how investment flows respond in the aftermath of a disaster.

This paper aims to assess the immediate changes in inward foreign direct investment (FDI) flows within a country on a local level, as well as the indirect effects through sectoral supply chain dynamics within the country following an earthquake event. Indonesia provides a good case study given its disaster environment as well as the importance of FDI on its economic activity. Population-wise, Indonesia is one of the largest economies in the world and has increasingly attracted foreign investment. For Indonesia, FDI inflows contribute in boosting the productivity of domestic firms (Suyanto, Salim, and Bloch, 2009), in accelerating structural transformation (Steenbergen et al., 2020) and in transitioning Indonesia to a low-carbon economy (Zhu et al., 2016; OECD, 2020). The country receives, despite these positive effects, less FDI in relative terms to GDP compared to other ASEAN countries given its tight regulatory environment and inefficient business environment (OECD, 2020; Lipsey and Sjöholm, 2011). Another likely reason for lower investment are earthquakes and other disasters, which increase the foreign firm's operational risk. Data from the Emergency Events Database (EM-DAT) (Sapir and Below, 2014) reveals that Indonesia encountered 48 natural disasters in 2019 alone, affecting roughly two million people, resulting in around 600 casualties, and causing an estimated 1.3 billion dollars in damages. Considering the significant role of FDI in Indonesia's sustainable development, it is essential to explore and unravel how FDI reacts to the growing challenge posed by these disasters.

To investigate the response of Foreign Direct Investment (FDI) to disaster shocks, I use FDI inflow data spanning 2003 to 2019, covering 416 Indonesian districts. This data is sourced from the Indonesian Investment Board. I link this district-wise data with event-specific geophysical earthquake intensity records for all significant earthquakes that occurred during the same period using the speed of ground movement in a metric called *modified Mercalli intensity*. The data is drawn from 896 earthquake events recorded by the United States Geological Survey. Then an event-study type difference-in-difference model is applied to account for the temporary dynamic response of FDI inflows. To analyze the indirect effects of a disaster through supply chain linkages, this study adapts a panel model from Acemoglu, Akcigit, and Kerr (2016) to the context of a multiregional input-output matrix over 32 Indonesian provinces. In contrast to previous work, the study is structured to differ between direct and indirect effects of a disaster following Antonioli, Marzucchi, and Modica (2021). Direct effects affect a firm's production capabilities, while indirect effects disrupt firm partners and business associates. This distinction is important, because neglecting the indirect effects of a disaster could worsen the adverse impact of a disaster shock and thereby underestimate the observed economic effects of a disaster.

When I study the direct effects of an earthquake, which is recorded to be destructive, I observe that

affected districts see a reduction of FDI inflows by around 90% in the first year following a shock before returning to pre-disaster levels and remaining thereafter. This decrease in FDI is primarily observed in regions with low pre-existing disaster risk, where such shocks are less anticipated. On the contrary, areas with high disaster risk do not experience significant fluctuations in FDI inflows. This underscores the importance of disaster preparedness and anticipation in shaping the response to earthquakes. The indirect effects of an earthquake considered in my study are spatial spillover effects and, notably, shocks propagating along the national supply chain. Local spillover effects from adjacent districts insufficiently explain the effects found, likely due to the high concentration of FDI around economic centers and special economic zones. However, the adverse effects on FDI can be partly attributed to shocks occurring in upstream industries, with the most pronounced impact seen in the manufacturing sector, which is the primary recipient of FDI in Indonesia. These negative effects are more significant if the affected upstream industry is located within the same province. Demand-side shocks, in contrast, can potentially boost FDI inflows, notably in the construction sector. However, this is typically the case when foreign firms in the construction sector remain unaffected and only their customers are impacted. In the robustness section, I find that similar effects occur for flood events, but FDI inflows recover already within the treatment year.

The paper aims to connect several related literature streams. Chiefly, the paper contributes to the literature on the impact of disasters on FDI. The vast majority of these studies focus on a macroeconomic dimension and study different samples: on a global scale (for instance Gu and Hale, 2022; Doytch, 2019; Neise et al., 2022), on middle and low-income countries (Drabo, 2021) and on Sub-Saharan Africa (Katoka, 2021). Most papers find a negative effect of disasters on FDI inflows. Only a few papers consider a singular country of study (Anuchitworawong and Thampanishvong, 2015; Friedt and Toner-Rodgers, 2022). Friedt and Toner-Rodgers (2022) focus in their work in-depth on the within-country effects of disasters on FDI. Analyzing the effect of six extreme flood and storm events over 16 of India's provinces, they show that FDI tends to spill over to developed regions with large market potential following the months of an extreme event. Instead of analyzing floods, I focus on earthquakes given their short but highly destructive occurrence, which provides a better cut-off in time than flood events. Unlike earthquakes, floods are more likely to lead to secondary disasters such as the spread of waterborne diseases, potentially inducing bias in post-treatment outcomes. My study focuses on a smaller disaggregated level, which accounts better for the local variation of earthquake intensity. Lastly, I also consider the sectoral dimension of FDI inflows. In contrast to Friedt and Toner-Rodgers (2022) I do not find long-term effects of FDI reduction, which is likely due to the aforementioned differences in disaster category and level of observation considered.

Studies focusing on an even more disaggregated level utilize firm-level data. Notable examples of that literature are, for instance, a study on the impact of typhoons on plant sales (Elliott et al., 2019), several firm-level studies on the Kobe and Tohoku earthquakes in Japan (Cole et al., 2019; Inoue and Todo, 2019; Boehm, Flaaen, and Pandalai-Nayar, 2019; Carvalho et al., 2021) or studies of floods on firms in Tanzania (Rentschler et al., 2021) or tropical storms in India (Pelli et al., 2019). Relevant for this study is the paper by Brucal and Mathews (2021). They combine data from 1990 to 2015 from Indonesian

plants and connect them with the EM-DAT database, on a district level, for flood exposure and find a persistent decline in output per worker for foreign-owned firms. I extend their approach by using a more geolocated version of disaster exposure while putting more spotlight on the sector-network aspects of financial flows.

The above-mentioned studies have improved our understanding of how FDI flows patterns evolve in the aftermath of natural disasters on a macro-level and how firms in general respond to disasters on a micro-level. My study attempts to build a bridge between these two strands of literature. It connects the within-country analysis of FDI inflow data as in Friedt and Toner-Rodgers (2022), similarly focusing on temporal and spatial aspects of FDI inflow on a smaller geographic unit (district level), with the sectoral-network perspective often found in literature on effects on firms (e.g. Carvalho et al., 2021; Inoue and Todo, 2019; Boehm, Flaaen, and Pandalai-Nayar, 2019; Huang et al., 2022).

The rest of this article is structured as follows: Section 2 presents more context on the FDI and disaster environment in Indonesia along with the corresponding data used in this paper. Section 3 shows the empirical strategy. Then, in Section 4 the results are presented divided into direct and indirect effects of earthquake exposure, followed by a conclusion in Section 5.

## 2 Context and Data

### 2.1. Defining the Earthquake Shock

To study the effects disasters have on FDI inflows in Indonesia, I particularly chose earthquakes as a disaster category. Indonesia, located amid multiple tectonic plates, including the Australian and Eurasian plates, is among the world's most seismic regions. It received tragic notoriety due to the 2004 tsunami, which followed a tectonic shift and killed thousands of people in Indonesia and neighboring nations. Its equatorial position also makes Indonesia susceptible to heavy rainfall, leading to hydrological disasters like landslides and floods. Finally, the northern and southern regions face occasional storms and cyclones. However, as shown in Figure 1, earthquakes and their associated tsunamis account for more than half of all recorded damage and are the deadliest disaster categories. Floods, in contrast, tend to affect the daily lives of Indonesians more. Despite measures for disaster preparedness through national agencies, disaster risk remains a major operational risks for foreign firms. As earthquakes are the most destructive and lethal disaster category, I chose them as the treatment category<sup>1</sup>.

Earthquakes are frequent in Indonesia and affect a large part of the country. In order to connect them to other variables on a yearly district-level, I combine data from several sources. Recent literature has pointed out the issues associated with relying solely on victim or damage data in disaster studies (Felbermayr and Gröschl, 2014; Felbermayr et al., 2022). Yet, this information might still be valuable to assess the severity of a shock, especially in local labor markets. Thus, I combine data on the share of the local population affected with an exogenous earthquake intensity measure called *modified Mercalli*

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<sup>1</sup>Yet flood, as the second most common category, is also assessed for robustness.

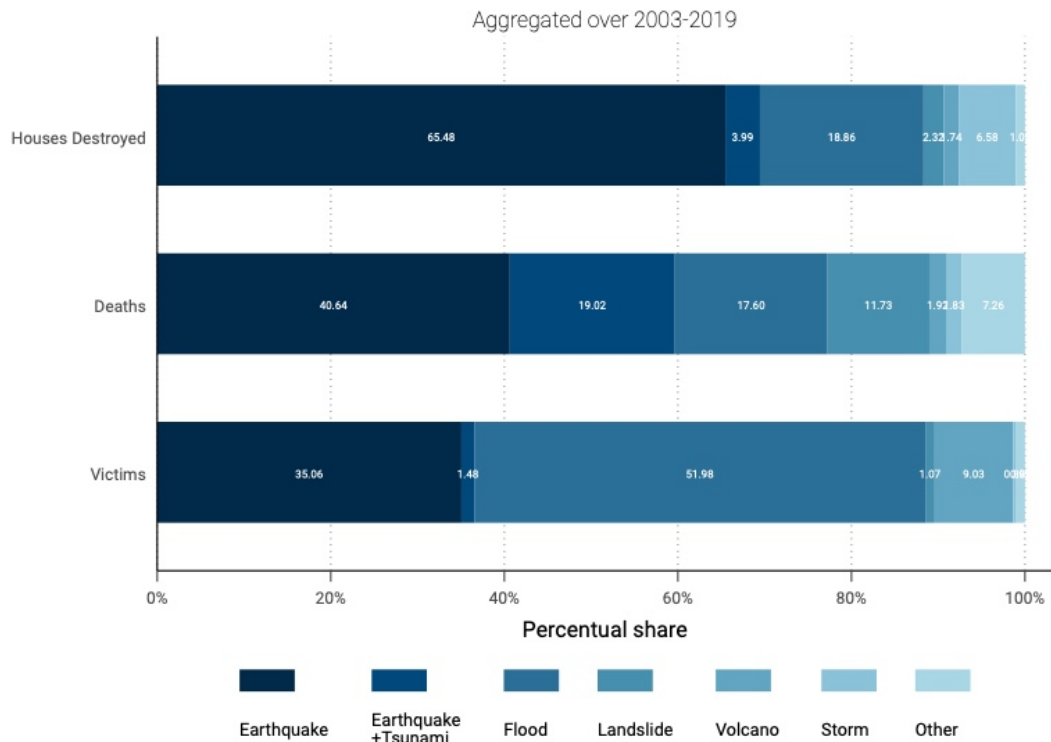


Figure 1: Overview on Disaster Relevance

Notes: Source: UNDRR (2022b). Calculations are the author's own. The category "other" includes forest fires, tsunamis, droughts, and tidal waves. In absolute numbers there are 10 014 145 victims, 22 454 deaths, and 857 275 houses destroyed recorded. The 2004 Bandah Aceh Tsunami is excluded.

intensity (MMI).

The data on the affected population is taken from the Desinventar database, hosted by the UNDRR (2022b) and is, in case of Indonesia, updated by the Indonesian National Board for Disaster Management (BNPB). Similar to the commonly used EM-DAT database, it also records information on damages and the affected population. In contrast to EM-DAT, however, it records information not only on an event-level but also on a geographically narrow area. I draw from Desinventar three variables to measure whether a person is affected: deaths, victims and affected<sup>2</sup>. I build the sum over the three variables given that these people are either permanently affected, by being dead, or indirectly affected, by suffering losses. In both cases, individuals drop out of the labor force. Additionally, I consider earthquake-induced tsunamis victims as with the database, they can be specifically attributed to a related earthquake event. To obtain the share of people affected, the number of people is weighted by the one-year lagged local population with data from the INDO-DAPOER database (The World Bank, 2022b)<sup>3</sup>.

<sup>2</sup>Per UNDRR (2022a) definition direct refers to victims: "persons whose goods and/or individual or collective services have suffered serious damage, directly associated with the event" and indirect refers to affected: "people, distinct from victims, who suffer the impact of secondary effects of disasters for such reasons as deficiencies in public services, commerce, work"

<sup>3</sup>The population data is only available until 2014. All years after 2014 are imputed using the district-specific linear population trends

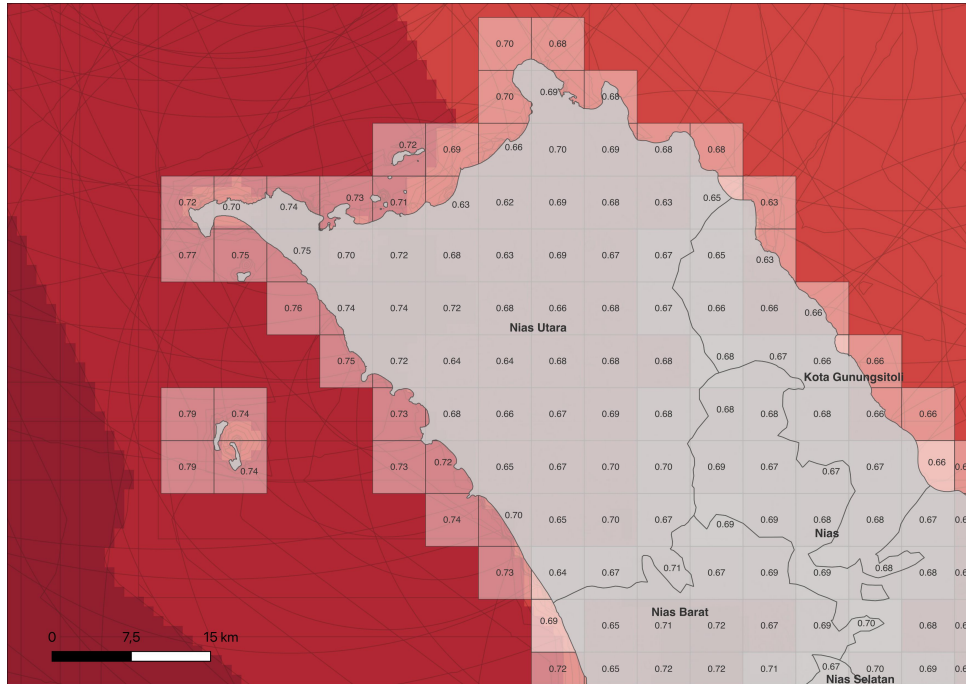


Figure 2: Example of a District Exposure in 2005

Notes: The figure shows the exposure of the Nias district to the earthquakes taking place in 2005. It is overlaid with the 5x5 km grid. The red background color indicates the discrete predicted earthquake intensity. A darker red indicates a closer proximity to the epicenter, thus a stronger intensity. The numbers show the mean *peak ground acceleration* within the given grid cell. The map is created in Quantum GIS.

The exogenous earthquake intensity within a year and district is based on 897 so-called ShakeMaps from the US Geological Survey, 2020 between  $6^\circ$  and  $-11^\circ$  geographic latitude and between  $95^\circ$  to  $142^\circ$  longitude. These event-specific maps show the intensity of ground movement in proximity to an epicenter<sup>4</sup>. For each year, I compute the highest measured *modified Mercalli intensity* (MMI) recorded by any of these events within a self-designed 5x5km grid of Indonesia<sup>5</sup>. An example for a singular event in 2005 is shown in Figure 2. The MMI intensity scale ranges from zero to ten, while damages on buildings start to occur above level five (USGS, 2022). As earthquakes are highly local events, even on a district level, they might not necessarily occur where firms are located. Thus, to improve the quality of the measure, I identify economic centers within each district using nighttime light data by Chen et al. (2021) and population density for four time periods by SEDAC-CIESIN (2017) for poorer areas. This is done under the assumption that FDI is allocated, where economic activity is located. The final variable will be the highest MMI value recorded within the economic center of a district within a year. To obtain a binary dummy, only districts with an MMI above five are considered treated as with this intensity minor damage can be expected.

The final treatment dummy combines both datasets in the form of one binary dummy if the local pop-

<sup>4</sup>In contrast to the scale, which is measured at the epicenter.

<sup>5</sup>Precisely, the ShakeMap values assigned are values for *peak ground acceleration*, another metric for velocity of the ground, which in a second step is transformed to the MMI based on values provided by Wald et al. (1999). This conversion is also done by Gignoux and Menéndez (2016)



ulation is affected, the labor shock, and one binary dummy if districts are exposed to a potentially destructive earthquake, the capital shock<sup>6</sup>. Both shocks, labor and capital, can lead individually to a re-evaluation of the foreign firm’s investment decision, but together they reflect the complex consequences of a disaster. If the labor market is disrupted, foreign firms with reserve assets might be able to hire workers from further away, while if capital is affected, firms might substitute, if possible, with a larger work force. If both inputs, however, are concerned, foreign firms might not be able to cope so easily. Thus, the final treatment dummy is the product of the two dummies. In the appendix, the shocks individually are also assessed.

## 2.2. Foreign Investment into Indonesia

The contribution of FDI inflows to GDP in Indonesia mirrors the trends in neighboring Southeast Asian nations. Initially, they rose steadily, reaching 2.8% of GDP in 2014, but then dropped sharply to 0.5% in 2016, before gradually recovering to 2% in 2019 (The World Bank, 2022a). The drop and the slow recovery can be attributed to stolid merger and acquisition (M&A) processes and also to the withdrawal of some multinational companies (UNCTAD, 2017). Jakarta, Indonesia’s capital, initially received the bulk of FDI, but its share decreased from 60% in 2003 to approximately 15% in 2019. In contrast, West Java, being close to Jakarta, witnessed a consistent increase, making up about 20% of all FDI inflows in 2019. Regarding sectors, manufacturing attracted the most FDI, with greenfield investments being prevalent. Agriculture and services saw larger shares of M&A. However, manufacturing’s overall share of FDI inflows has declined recently due to difficulties in recruiting workers OECD (2020). These trends are illustrated in Figure 5. To study the effect on FDI inflows, the paper relies on data from the Indonesian Investment Co-ordinating Board (BKPM) (2021) (*Badan Kordinasi Penanaman Modal*). The data contains extensive information on sectoral investment for foreign investment since the early 1990s and is based on firms holding business licenses, excluding investments through mergers or acquisitions. It is measured in per-1000 USD terms. In total, the FDI data extends over 24 sectors and is later assigned an industry code using the ISIC Revision 3 classification. Unfortunately, the database does not capture all levels of FDI received as it excludes investments in oil and gas, banking, financial and portfolio investment, as well as household investments, as it focuses on business licenses issued. The other investment types fall under different jurisdictions, which is why they are excluded from the data set. According to OECD (2020) the data covers investment realizations by foreign capital investment companies, including those below 10% share and with joint ventures with local partners. This practice is likely to inflate the FDI inflow recorded. Yet, it is the only data available on a second-level administrative level. In order to be able to connect the data later, the investment information by district is geocoded by using the second-level administrative boundaries from OCHA’s Regional Office for Asia and the Pacific (2021). All additional sources used are shown in Table 3.

<sup>6</sup>The precise definition for district  $i$  and year  $t$  is

$$\text{Shock}_{it} = \underbrace{(\text{MMI}_{it}^{\text{urban}})}_{\text{Capital Shock}} \times \underbrace{\left( \frac{\text{Deaths}_{it} + \text{Victims}_{it} + \text{Affected}_{it}}{\text{Population}_{i,t-1}^{\text{imp}}} \right)}_{\text{Labor Market Shock}}$$

Table 1: Descriptive Statistics

	(1)	(2)	(3)	(4)
	Full sample	Control	Treated (MMI6+)	Difference (3)-(2)
<b>Dep. Variable</b>				
Arcsin (FDI inflows) in 1000 USD	5.70 (5.379)	5.82 (5.458)	4.87 (4.726)	***
<b>Main controls</b>				
Log of mean homogenized NTL in district	-3.32 (2.897)	-3.28 (2.910)	-3.59 (2.788)	**
Log of population (imputed after 2014)	12.78 (0.928)	12.81 (0.923)	12.56 (0.933)	***
<b>Risk Measures</b>				
Composite Multi-Hazard Index	13.43 (2.681)	13.35 (2.713)	13.97 (2.381)	***
Earthquake: Mean std. Risk	2.07 (0.856)	1.95 (0.786)	2.91 (0.854)	***
<b>Additional Controls</b>				
Arcsinh (Domestic Inflows) in 1000 USD	5.85 (6.560)	6.08 (6.615)	4.28 (5.936)	***
Arcsinh (World Bank Foreign Aid)	14.80 (1.682)	14.87 (1.664)	14.36 (1.745)	***
Log (People in Labor Force)	12.06 (0.948)	12.09 (0.942)	11.83 (0.959)	***
Poverty Rate (in % of population)	13.75 (7.998)	13.46 (8.026)	15.73 (7.519)	***
Morbidity Rate (in %)	29.09 (8.062)	29.10 (8.030)	29.00 (8.287)	
Bartik-like Migration Control (standardized)	0.02 (1.052)	0.04 (1.118)	-0.10 (0.326)	***
Manufacturing Share (as share of total GDP)	0.15 (0.147)	0.16 (0.153)	0.08 (0.0626)	***
Observations	4838	4224	614	4838

Mean coefficients; standard deviation in parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

### 2.3. Discussion

The final dataset is a balanced panel of Indonesia's 514 *districts*<sup>7</sup>, the second administrative level, for 17 years, of which 422 are included in the analysis. This is due to two reasons: first, not all districts have sufficient data available, but notably, second, due to Indonesia's decentralization policy in 2001, many districts have changed their names. (OECD, 2020, chapter 7). To avoid FDI values being assigned to the wrong districts, all observations are standardized to the identifiers of the Indonesian statistical agency (*Badan Pusat Statistik*) in 2003. If a district has been divided after 2003, all offshoots are collapsed into the one district named as in 2003. An overview of the final data is provided in Table 1. The treated and control districts are significantly different along the dependent and independent variables. This is not unexpected given that earthquake exposure might, after all, have substantial effects on economic and social development. While earthquake events are random in time, they might not be in space, which is why economic and human activity might tend to self-select themselves accordingly. The resulting selection into treatment of foreign firms will represent one of the key limitations of this paper. In terms of systematic differences across districts, the paper will include the differential controls in an extended

<sup>7</sup>Indonesia is divided into provinces (level 1), regencies and cities (level 2), districts (level 3) and villages (level 4). So the second administrative level refers to 416 regencies (*kabupaten*) and 98 cities (*kota*), but for simplicity all second-level entities are called districts to align the name with the common perception of districts being the level below provinces.

baseline model.

### 3 Empirical Strategy

The paper investigates the impact of earthquake exposure from three different angles: first, it takes a temporal perspective to see how foreign firms respond to a disaster shock. Second, for spatial aspects, the paper investigates whether the effect of an earthquake spills over to proximate and neighboring districts. Lastly, the paper examines the impact on a sectoral level, but not only within the same industry but also in linked industries via forward and backward linkages.

#### 3.1. Estimation Strategy

##### 3.1.1. The temporal perspective

For the temporal perspective, an event-study type difference-in-differences approach is used of the following form:

$$f_{ijt} = \alpha + \sum_{\substack{i=-4 \\ i \neq -1}}^4 \gamma_c D_{ij,t+c} + \Gamma X_{ijt} + \omega_i + \omega_t + \omega_{jt} + \epsilon_{ijt} \quad (1)$$

The dependent variable  $f_{ijt}$  is the hyperbolic sine transformed value of FDI inflows in district  $i$  in province  $j$  and year  $t$ .  $D_i$  in Equation 1 refers to a dummy, which is based on the computation of the total shock mentioned in Section 2. The dummy equals 1 if persons have been recorded as directly affected by an earthquake and the economic center of the district is exposed to an earthquake intensity with at least minor damage potential. Otherwise, if only one or none of the conditions is fulfilled, the dummy equals zero. In Equation 1 also the four leads and four lags around the treatment year of any earthquake between 2003 and 2019 are included to add pre-trends and post-treatment periods, while excluding the first lead. These leads and lags are created by using the years around treatment and by conditioning that only a single earthquake took place (as treatment reversal complicates the baseline DiD model). In all models  $X_{ijt}$  contains the constant, the logged total population and the inverse-hyperbolic sine transformed nighttime-light intensity lagged by one period to account for the population affected and the economic situation of the district.  $\omega$  are the district, year and province-year fixed effects. They shall rule out unobserved time-invariant heterogeneity within districts like distance to the coastline or availability of a port, time-variant constant shocks across years like the financial crisis shock of 2008 and for instance time-varying province-specific regulatory changes and policies due to province-level political decisions. The standard error is clustered on the district level. The baseline model is always conditioned on excluding from the sample districts that are treated more than once, which is assessed in the robustness section with an estimator as suggested by De Chaisemartin and d'Haultfoeuille (2022) allowing for treatment reversal. Furthermore, in order to isolate the effect of earthquakes on FDI without contagion through other disasters, a dummy is created to control for simul-

taneously occurring other disaster types<sup>8</sup>. Every baseline regression is conditioned on the dummy for simultaneous disasters being 0 to ensure that no other disaster than earthquakes materialized within year t.

### 3.1.2. The spatial perspective

Papers such as Felbermayr et al. (2022) or Friedt and Toner-Rodgers (2022) use models relying on spatial weighting matrices in their spatial specification. This paper uses a simplified version of their approach by first identifying neighboring districts and then by applying a modified version of Equation 1 using an interaction term:

$$f_{ijt} = \alpha + \sum_{\substack{i=-4 \\ i \neq -1}}^4 \gamma_c D_{ij,t+c} \times \gamma_c D_{kj,t+c}^{k \neq i} + \Gamma X_{ijt} + \omega_i + \omega_t + \omega_{jt} + \epsilon_{ijt} \quad (2)$$

In essence, the model compares the changes of FDI inflow if a district  $i$  is treated with a non-treated district under the condition that either none or at least one adjacent neighboring district  $k$  is also treated at the same time.

### 3.1.3. The sector-network perspective

For analyzing the sectoral outcomes, the paper broadly follows the approach by Acemoglu, Akcigit, and Kerr (2016). Using a multi-regional input-output table for Indonesian provinces from 2016 (Badan Pusat Statistik, 2021), up- and downward linkages are calculated<sup>9</sup>. Upstream linkages are used to show the impact of a supply-side shock on foreign investment, whereas downstream linkage shocks correspond to the demand-side shock. The shock is different from the one in the temporal and spatial approach. The methodology still relies on the dummy variable D as in Equation 1. Yet two extensions are included: the sectoral dimension is added and the input-output data is at the province-level only, so the shock needs to be aggregated and account for the sector dimension. To incorporate both the new within-sector shock  $Shock_{s jt}$  in sector  $s$ , province  $j$  and year  $t$  over district  $i$  is defined as

$$Shock_{s jt} = \sum_i^{i \in j} w_{ijs} \times D_{ijt} \quad \exists w_{ijs} = \left( \frac{\sum_t GDP_{ijst}}{\sum_t \sum_i^{i \in j} GDP_{ijst}} \right)$$

The sectoral shock decomposes into the sum of two parts: a district-time-invariant share of sector relevance within a province and the previously used sector-invariant but time-variant dummy on earthquake treatment. The district-time-invariant share of sector relevance is the mean GDP within a district and sector over the mean GDP within a province over all 17 years. The interaction of district-sector weight and dummy of exposure is then aggregated at the province level. The total shock corresponds

<sup>8</sup>Based on victim records within the Desinventar database. This dummy equals one if more than 20 people are affected by any disaster type other than earthquakes or earthquake-induced tsunamis.

<sup>9</sup>The I-O table is sector-wise aggregated to match the corresponding FDI sectors and converted to the Leontief inverse matrix

to the share of sector GDP affected within a year and province. For instance, if only one district is affected within a province but it makes up 80% of the production within a year, then the shock variable is 0.8 for this sector and this province within this year.

Then, to account for shocks along the supply chain, the time-variant shock by sector and province is combined with information from the input-output Leontief inverse matrix. The resulting supply-side upward or demand-side downward shocks are created in the following ways:

$$Upstream_{jst} = \sum_k (Input_{k \rightarrow s}^{2016} - 1_{k=s}) \times Shock_{kjt}$$

and

$$Downstream_{jst} = \sum_k (Output_{s \rightarrow k}^{2016} - 1_{k=s}) \times Shock_{kjt}$$

Hereby, input refers to row entries of the Leontief inverse matrix, whereas output refers to column entries of the Leontief inverse in each respective province and sector. The 1 is an indicator function if the connected sector is the sector in consideration, so if  $s = k$  (to avoid double accounting from within sector shock and again shock through linkage values). In other words, the up- and downstream shocks are linkage-weighted sectoral shocks that occur in other sectors than the sector  $s$  and within the same or other provinces in Indonesia. The final model to be estimated has the following form:

$$f_{jst} = \gamma f_{jst-1} + \beta_1 Shock_{jst-1} + \beta^{up} Upstream_{jst-1} + \beta^{down} Downstream_{jst-1} + \Gamma X_{j,t-1} + \epsilon_{jst} \quad (3)$$

Here the dependent variable is again the arcsin transformed FDI inflow, yet not within a district but on a province level  $j$  and by sector  $s$ . Then a lagged variable of the dependent variable based on the model by Acemoglu, Akcigit, and Kerr (2016) is also included, followed by three shocks defined above: the sector-specific direct shock, a shock in the upstream and a shock in the downstream sectors to sector  $s$ . The  $X_{j,t-1}$  encompasses the aggregated mean nighttime light and the population by province, which are logged and lagged by one year. Equation 3 compares the effect of within-sector-province shocks to those provinces within the same sector that are not or are less affected. The shock variables are measured in percent, so a unit shock within sector-province or upstream/downstream refers to a 1% increased affected GDP share in either the same sector of the supplier- or the customer-network. It is important to mention that, in contrast to Equation 1 and Equation 2, this model does not condition the regression of only single treatments. If one takes a network perspective, multiple treatments are by definition likely as somewhere in Indonesia over the time earthquakes take place, which is why multiple treatments are explicitly allowed. As an extension, I later also split the up- and downstream shocks of Equation 3 into shocks occurring within a province versus shocks occurring outside a province. This will proxy different outcomes from shocks within tight local production networks versus potentially less damaging shocks within nation-wide production networks.

### 3.2. Identification Strategy

Identification in the models comes from the random timing and the intensity of an earthquake event. While earthquakes appear random in time, there might be the pressing matter of selection into treat-

ment, as after all [Table 1](#) shows that control and treatment group are different along a wide range of controls. To address this issue in the baseline regression, all controls are also included to account for the differences in covariates. Using the three dimensions of fixed effects, district, time and province-year, it is attempted to rule out large parts of unobserved heterogeneity, such as sector-province-specific FDI restrictions or nationwide shocks through the financial crisis in 2008. Lastly, and as the largest concern in this study, there is the risk of a violation of the Stable Unit Treatment Value Assumption (SUTVA), a key assumption that includes that all potential temporal or spatial spillovers are accounted for. It is a key assumption in the difference-in-difference literature and would, for instance, be violated if outcomes were impacted by the treatment status of other units, such as spatially proximate ones or temporally related ones. With [Equation 2](#) to a certain extent, spatial correlation is tested. Finally, all models mentioned above ignore the staggered adoption design of treatment, which according to Goodman-Bacon (2021) might lead to biased estimates due to negative weighting of estimates. In the robustness section, it is assessed to what extent the negative weighting biases the estimates, and it is also evaluated if results still hold if one allows for treatment reversal using a method developed by De Chaisemartin and d'Haultfoeuille (2020). The issue of violation of SUTVA, which is indeed a main concern for this paper, is extensively discussed in [Appendix B](#).

Lastly, to account for the complexity of connected disaster types, in [Appendix E](#) it is at least discussed how classes of natural disasters (such as climatological events as a whole) compare to specific earthquake shocks as a robustness check. Hereby, especially flood, as second most devastating disaster category in Indonesia, is considered in depth in [Appendix D](#).

## 4 Results

### 4.1. The Direct Effects of Earthquake Exposure

The key effect of experiencing an earthquake within the economic center of a district can be seen in [Figure 3](#). One can clearly observe the drop in negative hyperbolic sine transformed FDI inflows, especially in the year following a disaster. The three models in [Figure 3](#) use different specifications: the first is the unrestricted baseline model (dark blue connected line), which follows the model described in [Equation 1](#). The second model (lighter blue with a dashed line) excludes additionally, besides districts with another disaster exposure or multiple earthquakes over time, also districts in which in the five years prior to 2003 (the first year of observation) disasters occurred. This is to rule out any carryover effect to the treatment period. Lastly, the final model adds a set of extended controls. An overview of the results can be found in [Table 4](#). In terms of percentage change, the three models would predict a reduction of around 90% in the year after an earthquake significant on a 1% level<sup>10</sup> in comparison to non-treated or not-yet treated districts in the same year. For the main controls, only lagged nighttime light emissions are positive and significant. Not surprisingly, the economic proxy predicts higher FDI inflows through more economic activity measured. The log of population density is not significant, likely because aggregated FDI inflows cover all sectors and, for instance, for agriculture population density might play less of a role than for labor intensive industries. The extended controls in Column

<sup>10</sup>Conversion follows Bellemare and Wichman (2020) (equation 11) of arcsin-dummy conversion:  $\exp(\beta) - 1$

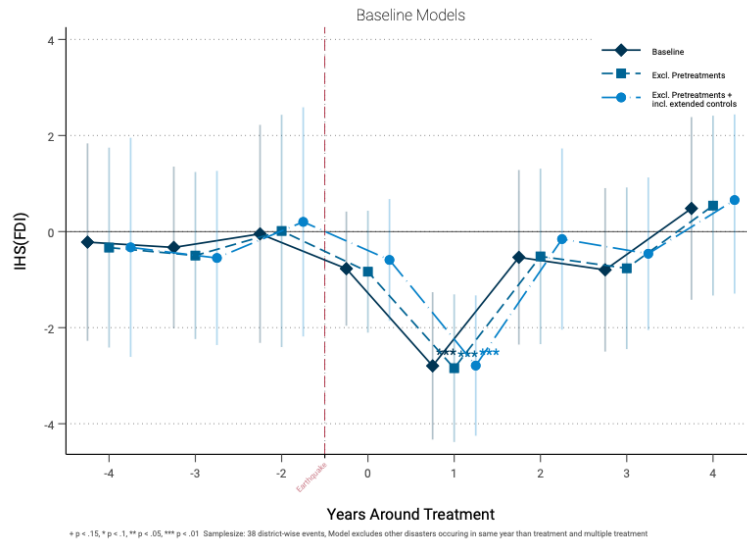


Figure 3: Dynamic Treatment Graph of Exposure to Earthquake

Notes: The figure shows the dynamic treatment graph estimated based on Equation 1. FDI inflows are inverse hyperbolic sine transformed. The bars depict the 95% intervals. Point estimates are based on at least 4 692 observations with at least 47 districts in the treated group. Each model includes year, district and province-year FE as well as lagged  $\log(\text{nighttime-light})$  and lagged and lagged population as core controls. The corresponding  $R^2$  is approximately 0.68 and the estimates are based on district-clustered error-terms.

(3) show positive effects of domestic investments and a higher manufacturing share within districts. Migration and morbidity are insignificant, whereas a higher poverty rate tends to decrease FDI inflows, which all follow the standard economic theory. Several factors can explain the temporary reduction and subsequent recovery of FDI inflow. Foreign firms may require time to make decisions on how to respond to the shock, conduct risk assessments for future investments, await improvements in market conditions, or anticipate governmental responses. Once these obstacles are addressed, foreign firms may reinvest. The results do not necessarily conflict with the findings by Friedt and Toner-Rodgers (2022) of a long-term reduction in FDI inflow, as they consider a larger geographic unit and a different disaster type.

On a sector-level, Figure 6 shows the results of Equation 1 if one extends the model to the district level over ISIC Revision 3 classified sectors. On a district level, in the year after the earthquake (right panel) one can observe direct negative effects for all sectors. Manufacturing, utilities and transport, storage and communications tend to be the most affected sectors. The least affected are mining and construction. Nonetheless, all the effects found are comparable to the baseline aggregated estimates.

#### 4.1.1. Robustness Checks

In order to validate the base results of this paper, a reduction of FDI inflows in the year following an earthquake exposure, multiple robustness checks are conducted. First and foremost, there are potential issues with the econometric approach. In the recent Difference-in-Difference literature, the issue of negative weighting is more and more emphasized (see for instance Sun and Abraham (2021) and Xu (2022)). In the current dynamic difference-in-difference estimation this issue is entirely ignored, which



might lead to wrong estimates. [Figure 7](#) shows the same results using recent methods from literature, which account for the negative weighting issues in different ways. The results tend to be comparable to those of the baseline specification in their extent and significance<sup>11</sup>. More information is provided in [Appendix B](#). By using the DiDi estimator of De Chaisemartin and d'Haultfoeuille (2020) within this section, it is also evaluated, if the results of the baseline estimation still hold if one allows for treatment reversal. In this case, districts with multiple treatments are also included in the regression model. The results seem to be broadly comparable. Lastly, it is tested to see if specific outlier events drive the results by dropping one district-event at a time. This does not seem to bias the results.

#### 4.1.2. Heterogeneity : Do Risk Anticipation and Investment Stock Matter?

In this section, the sample of the baseline regression of [Equation 1](#) is broken down into a subgroup analysis focusing on risk and investment stock. This is done as there is likely a selection into a treatment pattern: firms settling in earthquake prone areas might have ex-ante the expectation that earthquakes might emerge as earthquake risk is public knowledge and start adapting to the disaster risk. Firms in less risky areas, in contrast, might respond stronger to disaster events as their anticipation of risk is lower or nonexistent. Similarly, the response of FDI flows might depend on the stock previously invested. The more one has invested in a region, the higher the individual cost of an earthquake. These two channels, risk expectation and capital stock, are investigated in this subsection.

In order to divide the sample into the relative risk likelihood, I create an earthquake risk and overall disaster risk (*composite hazard score*) dummy following the idea of Emrich et al. (2022). The thorough computation of the risk metrics and their validation are described in [Appendix H](#). Column (1) and (2) of [Table 2](#) divide the sample into the above and below median overall disaster risk, while Column (3) and (4) focus on time-invariant earthquake risk. Column (5) and (6) divide the sample into approximate initial FDI stock in 2003. To approximate FDI stock by district, data on FDI stock within Indonesia as a country is obtained for each year from UNCTAD (2021). Then, for each district, the share of individual FDI inflow over total FDI inflow across all 17 years is calculated and interacted with the value of Indonesia's FDI stock in 2003 to obtain a proxy for FDI stock by district. This requires the admittedly strong assumption that FDI inflow is a sufficient proxy for relevance in FDI stock.

The results show that for Column (1) and Column (3) in [Table 2](#) significant effects are only found in the treatment year and the year after if the overall disaster risk or earthquake risk is below the median national risk. The prediction suggests that FDI inflows are reduced by 90 to 95% being significant on a 5% level in the treatment year and the year after. These effects are not found for above-median-risk districts or after period 1 past disasters. Assuming that disaster risk is public information, these results would align with the hypothesis that foreign inflows are more affected if the shock is less anticipated than in high risk areas. Focusing on Column (5) and (6) one can observe that if more initial FDI stock is present in 2003 (Column (6)), one observes a reduction up to 95% of FDI inflows on a 5% significance level in period one after the earthquake, but not for those with lower initial FDI stock. This would

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<sup>11</sup>Two estimators suggest a small pre-trend. This trend is, however, not significant on any standard level.



Table 2: Dynamic Difference-in-Differences: Heterogeneity

	Composite Hazard		Earthquake Risk		Initial FDI Stock (2003)	
	(1) Below Median	(2) Above Median	(3) Below Median	(4) Above Median	(5) Below Median	(6) Above Median
Event Year	-2.332** [-4.382,-0.281]	0.171 [-1.836,2.178]	-2.282* [-4.948,0.383]	0.529 [-1.533,2.592]	-0.475 [-2.230,1.280]	-1.182 [-5.109,2.745]
Event Year +1	-3.343*** [-5.744,-0.942]	-1.476 [-4.215,1.264]	-4.505*** [-7.299,-1.711]	-1.280 [-3.573,1.012]	-1.579 [-3.647,0.489]	-3.724** [-6.616,-0.831]
Event Year +2	-1.359 [-4.492,1.774]	-0.811 [-3.663,2.041]	0.201 [-2.866,3.268]	-0.420 [-3.234,2.393]	-0.0101 [-2.533,2.513]	0.142 [-6.806,7.090]
Event Year +3	-1.425 [-4.727,1.877]	-0.820 [-3.456,1.816]	-1.695 [-5.392,2.002]	1.013 [-1.153,3.178]	-0.335 [-2.277,1.607]	1.299 [-3.266,5.865]
Event Year +4	0.00474 [-2.716,2.726]	-0.699 [-5.323,3.925]	1.384 [-1.157,3.926]	-0.0148 [-2.511,2.482]	1.411 [-1.035,3.858]	-0.335 [-6.014,5.345]
Event Year +5	-2.091 [-4.940,0.758]	-0.300 [-2.261,1.662]	0.827 [-1.634,3.287]	-1.916 [-4.234,0.403]	-2.482*** [-4.329,-0.634]	0.586 [-2.784,3.956]
<i>N</i>	2679	2005	3411	1353	2265	2472
<i>R</i> <sup>2</sup>	0.700	0.715	0.685	0.703	0.545	0.674
Districts Treated	25	23	14	34	32	16
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	✓	✓	✓	✓	✓	✓
District FE	✓	✓	✓	✓	✓	✓
Province× Year FE	✓	✓	✓	✓	✓	✓

\*<0.1, \*\*<0.05 and \*\*\*<0.01 p-value. Dependent variable: IHS(FDI inflows). All regressions contain also pre-trends, which are excluded in the output and log NTL and log population density as controls. All errors are clustered at the district level.

confirm the hypothesis that higher initial investment might cause a stronger response to shocks than if less is invested.

#### 4.2. The Indirect Effects of Earthquake Exposure

After having investigated the repercussions of earthquake events over time and different subgroups, the indirect impacts on FDI are analyzed, referring to shock transmission through proximity and network linkages.

Table 5 presents the impact on FDI inflows based on the interaction terms of district shocks and of shocks materializing in at least one or more adjacent districts. In Column (1) one sees the effect using the definition of shock as mentioned in the data section. One notices a negative outcome of within district shock on FDI of -2.932 significant on a 1% level. If neighbors are also affected, the shock is reduced by approximately 0.5% in the year after the disaster. No other time period is significant. Column (2) and Column (3) change the definition of the treatment dummy. So the treatment dummy in Column (2) considers only districts where persons are recorded to have either died or are directly affected as treated. Using this treatment dummy, in the period after the disaster, all three coefficients are significant in comparison to districts without any shock or shock in proximity. The effect is smaller and predicts with -1.2 a reduction in FDI inflows of only 70%, not like 90% in Column (1). If one adds the neighboring shock, this effect increases significantly at a 10% level. These effects tend to persist for up to two years after the disaster. Column (3) only regards districts where the economic centers are physically exposed to a damaging earthquake. Here, no positive effects are found. As a bottom line,

it can be deduced that on a highly local level, it mildly seems to matter if shocks also affect neighbors. The extent, however, remains small and is not entirely clear in terms of direction. The finding that spatial spillovers are common after disasters is also found, for instance, in the growth literature (see e.g. Felbermayr et al., 2022), but also in the FDI literature (Friedt and Toner-Rodgers, 2022). Yet, in contrast to Friedt and Toner-Rodgers (2022) in this case study no long-term outflow of affected regions is observed and a recovery to pre-disaster trends is found.

Figure 4 employs Equation 3 and how sectoral shocks impact FDI across various sectors at the provincial level through the supply chain. Specifically, it quantifies two distinct effects. First, it examines the sector- and province-specific consequences of an earthquake. In simpler terms, it measures the response of FDI inflows in a particular sector within a province when there is a 1% increase in the affected sector's GDP in that province within a given year. To illustrate, let's consider a scenario where certain districts within a province experience an earthquake during a specific year. If these affected districts contribute to 60% of the province's GDP within a specific sector, the shock variable quantifies how the FDI inflow into that sector changes when one additional percent of the sector's GDP is affected. The effects of higher shock exposure can be found in the first column of the upper panel in Figure 4a converted into a percent change. Only cells in which the p-value of the coefficient is below the 10% threshold are filled. All other values above are shown in gray. One can notice that especially manufacturing and services appear to see an increase in FDI inflows in the year following the disaster by 7 and 18% correspondingly. The results are different to the ones on a district-level shock, which are strongly negative. Four reasons might explain the difference: first, the shock used is on another scale (one percent GDP shock versus dummy if an economic center within a district is exposed to an earthquake). The second reason is the difference in aggregation level, on a province level, there might be positive effects, whereas within the district the effects are negative. Thirdly, here disasters are defined on a sector-level not solely on the treatment dimension. Thereby, the treatment group varies, which might also affect the direction of the coefficients. Lastly, the district analysis captures the overall effect on FDI, yet it could also be that FDI inflow is reduced due to supply-chain shocks aggravating the negative effects on a district level, which is discussed in the next paragraph.

The other two columns in Figure 4a show the consequences of a one percent increased shock through sectoral GDP weighted up- and downward linkage values. In simpler terms, one considers how much a 1% increase in indirect supply and demand side shocks on the change in FDI inflow in the affected sector. The second column upper panel in Figure 4a indicates that downstream-demand side shocks lead to an increase in FDI received in manufacturing by around 5% and by an astonishing 60% in construction FDI. In contrast, supply-side shocks (last column upper panel) lead only in manufacturing to a reduced FDI inflow of around 13%. Collectively, the tables show that after an earthquake at the provincial level, the manufacturing sector is often the most affected. The shock is not consistently negative; instead, it seems to depend on how the shock affects FDI, with supply-chain disruptions being particularly troublesome for foreign investment. One should keep in mind while interpreting the results as shown in Figure 5 that due to the used data source the manufacturing sector tends to be the industry with the least non-zero FDI inflow data.

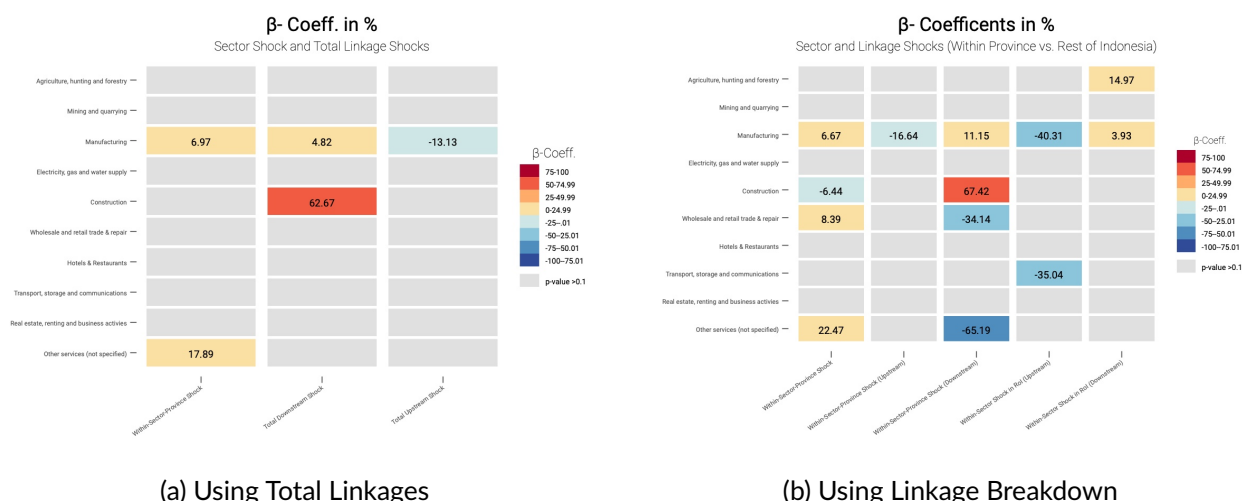


Figure 4: Effect on Sectoral FDI via linkages

Notes: The two panels show the sectoral response of IHS-transformed FDI inflows based on a 1% earthquake-induced GDP shock. The first columns in both panels refer to a 1% shock occurring within the sector of FDI considered. The other two columns to up- and downstream shocks, described as Leontief-inverse matrix weighted GDP shocks. In contrast to the first panel, the second differs also by origin of the shock. Coefficients are transformed using  $exp^{\beta} - 1$  as transformation. Grey fields are below the 10% significance threshold. Estimations are based on Equation 3. All earthquake events are included and each regression includes lagged and logged nighttime-light and population values as core controls.

The right panel of Figure 4b explores another aspect. It looks at both upward and downward linked shocks and distinguishes between two types of linkages: those within the province and those outside the province. The underlying hypothesis is that shocks will have a greater impact within provincial networks, primarily due to the presence of more localized production networks. The first column shows the effect of a within-sector-province shock. A one percent increase in within-sector-province shock increases FDI inflow into manufacturing by 6%, into wholesale, trade and repair by 8% and into other services by 22%. It reduces FDI inflows into construction by 6%. Construction faces a reduction in FDI inflows, likely because foreign firms benefit less from construction contracts if the industry itself is affected.

For a one percent supply-chain shock (next column), FDI inflow into manufacturing is reduced by 16%. A shock in the demand side for goods (downstream) sees an 11% increase in manufacturing and up to 68% in construction. Yet, wholesale, trade and repair FDI inflows reduce up 34%. Service FDI inflows reduce even up to 65%. The final two columns show the effect of a one percent shock within linkages outside the province. A one percent linkage-weighted supply-chain shock in manufacturing reduces FDI inflow by around 40% and transport and storage by 35%. In contrast, agriculture and manufacturing see a rise in FDI inflows concerning a shock on the linkage-weighted demand side.

A one percent increase might weigh more in the regression models for the rest-of-the-world shocks. As mentioned before, the shock here is an interaction term between the province-sector-specific shock and the province-sector-specific linkage value. Table 6 shows the descriptive statistics of the shocks, and one can notice that the mean of shocks within province-sector linkages are larger within provinces than within the rest of the world, which leads to larger coefficients in the rest of the country metrics as a 1% increase will have a larger weight on the regression.

The found effects illustrate the complexity of effects on sectoral FDI and thereby also aggregate FDI inflows. While specific shocks within the own sector might actually increase FDI received in the year following a disaster, the aggregated effect can still be negative if the production relies heavily on intermediate input goods, which are affected by the disaster, chiefly within the own province. Especially shocks taking place on the customer side tend to benefit the manufacturing and construction sectors, as it is likely that the demand for intermediate goods, for instance, for reconstruction might increase. Shocks occurring upstream reduce FDI inflow as it might cause production interruptions, which is generally bad for business.

#### 4.2.1. *Robustness*

In order to validate the effects found in space and sectors, several robustness checks are run. First, it is tested to see if one finds reallocation patterns of FDI from affected districts towards proximate economic centers. It is found that this hypothesis does not appear to be true in this study. In contrast, it seems that the closer an economic center is located to an affected district the greater is the reduction of FDI inflows observed, as discussed in [Appendix C](#).

Second, for the sectoral analysis it is tested if the results change if one uses as shock weight sectoral employment share instead of sectoral GDP share. While the effects for manufacturing are in part comparable to the results discussed above, especially for construction, utilities, and services, different effects are found. A likely explanation is that GDP and employment represent different channels, as GDP, for instance, already includes productivity per worker. These different channels are the most likely reasons for the differences. Both regression results are similar to the extent that upstream shocks tend to have a negative impact on FDI, whereas downstream shocks generally have a positive impact on FDI.

#### 4.2.2. *Limitations*

Although they are often used in post-disaster analysis, multi-regional IO (MRIO) tables suffer extensively from the fact that they are static. The linkage values used here are from 2016. Yet, a disaster might change supply-and demand networks within a country, which is ignored in this setting due to data limitations. Furthermore, alternative models such as the adaptive regional input-output models (ARIO) (Hallegatte, 2008) suggest improvements to identify production bottlenecks and to add more flexibility within production systems. Other recent methods also consider, for instance, the interaction between households, firms resources, and other agents in post-disaster recovery (see e.g. the ECAM model by Lehman et al. (2022)). A good overview on shortcomings of the IO is provided by Galbusera and Giannopoulos (2018). Due to data limitations, unfortunately, the analysis is just based on a singular MRIO table. Future studies should re-evaluate the results in a more dynamic setting.

#### 4.3. *Additional Robustness Checks*

In addition to the previously mentioned robustness checks, it is also tested if the re-aggregation of districts before the decentralization policy in Indonesia induces a bias ([Appendix A](#)). This does not seem to be the case. Furthermore, multiple checks are conducted on the regressors included in the main

approach. [Appendix F](#) shows how reliable the shock metric is by re-running the baseline regressions with one shock or the other. While the shocks individually seem to matter, together the effect becomes stronger, highlighting the importance of considering both labor and capital in disaster studies. In terms of controls, nighttime-light overall tends to sufficiently proxy GDP in the case of Indonesia ([Appendix G](#)) except for one outlier province. Furthermore, the classification of economic centers using nighttime light seems to accurately represent the location of cities in Indonesia. In this section, it is also tested how reliable the main disaster data of Desinventar is. Overall, the data is strongly comparable to alternative datasets.

A last remark refers to additional checks on other disaster types. [Appendix D](#) and [Appendix E](#) test the regressions for flood events and show general effects using other disaster categories such as storms or hurricanes. Most districts are treated more than once with flood events; thus, to obtain a sufficiently large treatment sample, one has to allow for treatment reversal. In the appendix, it is found that, similar to earthquakes, flood events tend to reduce FDI inflows temporarily in the treatment year without long term effects. Sector-wise, fewer effects are found than for earthquakes, likely due to the lower destruction potential and better disaster preparedness in comparison to earthquakes (Neise and Diez, 2019). In terms of disaster categories, geophysical and climatological events (forest fires and droughts) tend to have the most severe impacts on FDI inflows, whereas hydrological and meteorological events only play a minor role. Yet this analysis is distinctly limited, so the results disaster category-wise should be taken with caution in their extent.

## 5 Conclusion

Previous literature dealing with the impact of disasters on foreign investment is mostly based on cross-country studies or firm-level data. Only a few papers focus on the impact of FDI within a country. I contribute to the literature by answering questions on the temporal, the sectoral and to a limited extent on the spatial dynamics of FDI inflows following the occurrence of earthquake exposure in Indonesia's economic centers between 2003 and 2019. For this reason, I use a shock variable accounting for labor and capital shocks to foreign firms. Using dynamic difference-in-difference models it is found that quite evidently in the case of Indonesian districts, FDI inflows tend to be reduced up to 90% in the year following a disaster event before returning to pre-disaster levels. The effect is mainly dominant in districts with a lower ex-ante risk as the disaster might be less anticipated, as well as in districts with a higher initial FDI stock, where each disaster can cause relatively more damage. These effects are robust against a set of alternative specifications, including recent methods taken from the difference-in-difference literature. In terms of spatial effects, it is found that effects on FDI inflow are aggravated once a bordering district is also affected. A potential reason might be the supplier-customer network and the integration of foreign firms within that network. Using a multi-regional input-output table, I find that the strongest effects are found within manufacturing, which is also the sector that receives the most FDI in Indonesia. Hereby, especially upstream shocks, so shocks in the supply side towards foreign firms, tend to reduce FDI inflow substantially. Downstream shocks, in contrast, might benefit

foreign firms, as one can see a rise in FDI inflow in most sectors in the year after the disaster. Construction seems to be one of the sectors benefiting from earthquake events, especially if they take place within the same sector or downstream in the supply chain. Thus, overall, one might carefully claim that the negative effects of FDI inflows are caused by intermediate disruptions in the supply of goods, which are necessary for production and predominantly play a role within regional production networks. This story would be in line with the prediction of Kato and Okubo (2022), who state in their paper that foreign firms are likely to remain in domestic markets if these firms are tightly linked with local suppliers.

The overall finding of the reduction in FDI inflow is consistent with most papers in the literature such as Friedt and Toner-Rodgers (2022) or Batala et al. (2021). Yet instead of a long term reduction, similar to the paper by Doytch (2019), I observe a rebound effect for FDI in the years following a disaster. This difference in long-term effects in the literature also contours one of the limitations of this paper: its external validity. Countries are globally unequally affected by disasters, specifically now through climate risk. On a provincial or district scale, there is a similar heterogeneity of disaster exposure. Each disaster might change a country's, province's or district's growth trajectory, which makes it econometrically complicated to compare multiple districts with each other. So, externally speaking, such assessments on effects of disasters should be repeated on a country-by-country basis.

There are real-life implications from the results. Overall, the results show a positive picture. While FDI inflow seems to be reduced in the aftermath of earthquakes, on the long term, they do not seem to substantially reallocate or to withdraw from the Indonesian markets. Foreign firms, thereby, can play an important role in post-disaster recovery if they support the local labor market and indeed provide positive spillovers to domestic firms. The more integrated such foreign firms are within domestic intermediate goods production and consumption, the less likely a total withdrawal of these firms after a disaster might take place.

Future research should extend the scope of this study to other disaster categories while distinguishing issues such as the expectation of exposure to a disaster as well as the supply-chain linkages of individual sectors. Thereby, the research shall include more dynamically weighted linkage models, that take bottleneck productions into account, as for instance described in Hallegatte (2008). Lastly, future research should take a perspective of multi-hazard disaster risk as climate change makes connected disasters more likely (e.g. floods and extreme rainfall induced landslides). Papers with a focus on a single disaster type tend to fall short in accounting for the complexity of the repercussions of disasters such as compound events. However, on a local level, differences between different disaster categories matter, as disaster risk might be unequally distributed within sub-national districts. I only contoured this by including, besides earthquakes, additionally earthquake induced tsunamis (yet excluding earthquake-induced landslides).

In recent years, the literature on disaster risk has seen a renaissance. Disaster risk, especially through the lens of climate-related disaster risk, plays a key role in adapting countries to the long-lasting effects of anthropogenic climate change. Given the likelihood of increasing disaster frequency in the upcoming

decades, it is important to prepare stakeholders, including local communities, and foreign firms, for the changes and challenges they might increasingly face. Research on historic data can serve as a helpful tool here. Findings resulting from such research can help the public and private sector to develop the best strategies for adaptation against disasters in order to minimize the loss of capital, safeguard the development progress of the last decades, and last but not least to minimize the impact on the livelihood of millions of people.



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## 6 Tables

Table 3: Overview on Variables

Variable Name	Source	Modification	Description/Reasoning
<b>Main Controls</b>			
Harmonized Night-time Light	Chen et al., 2021	Averaged on district-level and Arcsin-transformed	Proxy for economic activity, especially in rural areas (see e.g. Sutton, Elvidge, and Ghosh, 2007; Hu and Yao, 2019)
Total Population	The World Bank (2022b)	Logarithmic-transformed	Might attract foreign investment through labor market potential and higher infrastructure
<b>Extended Controls</b>			
Annual Manufacturing share ( % on district GDP)	The World Bank (2022b)	Based on sectoral GDP in million IDR (domestic currency). Is only available from 2010 onwards. Before 2010 value imputed based on 2010 values.	Incentivizes FDI through tightly-linked local supply-chains
Domestic Investment Flows	Indonesian Investment Co-ordinating Board (BKPM) (2021)	Arcsin-transformed	Might facilitate foreign greenfield investment, if they create local supply chain networks towards foreign company
World Bank Foreign Aid	AidData GeoQuery (Goodman et al., 2019)	Arcsin-transformed	Might attract foreign investment e.g. through infrastructure improvements
Bartik-like Migration Shift-Share	Share:Minnesota Population Center, 2020 and Shift:UN Economic and Social Affairs (Population Division) (2019)	Interaction of: People being foreign born in each district with five-year migrant stocks. Standardized by z-score	Following Javorcik et al., 2011; Kugler and Rapoport, 2007, migration might have an impact on FDI
Poverty Rate (% of Population)	The World Bank (2022b)	-	Alternative proxy for economic situation of a district
Morbidity Rate (in %)	The World Bank (2022b)	-	Alternative proxy for economic situation of a district
Population in Labor Force	The World Bank (2022b)	Logarithmic transformed	Control for the labor market potential
<b>Other data</b>			
Multi-regional I/O Table (2016)	Badan Pusat Statistik, 2021	-	To compute sectoral up-/downward linkages within and across provinces.

Table 4: Event-Study Type Difference-in-Differences

	(1)	(2)	(3)
	Asinh(FDI)	Asinh(FDI)	Asinh(FDI)
Treatment Year	-0.725 [-2.035,0.586]	-0.843 [-2.260,0.573]	-0.548 [-1.975,0.880]
Treatment Year +1	-2.734*** [-4.387,-1.081]	-2.854*** [-4.521,-1.187]	-2.741*** [-4.312,-1.170]
Treatment Year +2	-0.491 [-2.399,1.416]	-0.524 [-2.441,1.394]	-0.121 [-2.103,1.862]
Treatment Year +3	-0.751 [-2.533,1.031]	-0.771 [-2.553,1.012]	-0.428 [-2.107,1.251]
Treatment Year +4	0.520 [-1.430,2.469]	0.536 [-1.394,2.466]	0.683 [-1.325,2.692]
<i>Main controls</i>			
Log(mean homogenized NTL)(Lag +1)	0.297** [0.0710,0.522]	0.301*** [0.0756,0.527]	0.229* [-0.00255,0.461]
Log(population (imputed after 2014)) (Lag +1)	0.342 [-0.754,1.437]	0.403 [-0.724,1.531]	-0.0898 [-1.757,1.577]
<i>Extended controls</i>			
IHS(Domestic Investment in '000USD)			0.0848*** [0.0565,0.113]
Poverty Rate (in % of population) (Lag +1)			-0.0795** [-0.154,-0.00471]
Morbidity Rate (in %) (Lag +1)			0.00958 [-0.0173,0.0364]
Bartik-like Migration Control			687.0 [-362.2,1736.2]
Manufacturing Share on Total GDP (in %)			16.40** [2.022,30.78]
Observations	4838	4794	4692
$R^2$	0.676	0.676	0.681
Districts in treatment group	48	47	47
Year FE	✓	✓	✓
District FE	✓	✓	✓
Province × Year FE	✓	✓	✓

\* $<0.1$ , \*\* $<0.05$  and \*\*\* $<0.01$  p-value. All regressions contain also pre-trends, which are excluded in the output. Bartik-like control is the initial share of migrants in 2000 interacted with 5-year national migration outflow. All models exclude multiple treatments and simultaneously occurring non-earthquake related disasters. Model (2) and (3) additionally exclude districts with earthquakes between 1997-2002. All errors are clustered at the district level.

Table 5: Dynamic Difference-in-Differences: Space

	(1) Shock: Labor+Capital Shock	(2) Shock: Labor Shock	(3) Shock: Capital Shock
<i>Base: No shock X No Neighbor Shock</i>			
No Shock x Neighbor Shock	0.616 [-0.411,1.642]	-0.368 [-0.954,0.217]	0.702 [-0.382,1.786]
Own Shock x No Neighbor Shock	0.128 [-2.008,2.263]	-0.749 [-1.884,0.387]	-0.470 [-3.043,2.103]
Own Shock x Neighbor Shock	-0.160 [-1.630,1.310]	0.0950 [-0.910,1.100]	0.635 [-0.778,2.049]
<i>Base: No shock X No Neighbor Shock (Lag +1)</i>			
No Shock x Neighbor Shock	-0.446 [-1.628,0.735]	-0.739** [-1.331,-0.146]	-0.361 [-1.342,0.619]
Own Shock x No Neighbor Shock	-2.932*** [-4.995,-0.869]	-1.213** [-2.345,-0.0796]	0.0337 [-1.608,1.675]
Own Shock x Neighbor Shock	-2.834*** [-4.740,-0.928]	-1.324* [-2.784,0.137]	-1.036 [-2.620,0.548]
<i>Base: No shock X No Neighbor Shock (Lag +2)</i>			
No Shock x Neighbor Shock	-0.822 [-2.104,0.459]	-0.768** [-1.424,-0.113]	-0.189 [-1.291,0.912]
Own Shock x No Neighbor Shock	-1.606 [-5.133,1.920]	-1.494** [-2.749,-0.238]	-0.144 [-1.468,1.180]
Own Shock x Neighbor Shock	-0.840 [-2.988,1.308]	-1.138 [-2.943,0.667]	-1.239 [-2.849,0.372]
<i>N</i>	4071	4071	4071
<i>R</i> <sup>2</sup>	0.674	0.674	0.673
Baseline Controls	Yes	Yes	Yes
Time FE	✓	✓	✓
District FE	✓	✓	✓
Province × Year FE	✓	✓	✓

\*<0.1, \*\*<0.05 and \*\*\*<0.01 p-value. Dependent variable: IHS(FDI inflows). Each model includes log NTL and log population as Lag +1 term. Both models exclude treatment reversal and simultaneous unfolding other disasters. Labor Shock is defined if any person is recorded to be affected by disaster. Capital Shock is defined as peak ground motion above level V. The sample chosen excludes districts, which divided themselves after 2003 as here the centroids will be wrongly allocated.

Table 6: Descriptive Statistics on Shock variables

	Sum	Mean	SD	Min	Max	N
Sectoral shock as % of GDP	9,067	1.58	9.66	0	97	5,746
Total Shock (Upstream)	4,326	0.75	4.22	0	87	5,746
Total Shock (Downstream)	7,132	1.24	5.66	0	102	5,746
Shock (Downstream) in Within Province	3,617	0.63	4.69	0	102	5,746
Shock (Downstream) in Rest of Indonesia	3,515	0.61	3.13	0	71	5,746
Shock (Upstream) Within Province	3,495	0.61	4.10	0	87	5,746
Shock (Upstream) in Rest of Indonesia	831	0.14	0.50	0	24	5,746

Shocks are computed as interaction of sectoral GDP of districts within a province affected by any earthquake together with associated linkage value from the Leontief inverse matrix.

## 7 Figures

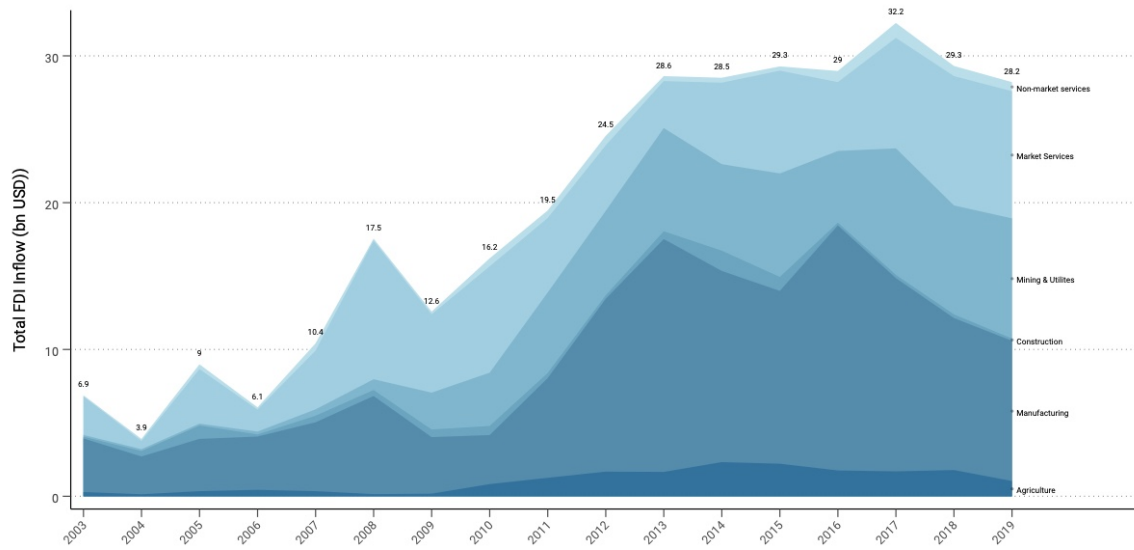


Figure 5: Development of FDI inflows over time by sector

Notes: Data based on Indonesian Investment Co-ordinating Board (BKPM) (2021). Author's own assignment.

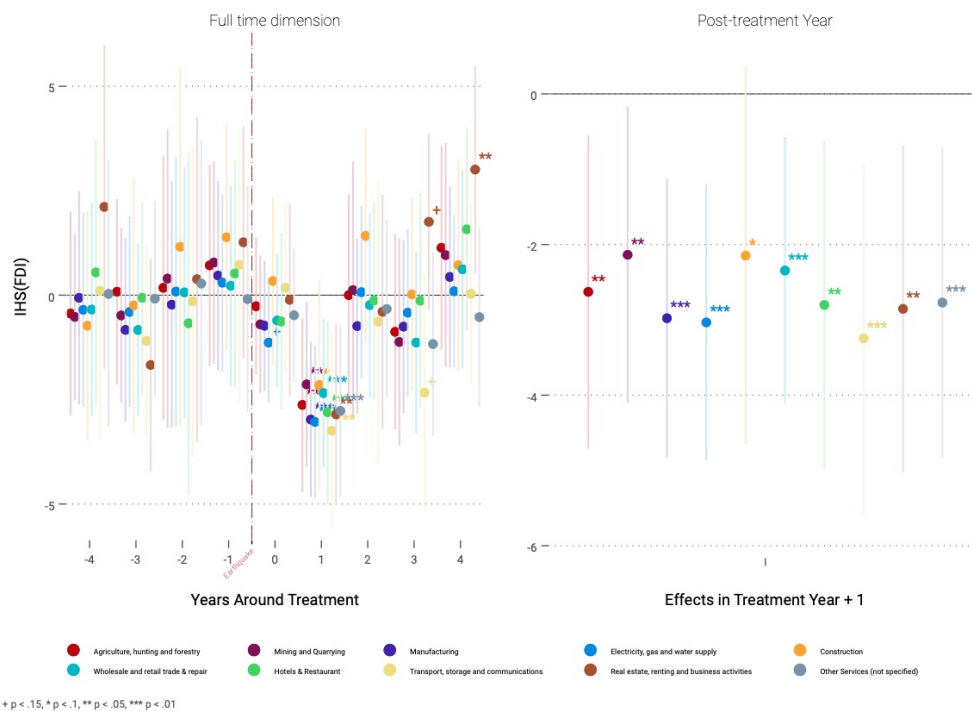


Figure 6: Effects on District-level

Notes: The two panels show the effects of Equation 1 if one extends the model towards the sectoral annual FDI space. Classification of FDI sectors follows broadly ISIC Rev. 3 level 2. The left panel shows the effect over time, whereas the right one shows the effect solely in the year after the earthquake event (yet using the same regression as before). The treated group includes 38 treated districts and excludes as before treatment reversal and simultaneously occurring disaster events.

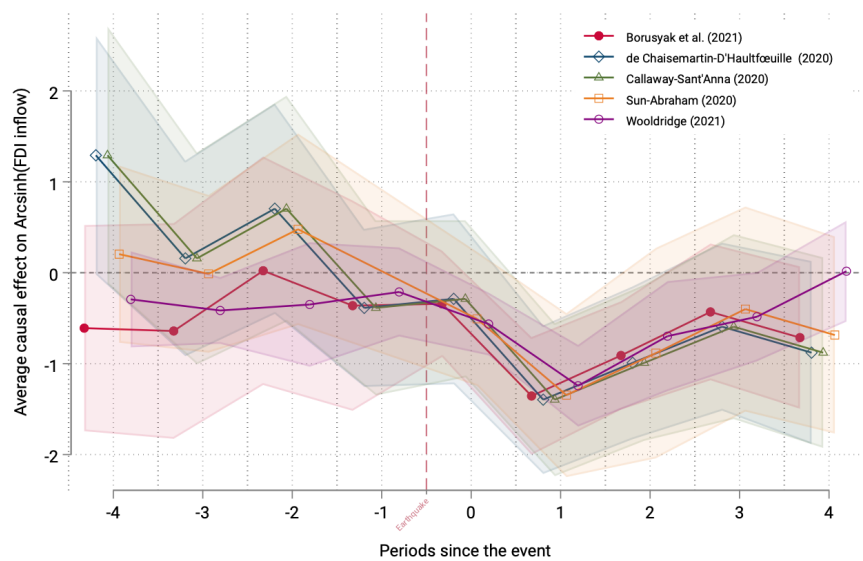


Figure 7: Comparison of different recent DiD estimators

Notes: All included estimates allow staggered treatment design, yet exclude the possibility of treatment reversal. Here, each individual regression excludes multiple treatments within unit and uses only a sample of districts, which did not change names over the period (omitting 5% of the sample), which does not affect estimates substantially. The code is inspired by Borusyak (2022) and presents estimators by Sun and Abraham (2021), Sant'Anna and Zhao (2020), De Chaisemartin and d'Haultfoeuille (2020), Borusyak, Jaravel, and Spiess (2021), and Wooldridge (2021). The chosen CI bandwidth is the 10% threshold.



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# Supplementary Material

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## A Indonesia's Decentralization Policy

Indonesia has decentralized many districts following the introduction of a decentralization policy in 2001. Thereby, the FDI inflow variable potentially accounts for different districts in different years, which could cause that earthquake shocks and FDI inflow data are mismatched.

Table A1: Impact on FDI Inflow Excluding Switching Districts

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Dynamic Treatment Trends</i>						
Event	-0.725 [-2.035,0.586]	-0.708 [-2.012,0.597]	-0.843 [-2.260,0.573]	-0.869 [-2.268,0.530]	-0.548 [-1.975,0.880]	-0.685 [-2.118,0.749]
Event +1	-2.734*** [-4.387,-1.081]	-2.868*** [-4.538,-1.197]	-2.854*** [-4.521,-1.187]	-3.032*** [-4.705,-1.358]	-2.741*** [-4.312,-1.170]	-3.002*** [-4.605,-1.399]
Event +2	-0.491 [-2.399,1.416]	-0.831 [-2.926,1.264]	-0.524 [-2.441,1.394]	-0.894 [-3.001,1.213]	-0.121 [-2.103,1.862]	-0.407 [-2.630,1.815]
Event +3	-0.751 [-2.533,1.031]	-0.710 [-2.445,1.025]	-0.771 [-2.553,1.012]	-0.754 [-2.486,0.978]	-0.428 [-2.107,1.251]	-0.342 [-2.024,1.340]
Event +4	0.520 [-1.430,2.469]	0.617 [-1.368,2.602]	0.536 [-1.394,2.466]	0.612 [-1.350,2.573]	0.683 [-1.325,2.692]	0.696 [-1.341,2.732]
<i>Baseline Controls</i>						
IHS(NTL) (Lag 1)	0.297** [0.0710,0.522]	0.298** [0.0604,0.535]	0.301*** [0.0756,0.527]	0.314*** [0.0758,0.553]	0.229* [-0.00255,0.461]	0.237* [-0.00801,0.481]
Log(Pop Density) (Lag 1)	0.342 [-0.754,1.437]	0.183 [-0.974,1.340]	0.403 [-0.724,1.531]	0.247 [-0.972,1.466]	-0.0898 [-1.757,1.577]	-0.0744 [-1.948,1.799]
<i>N</i>	4838	4345	4794	4318	4692	4223
<i>R</i> <sup>2</sup>	0.676	0.676	0.676	0.676	0.681	0.680
Districts Treated	48	45	47	44	47	44
Excl. Switching Districts	No	Yes	No	Yes	No	Yes
Excl. pre-2003 Events	No	No	Yes	Yes	Yes	Yes
Extended Controls	No	No	No	No	Yes	Yes
Time FE	✓	✓	✓	✓	✓	✓
District FE	✓	✓	✓	✓	✓	✓
Province × Year FE	✓	✓	✓	✓	✓	✓

\* <0.1, \*\* <0.05 and \*\*\* <0.01 p-value. Dependent variable: IHS(FDI inflows). All models exclude treatment reversal and simultaneous appearing other disasters. All regressions contain also pre-trends, which are excluded in the output. Extended controls included are lagged log of domestic investment, log of persons in labor force, manufacturing share, a Bartik like control for migration, and lagged values of log morbidity and poverty. All models exclude multiple treatments and simultaneous occurring non-earthquake related disasters. Model (2) - (6) additionally exclude districts with earthquakes between 1997-2002. All errors are clustered on district level.

To circumvent that problem, the paper standardizes the identification of districts based on their original 2003 names and identifiers. In other words, if a district is divided in the years following 2003, then it is re-aggregated to the name and the unique census identifier of 2003, the baseline year, to get a consistent level of observation over time. Out of the included 436 districts, this concerns approximately 51 districts, or 11% of the sample, that changed their names after 2003. The aggregation serves the purpose of not losing this data, yet it might be that thereby I overestimate the effects within these districts. Also, economic center identification might be inaccurate as it is done on the 2015 identifiers. By excluding the 51 districts from the analysis, one reduces the treatment sample by 31 of the 127 earthquakes recorded. This determines if and in how far these districts, if excluded, bias the main results. **Table A1** shows that the results are pretty much comparable to the baseline results. Hereby, each uneven column includes still name switchers, whereas all even columns completely exclude districts that have switched their names. The coefficients of the controls are comparable. Excluding this subsample will matter in the case of extreme outlier events, precisely on occasions where there are ex-ante fewer observations in the treatment group, as each additional lost observation might substantially pull the regressions in a particular direction.

## B Method: Heterogeneity Analysis of Empirical Strategy

### Introduction of the Problem

The chosen empirical strategy is a dynamic two-way fixed effects model that accounts for treatment heterogeneity by accounting for the time since last exposure. Similar to classic difference-in-difference designs, such a two-way fixed effects model relies on the parallel trend assumption. In research, this assumption is usually tested by considering pre-trends, yet given that, by nature, earthquake episodes are random in time, anticipation effects are unlikely in this study. The bias induced non-random allocation of earthquake exposure are assessed in the heterogeneity analysis.

Various problems can emerge with the method chosen: first, the treatment timing varies across groups of districts. If one would only consider those districts that are exposed once to a stronger earthquake, one would end up with what is often referred to as a "staggered Difference-in-Difference adoption design". This would correspond to the treatment pattern shown in Panel (a) in Figure B1. Choosing this pattern excludes districts with more than a single earthquake event (around 5% of the total sample), whereby important information might be lost. Panel (b) shows the true treatment pattern, which is empirically more difficult to address due to the possibility of treatment reversal. To correct for this staggered adoption design, one needs to weight different treated groups differently. If one does not account for the weighting, a bias arises (discussed, for instance, by Xu, 2022, De Chaisemartin and d'Haultfoeuille (2020), Goodman-Bacon (2021), Callaway and Sant'Anna (2021), Sun and Abraham (2021), Borusyak, Jaravel, and Spiess (2021)).

A second problem is that the treatment definition relies on the strict exogeneity assumption. Following Xu (2022) and Imai and Kim (2019) strict exogeneity relies on four main assumptions, namely the absence of confounding variables that vary over time, the absence of lagged dependent variables, the absence of an effect of past outcomes on the likelihood of being treated and lastly, that treatments from the past do not impact future outcomes. If these assumptions do not hold, then estimates are likely to be biased. To check for time varying confounders, one usually includes dynamic treatment ef-

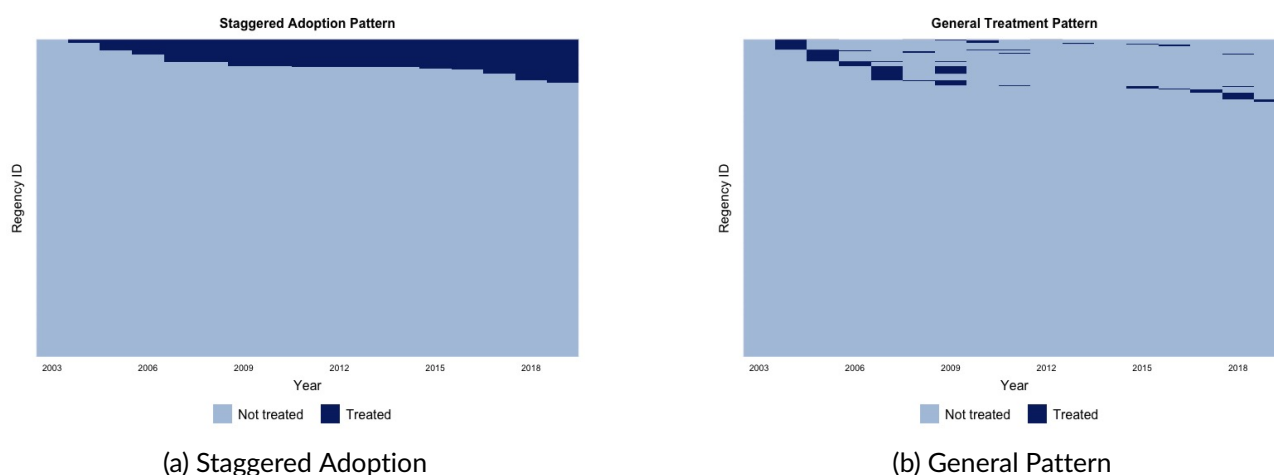


Figure B1: Different DGPs

The graphs have been generated using Xu and Licheng (2018) `panelView` command and the main data frame created for this study.

fects, which I respect by differing between different timings since the last treatment. So far, it has not been considered how past outcomes impact current ones. Such a case could arise if foreign firms withdraw from local markets following a disaster. That past outcomes (FDI inflow) impact the treatment's existence is excluded by design in my case. So, to summarize, the carryover effects of past treatment on current outcome and of past outcome on current outcome might potentially bias the estimates. Furthermore, in the chosen dynamic TWFE model it is likely that found effects are biased by effects of other periods (Sun and Abraham, 2021), which needs to be addressed.

### B.1. *Dynamic Heterogeneous Treatment Effects*

In the following section, the above-mentioned models from the current difference-in-difference literature of staggered adoption design, assuming a single treatment, are shown and then compared with a method based on an interactive fixed effect.

At first, Figure 9<sup>12</sup> shows the comparison between a selection of different estimators from recent difference-in-difference literature (Sun and Abraham, 2021; Sant'Anna and Zhao, 2020; De Chaisemartin and d'Haultfoeuille, 2020; Borusyak, Jaravel, and Spiess, 2021; Wooldridge, 2021). All models exclude districts, which have been exposed multiple times to stronger earthquakes and use only districts for robustness, that have not been split over time in order to not overvalue FDI inflows in total. All these papers address the above-mentioned weighting problem in various ways. For instance, by using a binary treatment De Chaisemartin and d'Haultfoeuille (2020) suggest to use weighted average of two difference in difference estimators: the first compares districts switching from not being exposed to an earthquake to experiencing an earthquake with districts that have not experienced any in both periods. The second estimation compares districts that have experienced an earthquake at both points in time with those that switch between the two periods from not treated to treated.

Overall, all estimators follow a similar pattern post-treatment. The FDI inflow is measured as a hyperbolic sine transformed variable. Following a strong earthquake exposure, one sees a persistent decrease in FDI inflows in the years following the disaster with the most consistent decline found in the  $DiD_t$  estimator by De Chaisemartin and d'Haultfoeuille (2020) and the Sant'Anna and Zhao (2020) estimator. In terms of significance, all methods find a statistically significant reduction in FDI inflows in periods 1 and 2 after disaster occurrence at a 10% level. The coefficient is similarly large as in the baseline regression. Overall, the effects found effects, confirm the baseline results.

The key takeaway from this subsection is that even accounting for heterogeneous treatment timing across groups the results of the baseline seem to hold.

### B.2. *Allowing For Treatment Reversal*

The paper by De Chaisemartin and d'Haultfoeuille (2020) proposes the  $DiD_t$  estimator, which allows not only for dynamic effects<sup>13</sup> but also for treatment reversal. This allows the treated districts to switch

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<sup>12</sup>The code is inspired by Borusyak (2022)

<sup>13</sup>This refers to the idea that past treatments might impact current outcomes. This method complements previous models, assuming that only current treatments impact current outcomes (instantaneous treatment effects)

back from being exposed to an earthquake to not being exposed anymore, which increases the treated sample size. Similar to the estimations above, one observes a small "dip", the sole significant one on a 10% level in the year after the earthquake exposure. The result is shown in Figure B2, where the left baseline model includes only the controls, yet not in a lagged way. The extended model on the right adds linear year and district trends as well as non-linear province-specific trends. In all cases, standard errors are 100 times bootstrapped, and especially in the right panel for some replications, the p-value is marginally above the 10% threshold. While there is an indication of a pre-trend occurring four years before the treatment, the treatment reversal approach is somewhat hampered by the limited time available for recovery before the recurrence of earthquakes, which could potentially introduce some contamination to the pre-treatment periods.

Nonetheless, if one accounts for heterogeneity in treatment effects across treated groups and if one allows for treatment reversal, the effects go in a similar direction as in the baseline results and provide support for the stated results.

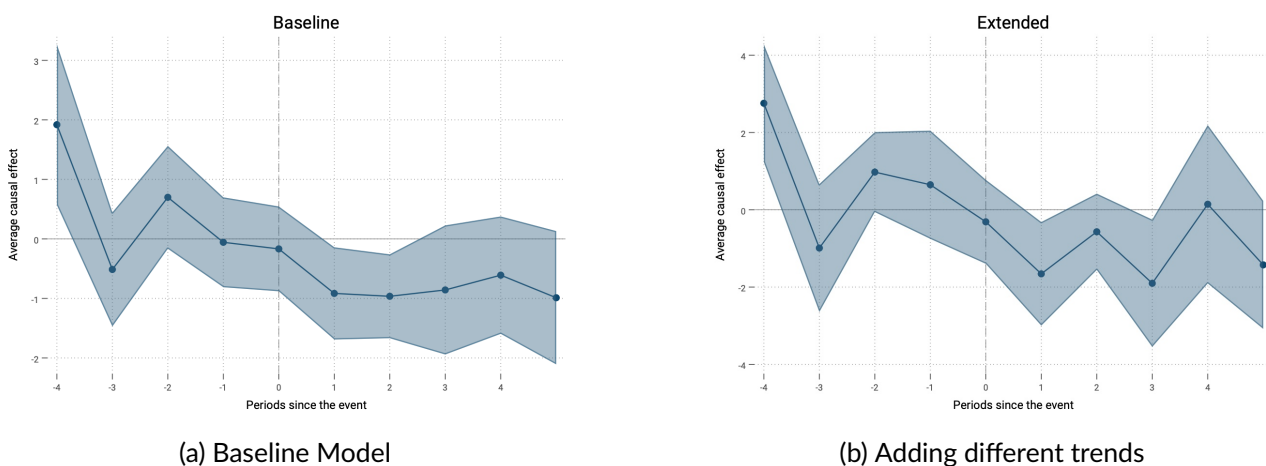


Figure B2: Allowing for Treatment Reversal

Notes: The graphs are based on De Chaisemartin and d'Haultfoeuille (2020) and plotted using Borusyak, Jaravel, and Spiess (2021). Panel (b) includes linear time and district trends, as well as non-linear province trends. Confidence intervals are based on a 10% level. Standard-errors are clustered-bootstrapped 100 times.

### Conclusion

The main strategy used in my paper ignores group-specific ATTs. Ignoring such ATTs might lead to negative weighting and bias in the estimates. Concerning my study, this section has shown that in most setups, similar negative short-run effects can be found. A key assumption made for the analysis is that the Stable Unit Treatment Value Assumption (SUTVA) holds. This is likely to be true in time given the temporal randomness of treatment, yet still, spatial spillovers or general equilibrium effects might pose a threat for the SUTVA, which cannot be ruled out with certainty. Overall, the results of this section taken together tend to confirm the results of the baseline regression.

## C Results: Reallocation Effects to Economic Centers

In the main paper, it is tested to see what the impact of a district's FDI inflow is if a neighboring district is affected. Yet, FDI might be predominantly allocated to economic centers.

In this section, not just the economic center of each district is used, but mainly the distance to the main economic center within each province, which is identified using nighttime light data. The main economic center within a province is, in essence, the district with the highest nighttime light intensity at the district-specific economic center. The classification of the main economic centers is validated with various statistical yearbooks. Then the distance from each economic center within a province to the closest affected district is measured. Hereby, it is also allowed for this district to be located in a neighboring province, yet what matters is the distance to an affected area. **Table C1** shows the results. One can clearly see that proximity matters: the closer an economic center is located to an affected district, the larger the impact on FDI inflows, ranking from a 98% reduction within 50 km significant on a 1% level, down to 92% within 100 km, to 90% within 200 km. After that, no significant effects were found anymore. A key limitation of this model is the small number of treated economic centers, as there are only 32 provinces, and thereby only 32 within-province economic centers are available.

Table C1: Impact on FDI Inflow in Economic Centers in Proximity to Disaster

	Distance to exposed district			
	(1) 50km	(2) 100km	(3) 200km	(4) 500km
Shock in distant district	-1.973* [-3.965,0.0192]	-1.020 [-3.065,1.024]	-1.198 [-3.497,1.101]	-0.309 [-6.118,5.500]
Shock in distant district (Lag +1)	-4.199*** [-6.650,-1.747]	-2.631** [-4.816,-0.447]	-2.400* [-5.047,0.247]	-1.162 [-6.495,4.170]
Shock in distant district (Lag +2)	-0.257 [-3.087,2.572]	-0.326 [-2.751,2.100]	0.158 [-2.817,3.134]	-0.223 [-10.52,10.08]
<i>N</i>	356	349	317	77
<i>R</i> <sup>2</sup>	0.727	0.722	0.725	0.560
Economic Centers in Treated Group	7	9	7	1
Baseline Controls	Yes	Yes	Yes	Yes
Time FE	✓	✓	✓	✓
District FE	✓	✓	✓	✓
Province× Year FE	X	X	X	X

\*<0.1, \*\*<0.05 and \*\*\*<0.01 p-value. Dependent variable: IHS(FDI inflows). Each model includes log NTL and log population as Lag +1 term. Both models exclude treatment reversal and simultaneous occurring other disasters. Also as centroids of each district are used, districts which switched names are systematically excluded.

## D Results: Effects By Floods

As shown in the introduction of the paper, earthquakes and the associated tsunamis account for the vast majority of deaths and damages recorded in all disaster categories in Indonesia. In terms of population affected, however, floods seem to be the most relevant disaster category. Thus, in comparison to earthquakes, the same effects are analyzed similarly.

### D.1. Identification

While for earthquakes, geophysical ground motion formulas and models are easily obtained, it is more complicated to account for a physical measure of flood exposure. I use extreme rainfall shocks as a proxy for flood risk. First, data from Abatzoglou et al. (2018) on monthly rainfall in mm since 1959 is used and overlaid with the 5x5km grid cells of Indonesia. As the time dimension in this paper is yearly, the monthly data needs to be re-aggregated on a yearly level. For this purpose, the paper follows Felbermayr et al. (2022) and the definition of a rolling window metric. This is calculated in the following way: First, the grid cell-month specific rainfall is standardized

$$\gamma_{i,m,t}^{\text{prec}} = \frac{x_{i,m,t}^{\text{prec}} - \bar{x}_{i,m}^{\text{prec}}}{\sigma_{i,m}^{\text{prec}}}$$

where  $i$  refers to grid cell identifier,  $m$  to month and  $t$  to year. For the calculation, the entire time period is used (since 1959), whereas in the final dataset, only the years 2003 to 2019 are included. Next, only positive deviations are assumed, as only positive rainfall shocks are likely to be associated with flood events. To aggregate it on a yearly level, one cannot just average it over the year as this would omit dry and wet seasons within the year, whereby rainfall shocks, especially in wet seasons, are likely to cause more damage. So in the aggregation formula, each month is weighted with the remaining number of months within a given year, while the right-hand term is a weight for the value in the next year:

$$D_{i,t}^p = \sum_{m=1}^{12} \left[ \gamma_{i,m,t}^p \cdot \frac{12-m}{12} + \gamma_{i,m,t-1}^p \cdot \frac{m}{12} \right]$$

The value of  $D$  in grid cell  $i$  year  $t$  is then the weighted average of positive deviations from the long-run monthly mean. Again, to identify economic centers, nighttime light is used. Then the rainfall shock metric is assigned to the economic center grid cells, if the rainfall metric is positive. Furthermore, using the historic risk maps from UNDRR (2017a) only economic centers are assumed to be treated with a continuous rainfall shock if the grid cells of the economic center are at historic risk of a 200-year flood. Then the mean value of these intensities in economic centers within each grid cell is finally used. So the rainfall shock measures the mean standardized rainfall shock over all historic monthly values in economic centers at risk within a district.

The shock on the labor market follows the share of flood victims over the lagged district population. As before, both shocks are interacted and ranked.

There are plenty of criticisms that can be brought forward with this methodology. Rainfall is an insufficient predictor of flood exposure, especially of riverine floods, as neighboring districts might be more affected by large rainfall upstream of the river. Also, the formula does not account for anthropogenic changes of urban landscape over time, which might cause areas at risk to change. Nonetheless, for a robustness check, this shall suffice as a method.

### D.2. Effect on Temporal Level

Figure D1 shows the temporal effects of flood exposure. Panel (a) differs between the impact of using a top 10 ranked flood event and those within the top 100 ranking, where the ranking is based on the product of the labor market and the rainfall shock. The problem is that for the top 100 ranking only 38 events are included, as the entire rest has more than one treatment. Panel (a) shows that there appear to be no significant effects on FDI inflows through floods in the case of Indonesia. Yet, allowing for treatment reversal in Panel (b) using the DiD<sub>t</sub> estimator by De Chaisemartin and d'Haultfoeuille (2020) one can see that FDI appears to be substantially reduced within the year of flood occurrence but not afterwards, so the effects appear earlier than in the case of earthquakes. Overall, the effects appear to be negative but not as obvious as for earthquakes since potentially flooding has other mechanisms through which it affects foreign investment. An effect on a sectoral level is discussed next.

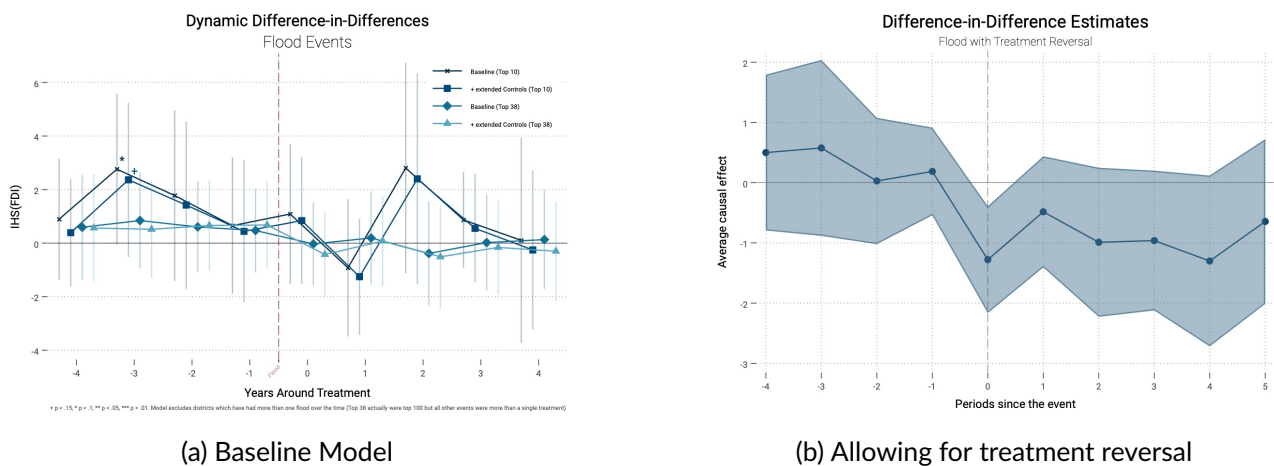


Figure D1: Temporal Effects on Flood

Notes: Graph (a) uses the main specification and distinguishes between Top 10 district-year events and Top 100 (out of which only 38 are included (as those districts with multiple treatments are in this specification excluded)). The used estimation model is the one from Equation 1, so using the same core controls, including district, year and province-year FE and applies district-clustered standard errors. The graph (b) is based on De Chaisemartin and d'Haultfoeuille (2020) and plotted using Borusyak, Jaravel, and Spiess (2021). Panel (b) includes linear time and district trends and allows for treatment reversal. Confidence intervals are based on a 10% level.

### D.3. Effect on Sectoral Level

Re-running the regression from equation 1 on a sectoral level for flood events, one finds mild positive effects of FDI in mining and stronger effects for wholesale and services. The differences in sectoral effects between flood and earthquake can be attempted to be explained through the distribution of the respective disaster hazards across Indonesia. Not all regions are affected by floods and earthquakes at





Neise and Diez (2019), for instance, discuss how small and medium firms tend to adapt to flood risk. While you can adapt to flood risk for instance by investing in backup technologies, earthquakes and their associated tsunamis tend to cause more long-lasting damage to local economies, which would explain why the effects found vary.

Secondly, the expectation of disaster risk might vary between the two categories. Earthquakes are prone to occur in proximity to tectonic plates, while their associates, tsunamis, are more likely to affect low-land coastal regions. Floods also tend to originate in lowlands, and especially in proximity to rivers. Yet, due to anthropogenic climate change, floods induced by extreme rainfall events tend to become more frequent in the upcoming years, which is potentially not yet as deeply incorporated in the risk mitigation strategies of foreign firms.

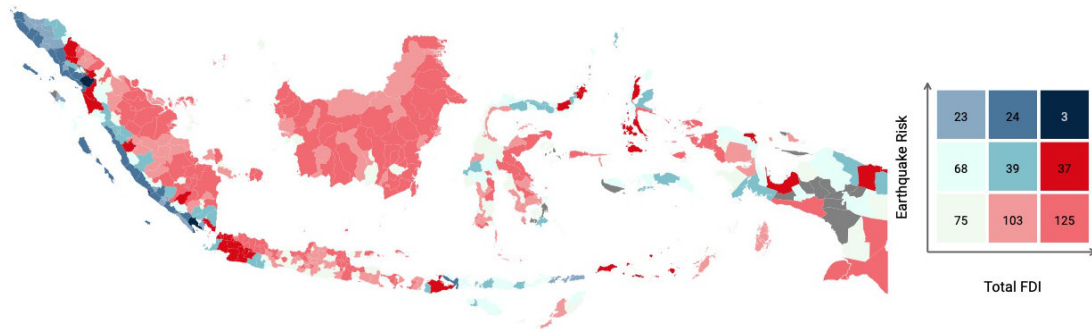
Lastly, as mentioned briefly before, the sectoral composition of affected districts might vary between the two disaster categories. Figure D3 plots in a bivariate map the FDI inflow against the calculated district-specific composite hazard index<sup>14</sup>. One can clearly see that areas (in blue) of high risk are located in different provinces for earthquake risk than for flood risk, which likely causes the sectoral effects to vary.

These are just a few of many reasons why floods might have different effects on foreign firms than earthquakes, yet nonetheless, it shows that flood events also do not contribute generally positively to FDI inflow, similar to earthquake events.

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<sup>14</sup>The risk index, as described in the respective section, is created by dividing a standardized grid cell specific mean of each district into quartiles over the entire country

(a) Earthquake Risk and FDI



Graph based on bimap command by A. Naqvi. Own colorscheme applied.

(b) Flood Risk and FDI



Graph based on bimap command by A. Naqvi. Own colorscheme applied.

Figure D3: Spatial Distribution of Risk

Notes: Graphs are based on the OCHA's Regional Office for Asia and the Pacific (2021), data from Indonesian Investment Co-ordinating Board (BKPM) (2021) and hazard maps on 250-year return periods for earthquake and 200-year return periods for flood risk (UNDRR, 2017a; UNDRR, 2017b). Composition based on percentiles. In gray there are the 14 districts non-matched. The graph likely overestimates FDI slightly in 51 districts.

## E Results: Impact of other Disaster Types

The paper predominantly focuses on the impact of earthquakes on FDI as they represent a major threat to human and economic life in Indonesia. In the previous section, it is more in-depth investigated what the effects of floods on FDI inflow by using another physical intensity proxy. This section only outlines the effects on FDI inflow, where disaster types are categorized into four major categories: geophysical disasters (earthquakes, tsunamis and volcanic activity), hydrological disasters (floods, landslides and tidal waves<sup>15</sup>), meteorological (storm and cyclone exposure) and lastly climatological disasters (drought and forest fires). All but geophysical events are described in the literature as being directly related to climate change. There is, however, even for geophysical disasters, a nascent literature that focuses on the impact of, for instance, changes in tsunami propagation due to sea level rise (e.g. Sepúlveda et al., 2021) or how related meteorological events might cause additional stress on tectonic crusts (Steer et al., 2020).

In order to analyze the differences between various disaster shocks on FDI inflows, quarterly FDI data is used to get as close as possible to the point in time when the disaster takes place. Here, this is possible, as for this study, there are no physical measures for the other disaster categories. Certainly, it would be possible to account for wind-speed models, volcanic ash fallout or wildfire spread using remote sensing and interpolation mechanisms, but this would exceed the scope of this paper. Thus, to measure disaster events, the Desinventar by the UNDRR (2022b) database is used. A disaster is considered a disaster if at least one person has died or been directly impacted by it. Admittedly, this is a very strong assumption, but in this way, the maximum number of disasters can be retained as a dynamic difference-in-difference specification used in the main part of the paper, whereby treatment reversal is excluded by definition. Most disasters occur more than once over the period of 17 years, which is why to include a larger sample of treated the very low threshold of at least a single person affected is used.

Figure E1 shows the results of the regressions. One can see that, similar to the models used in the main part, even by including other volcanic activity and other tsunamis, geophysical events cause a substantial reduction in FDI inflows in the aftermath. For hydrological events, there is a huge fluctuation, likely because the effects of landslides and floods are substantially different from each other. One can see that the FDI inflows fluctuate substantially in the years following an event. Similarly to this, meteorological events also see little to no significant effect in the years following storm events, only for climatological events one does find a persistent reduction in FDI inflows. A probable explanation is the FDI inflows into agriculture, especially palm oil, which are likely to decrease shortly following forest fires.

The results are too weak to generalize, but one can see that by using the same methodology it seems that especially geophysical events matter for Indonesian FDI.

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<sup>15</sup>Waves caused for instance by tidal gauges

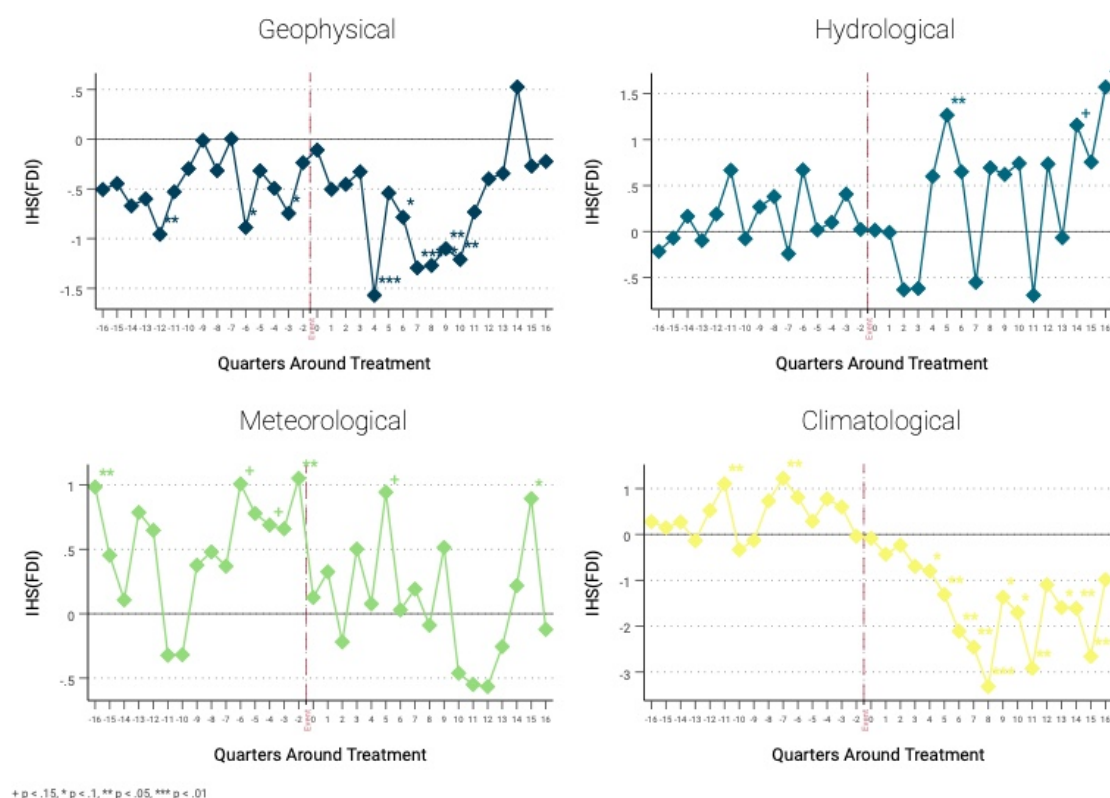


Figure E1: Overview on Different Disaster Types

Notes: Figure shows the effects of aggregated disaster events, classified by their characteristic, onto quarterly FDI inflows aggregated over sectors. Estimations are based on Equation 1 and are conducted on a district-level. Included are all events by disaster category, where only a single event within a district in this category occurred (districts considered treated: 72 for geophysical, 44 for hydrological, 59 for meteorological and 63 for climatological events). Other disaster events within a district in the same quarter are excluded. A district is considered treated, if at least a single person has died and/or is affected by a disaster.

## F Method: Assessment of the Shock Metric

The entire methodology as well as the interpretation of the results relies strongly on the way the shock is defined. In the binary treatment version of the shock parameter in the main paper, a district is considered treated if the economic center of the district is exposed to an earthquake with at least weak destruction potential and if people are recorded to be affected by the event. Figure F1 illustrates the impact of changing the shock definition, namely using either the capital or the labor shock individually instead of jointly. A similar trend to that in the baseline can be observed. The larger coefficient in the combined shock, according to the definition used in this paper, can be attributed to a smaller sample size if both conditions hold. Yet, it also highlights that if labor and capital are affected at the same time, the effects tend to be stronger.

Additional robustness tests include rerunning the results based on only stronger earthquakes. The problem is that the sample size become so small, especially for extremely destructive earthquakes above modified mercalli scale level 8 with 6 units, that there is no valid inference possible without changing the estimation strategy. A similar case applies to thresholds for the minimum amount of local

### Overview on the Shock Components

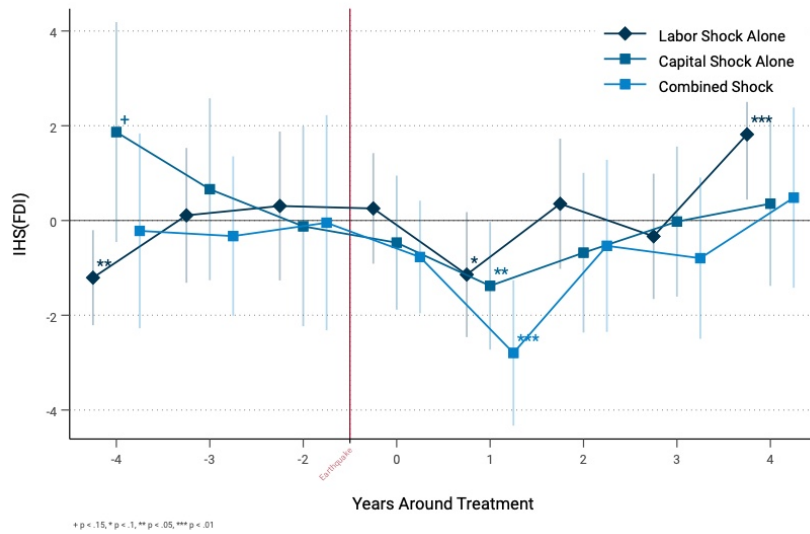


Figure F1: Definition of the Shock Variable

Notes: The figure shows how the results of the baseline estimation changes if only the labor shock (light blue), capital shock (darker blue) or the combined shock, as used in the main paper (in darkest blue) is used. The corresponding treated sample size is 431 treated for labor shock, 207 for capital shock and 126 for joint shock.

population that needs to be affected by an earthquake. In more than 90% of the cases, less than 5% of the local population was affected by losing their livelihood. Thus, the sample becomes incredibly small for valid inference. Overall, the results are more or less robust for treatment definition, yet with extreme outlier events a generalized dynamic difference-in-difference approach becomes increasingly less feasible given the small size of treated units.

## G Results: Robustness of Controls

### G.1. Nighttime-light as Economic Proxy

Nighttime light is frequently used in the development literature as a proxy for economic (Sutton, Elvidge, and Ghosh, 2007; Hu and Yao, 2019). However, a key criticism is that it overvalues richer areas, whereas deprived regions are still insufficiently accounted for by nighttime light. This test serves solely the purpose of checking how much logarithmic nighttime light in Indonesia correlates province-wise with logarithmic GDP. Data on GDP values<sup>16</sup> over time is drawn from the INDO-DAPOER data frame of The World Bank (2022b). Figure G1 shows the correlation by province over all years. One can see that the strongest correlations are found in DKI Jakarta and Banten, which are the richest provinces in GDP terms. Sumatera Barat and the islands of Bangka Belitung have extremely low correlations, despite ranking in the midfield for GDP ranking. The reason might be that there are plenty of districts that are relatively weakly illuminated at night, and thereby the correlation between GDP and nighttime light is low for these districts. The mean correlation on district level between NTL and GDP is 0.6, which is sufficiently high to say that nighttime light proxies GDP sufficiently well for this dataset. On

<sup>16</sup>The GDP is based on 2008 constant values

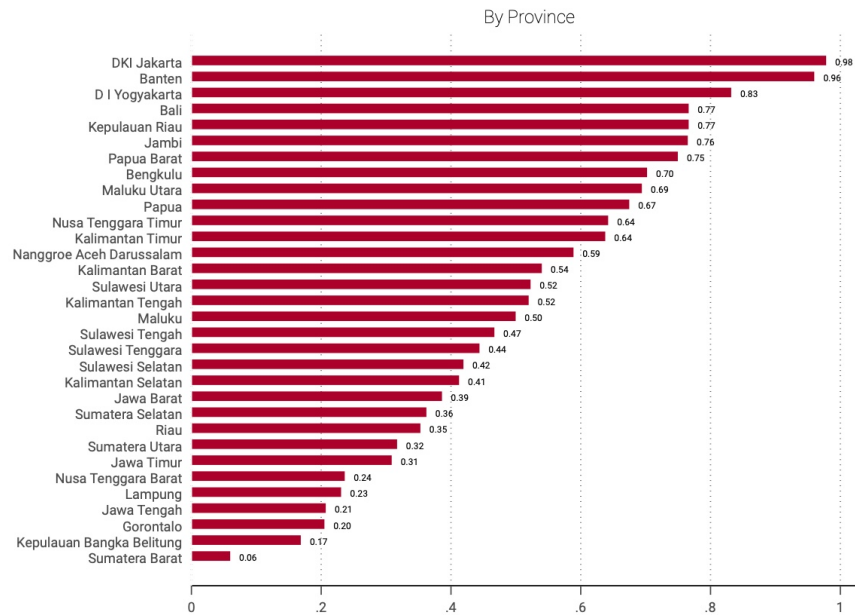


Figure G1: Correlation of Log(NTL) and Log(GDP)

Notes: Data source from The World Bank (2022b) and Chen et al. (2021). Author's own calculations.

a yearly basis, the correlation is never lower than 0.58. So despite the outlier of Sumatera Barat NTL serves as a sufficient proxy for GDP.

## G.2. Reliability of Economic Center Classification

Another important test is to assess if the economic centers within each district are accurately matched. In order to do so, information on the geographic coordinates of cities in Indonesia and their population is obtained from GeoNames (n.d.). The cities are then matched to district level and overlaid with the Indonesian 5x5km grid. One has to keep in mind that economic centers are classified based on quintiles of nighttime light or population density. Using descriptive statistics, it is assessed, whether most of the included cities from GeoNames (n.d.) are actually located within the highest quintile in mean grid-cell specific nighttime-light. One can see in Table G1 that most cities, indeed, fall into the fifth quintile. The cities in the first quintile are predominantly those that are later reclassified using the mean population density by grid cell. Then, by using information on the population within a city, it is also tested whether all major cities with more than a million inhabitants are classified in the highest quintile and indeed, all but one are. There is only one exception: the city Depok. Analysis at the grid cell level revealed that the city boundaries extend over multiple grid cells, the neighboring grid cells fall into the highest quintile, yet the centroid of the city from the dataset does not. Thus, this outlier can be ignored, as Depok is accounted for by the neighboring grid cell.



Table G1: Classification of NTL Quintiles onto City Geocoordinates

	Mean	Standard Dev.	N
First Quintile	14760.36	20868	14
Second Quintile	57184.5	80447	2
Third Quintile	14670.75	23722	4
Fourth Quintile	123394.2	227715	26
Fifth Quintile	163299.4	517996	364
Total	153729.1	492323	410

Only gridcells which match city coordinates are included. Mean refers to mean population of each city in each quintile.

### G.3. Reliability of Disaster Effect Data

A key criticism of the paper could be brought forward if one does not believe in the main data source from UNDRR (2022b). According to a report by UNDP Indonesia and BNPB Indonesia (2019) the management of the Desinventar database has been handed over from the UNDP to Indonesia's national agency for disaster management (*Badan Nasional Penanggulangan Bencana*) in 2008. It is constantly improving in tracking and recording disaster occurrences and has since also launched their geodata portal (DiBI). In the following, I compared the Desinventar data to the two most common other data source in Indonesia: the officially reported data by the national agency BNPB (*Badan Nasional Penanggulangan Bencana*, 2022) and the data provided on event and aggregated district level by EM-DAT Sapir and Below (2014).

Figure G2a shows the percentage of matched district-events between the two data sources. Differences in all categories but forest fires and tsunamis can be attributed to the fact that, before 2008, Desinventar has not been identically streamlined with the national agency. Since 2008, there are no matching errors found. The difference in tsunami is originating in different accounting. Desinventar differs between tsunamis themselves and tsunamis with simultaneous earthquakes, whereas in the BNPB data, tsunamis and earthquakes would be coded as tsunami events. Forest fires are also for accounted by BNPB, but in the data portal, where this comparison data is obtained, I have not been able to download the category for forest fires as well. Nonetheless, on a national reporting level, these events are also reported. This test is shown to illustrate that Desinventar is not any arbitrary database, but the data officially provided and managed by the National Agency for Disaster Management.

Moving on to the EM-DAT database, Figure G2b indicates that Desinventar accounts for substantially more events than the EM-DAT database, whereas approximately 10% of EM-DAT events are not matched on a district level with the Desinventar data. In absolute numbers, only 136 events in total remain in EM-DAT out of which 15% are earthquake events, 22% are landslides, and 20% are volcano eruptions. Now, one has to be careful not to make big claims based on that figure. First, it could be that EM-DAT only accounts for additional districts for the same event, thus having more or different districts included. It could also be that a certain percentage of matching errors result from switches in district names. While it is attempted that all district names are standardized and collapsed by 2003 Census IDs, it, nonetheless, could happen that some are mismatched. A key reason why Desinventar is likely to have substantially more events is that no threshold on when to include an event is used in



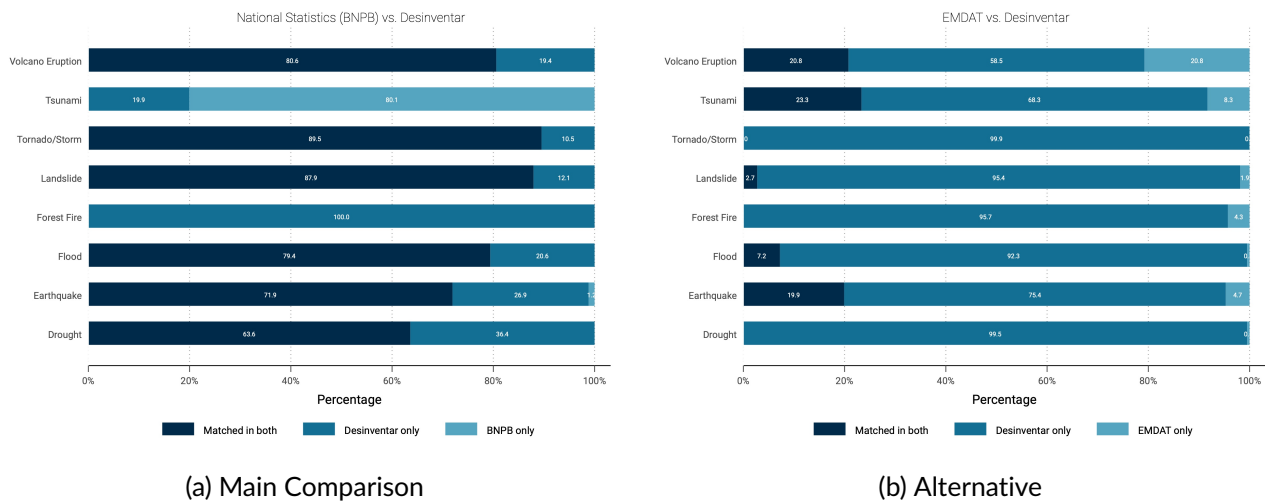


Figure G2: Comparison of Matched Results

Notes: Data is based on UNDRR (2022b), Badan Nasional Penanggulangan Bencana (2022), and Sapir and Below (2014) Calculations are the author's own. In both cases matching is done based on number of events recorded within districts of a year. The results should not be generalized and considered with caution as matching errors are likely to bias the 1:1 matching.

contrast to the EM-DAT database. EM-DAT uses thresholds in which, for instance, at least ten or more people are killed or 100 or more are affected, whereas Desinventar includes any potential event.

A key advantage of using Desinventar over EM-DAT is the use of district-event specific damage and victim statistics. EM-DAT tends to report the total number of damage and/or victims on an event level. Even if it includes affected districts, the impact of the disaster might be unequally distributed across these districts and even within the districts. This discussion provides further validation of the usage and reliability of the damage statistics used in the main part.

## H Method: Assessment of Hazard Risk Indices

### H.1. Creation

In order to account for risk, at first, models for disaster risk are obtained predominantly drawing from the Global Assessment Report on Disaster Risk Reduction of 2015<sup>17</sup>. These models show where different disasters are likely to take place based on historic data and probabilistic models. They serve the purpose of creating event-specific risk indices, which can be combined to an overall *composite hazard index*.

To create risk indices for the different disaster categories, it's essential to have a consistent measure of risk exposure. However, the five hazard maps used for different disasters (earthquake, flood, landslides, tsunami, and forest fires) have varying return periods, making direct hazard values incomparable. To

<sup>17</sup>Flood Hazard 200 years (UNDRR, 2017a), Landslides - Frequency (triggered by Precipitations) (International Centre for Geohazards and Smebye, 2018), Landslides - Frequency (triggered by Earthquakes) (International Centre for Geohazards / NGI and Smebye, 2018), Tsunami - Frequency (International Centre for Geohazards / NGI and Lovholt, 2009), Fire Density (UNEP/DEWA/GRID-Europe and Peduzzi, 2014), Peak ground acceleration 250 years (PGA is a metric to measure earthquake intensity) (UNDRR, 2017b)

address this, I merge the hazard maps with the 5x5 km grid of Indonesia, resulting in five grids, each representing a specific disaster type's risk per grid cell. These values are internally comparable within each disaster type but not across categories. To achieve cross-category comparability, I standardize the risk values using z-scoring. Each grid cell is then assigned a standardized risk value based on its respective category. District-specific values are obtained by averaging grid cell z-scores within each district, resulting in mean standardized risk scores for all Indonesian districts across the five disaster categories. For these five categories, the risk index is not endogenous to the occurrence of disasters, as it only represents the statistical likelihood of occurrence in a given year based on long-historic time series.

For volcanoes, storms, tidal waves, and droughts, where hazard maps are unavailable, I use a different method. Here their z-scores are based on the recorded number of events within each district, drawing from the Desinventar database (UNDRR, 2022b). This z-score represents the district's deviation in event occurrence from the average across all districts over 17 years, serving as a rough proxy for risk likelihood. Admittedly, the disaster risk for volcanoes, storms and droughts is endogenous to occurrences within the district, but might nonetheless reflect, to some extent the respective district's risk likelihood.

For an overall index of disaster-specific risk, a so-called *composite hazard index* is created. Following Emrich et al. (2022) first for each disaster category the averaged district-specific z-score is recoded to equal one if the score is below -0.5, two if the score is between -0.5 and 0.5, three if it is above 0.5 to 1.51 and four if it is above 1.51. These event-type specific dummies are then aggregated using the formula:

$$CHI_i = \sum_{c=1}^n x_{ic}$$

whereby  $x_{ic}$  refers to the recoded standardized risk score for district  $i$  and the disaster category  $c$  is. The composite hazard index reflects the district time invariant index for multi-hazard disaster risk, which will be used to validate if risk likelihood plays a role in investment response.

## H.2. Assessing Validity of the Two Main Hazard Indices

The heterogeneity analysis in this work relies on the validity of the created composite hazard index as well as the dummy for earthquake risk to accurately reflect the disaster risk in a region. In order to validate that the computed indices are relatively accurate, they are compared to existing studies.

### *Evaluating the Calculated Composite Hazard Index*

Foremost, **Figure H1** shows the computed composite hazard scores by district. Note here that as the map is based on boundaries as in 2015. The risk indices, in contrast, as the entire dataset is based on the 2003 district boundaries, causing some districts to remain without data (in gray). They, nonetheless, have risk values assigned in the dataset, they are just not plotted. One can see high risk scores (darker color) around the main island of Java.

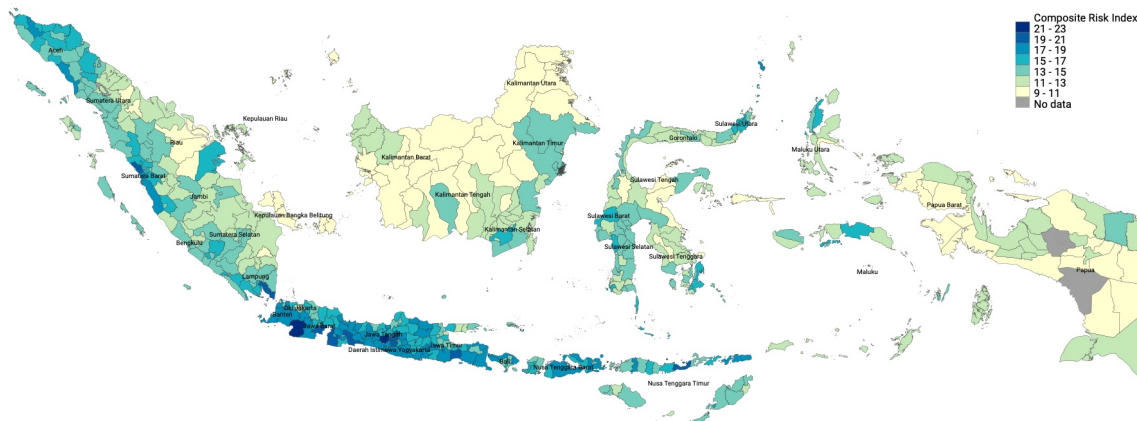


Figure H1: Visualization of the created CHI

Notes: Shapefile is based on OCHA's Regional Office for Asia and the Pacific (2021). Composite Hazard Scores are self-computed scores based on probabilistic hazard maps as described in the respective section. Composition based on percentiles. In grey there are the 14 districts non-matched. The graph likely overestimates FDI slightly in 51 districts.

### Evaluating the Calculated Earthquake Hazard

In order to evaluate the accuracy of the earthquake hazard dummy, it is visually compared to a pre-

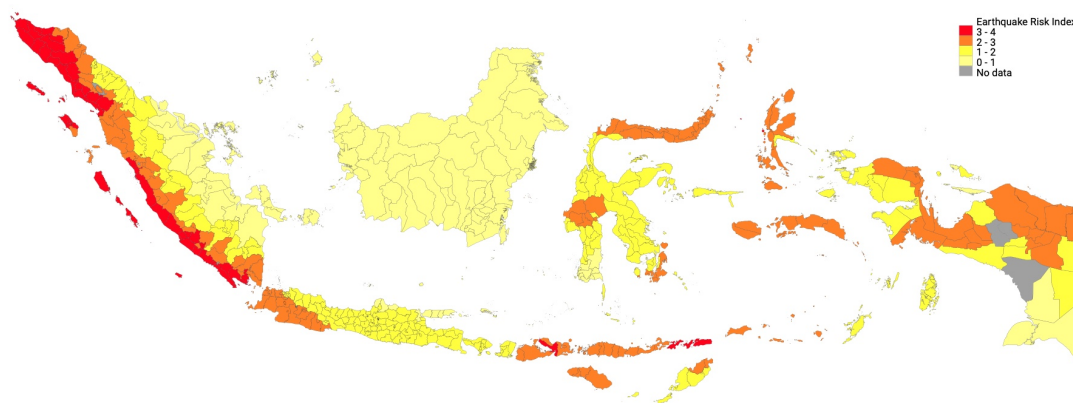


Figure H2: Visualization of the Earthquake Risk Metric

Notes: Graph is based on own calculation, shapefile from OCHA's Regional Office for Asia and the Pacific (2021) and probabilistic hazard map based on 250-year PGA return periods (UNDRR, 2017b). 14 districts are not matched (in gray).

existing map from UN OCHA Regional Office for Asia Pacific (OCHA-ROAP) (2011), which is also provided in Gignoux and Menéndez (2016) in Figure A.1.

One can see a similar pattern of earthquake risk, if one confirms Figure H2 with these maps. This broadly confirms that the risk metric is broadly correct.

In order to see whether the results of the heterogeneity analysis change if another hazard metric is used, instead of a z-scoring based on the hazard maps, a z-scoring using the number of events is used, as mentioned. In comparison to the results of the heterogeneity analysis, the results do not change. It is also tested to see whether the results hold if the hazard scores are calculated using only the hazard within economic centers of each district. Again, the results do not change. Overall, it appears that despite the hazard score not being perfect, it proxies disaster risk in this setting sufficiently well to be

used in the analysis.