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CES

Centre d'Économie de la Sorbonne
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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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December, 2022

Executive Summary: This study investigates which effect earthquakes have on the inflow of foreign direct investment (FDI) within a country from a temporal, spatial and sectoral dimension. It uses a dynamic difference-in-difference model of physical disaster exposure in 416 Indonesian districts between 2003 and 2019 in order to quantify the impact on investment behavior from abroad. Drawing geolocated data from a variety of sources, the results indicate that FDI inflows are temporarily reduced of around 90% in the year after the disaster. In this case study, spatial effects play a subordinate role, yet earthquake shocks affecting upstream industries tend to have substantial negative effects. Manufacturing appears to be the most affected sector.[†]

Keywords: Foreign Direct Investment, Disasters, Risk, Economic Growth, Input-Output

JEL: F21, O12, Q54, C67

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1 Introduction

Most people born before 1990 may still remember the images, when in late December 2004 the news reported about a devastating earthquake in Indonesia causing a tsunami wave, which grew to the size of a seven-story building and leaving a trace of destruction and tragic death behind. While being recorded one of the strongest disaster events of that type in recent times, Indonesia as well as other regions in proximity to tectonic plates suffer extensively from risk induced by earthquakes. Aggregated over time, disasters in general not only affect the livelihood of millions of people, but also render a large uncertainty into investment made by multinational companies operating in countries with elevated disaster risks. The question of how to adapt to disaster risk has seen a renaissance in literature in the last decade, notably due to the fact that climate induced disasters are likely to increase in the upcoming decades due to climate change (Thomas and López, 2015).

This paper aims to contribute to the growing literature by assessing how foreign direct investment (FDI) flows change within a country on a local level and across sectors in the aftermath of disaster events, chiefly earthquakes. As a country of study Indonesia is used given its frequent exposure to disasters of all sorts. According to the Emergency Events Database (EM-DAT) by the Center of Research on the Epidemiology of Disasters (CRED) (Sapir and Below, 2014), in 2019 alone Indonesia experienced 48 disaster events ranging from wildfires, volcano eruptions up to earthquakes, affecting around two million people, leaving an estimate of 600 people dead and causing approximately 1.3 billion USD in damages. In post-disaster environments, changes in the amount of foreign direct investment (FDI) are understandably not at the center of interest of policymakers, yet the effect of FDI on boosting productivity, on job creation and on reduction of CO₂ emissions in Indonesia (OECD, 2020) motivates to investigate how FDI responds to disaster exposure.

The study attempts hereby to answer essentially the question of how earthquakes impact FDI inflows in Indonesia by differing between direct and indirect effects. Direct effects, as for instance brought forward by Antonioli, Marzucchi, and Modica (2021), refer to the idea of channels impacting different aspects of the business environment for foreign firms directly. Examples are, for instance, labor market fluctuations or the destruction of physical production capital caused by the disaster event. In order to focus on direct channels, the paper investigates how a combination of a labor shock, measured by the share of population affected, and a capital shock, measured by physical earthquake intensity, impacts FDI inflows in the years following the disaster. The ex-ante expectation of the study is that FDI inflows are likely to be reduced temporarily as long as the labor market is disrupted or capital is rebuilt. This hypothesis is tested using a dynamic difference-in-difference model and yearly FDI inflow data of 423 districts in Indonesia between 2003 and 2019. The key insight from the analysis is that the hypothesis seems to hold true and FDI inflows are reduced by up to 90% in the year after a severe earthquake

exposure before returning to the pre-disaster levels. Thereby, especially areas with a lower historic disaster risk and with higher initial FDI stock see the largest effects. So it is likely that the amount invested by foreign firms as well as the anticipation of the disaster play a role in this mechanism.

Indirect effects refer in this study to two channels: indirect effects through spatial spillovers and indirect effects through supply-chain-disruptions. Firstly, one might think of a spatial mechanism increasing the negative direct effect. Focusing on a labor market shock in a given sector, if bordering districts are also affected by an event, the overall labor supply in the entire region will be reduced and a substitution of workers will not be possible, thus increasing indirectly the direct effects of a shock. For this purpose, the study tests if the direct effects augment if bordering districts to an affected district are also affected. The findings for this case study reveal that neighbor shocks seem to matter, but not as much as the direct effect of a shock. Secondly, and associated with the first indirect effect, disruptions in the supply-chain of foreign firms might follow, especially if production networks are highly local and multiple districts within a region are affected. Such outages in the production due to a shock might increase direct negative effects more. For this purpose, the study adapts a methodology from Acemoglu, Akcigit, and Kerr (2016) and analyzes the impact of shocks occurring along the supply chain onto sectoral FDI by utilizing the multi-regional input-output table for Indonesia of 2016. A key insight gained from this analysis is that, in general, the negative effect on FDI inflows can largely be attributed to supply-chain shocks, especially centered around the manufacturing sector. Downward-demand side shocks, in contrast, seem to benefit FDI inflows after earthquake occurrence. Most effects are found within local province production networks and not necessarily through linked supply and demand in the rest of the country. So it is conjectured that mechanism-wise the province-specific integration of foreign firms into local supply-and demand chains tends to explain the found negative effects in FDI flows. While the key focus of the paper is on the exposure to earthquakes, other disaster types, which are more climate related, are also assessed in the robustness part given their likelihood of increased occurrence in the upcoming decades.

The aim of the study is to connect several related literature streams. Chiefly, the paper contributes to the literature of the impact of disasters on FDI. The vast majority of these studies focus on a macro dimension and compare the effects on a panel of countries (on a global scale (for instance Gu and Hale, 2022; Doytch, 2019; Neise et al., 2022), on middle and low-income countries (Drabo, 2021) or on Sub-Saharan Africa (Katoka, 2021)). Only a very small subsample of this literature considers a singular country of study, for instance Anuchitworawong and Thampanishvong (2015). Most studies find negative effects on FDI inflows on a country level. Only recently, the paper by Friedt and Toner-Rodgers (2022) focuses more in-depth onto within-country effects of disasters, in their case extreme flood events, onto FDI inflows. Analyzing the effect of six extreme flood and storm events over 16 of India's provinces, they provide a key insight that FDI tends to spill over to developed regions with a large market potential following the months of an extreme event. Similar to the paper by Friedt and

Toner-Rodgers (2022) this study also considers within-country allocation patterns, yet focusing on a different disaster type on a smaller disaggregated level (districts) while considering additionally the sectoral dimension of FDI inflows.

Studies focusing on an even more disaggregated level usually utilize firm-level data. The literature on disaster effects on firm performance is a well-researched field. Notable examples of that literature are, for instance, Elliott et al. (2019) focusing on the impact of typhoons to plant sales, Cole et al. (2019) on the 1995 Kobe earthquake in Japan, Rentschler et al. (2021) on floods in Tanzania, Pelli et al. (2019) on tropical storms in India or Brucal and Mathews (2021) on Indonesian manufacturing plants after floods. Notably, Brucal and Mathews (2021) combine data from 1990 to 2015 of Indonesian plants and connect them with the EM-DAT database, similar to this study, on a district level. Their study also distinguishes between domestic and foreign-owned firms and finds that foreign-owned firms tend to see a persistent decline in output per worker. This is one of the few studies, specifically taking effects onto foreign firms within a country also into account. In contrast to their paper, this paper will consider, however, a more geolocalized version of disaster exposure while putting more spotlight on the sector-network aspects of financial flows.

While the above-mentioned papers have improved our understanding of how FDI flows change after natural disasters on a macro-level and how firms in general respond to disasters on a microlevel, my study attempts to fill in the gap between the different streams 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 of firms (e.g. Carvalho et al., 2021; Huang et al., 2022). It thereby aims to unify the different streams of literature by investigating more in-depth how FDI flows respond to disaster across time and in sector-space on a local level.

Furthermore, the paper also adds to the literature on the consequences of disasters in Indonesia. Different studies in the past have aimed their attention on the long-lasting effects of disasters in Indonesia, such as, for instance, the effects on labor markets (Kirchberger, 2017), household outcomes (Gignoux and Menéndez, 2016) or on the adaptation of manufacturing firms to disaster (Neise and Diez, 2019). This paper contributes here to the discussion by finding that disaster play only a minor role for long term trends of foreign investment flows on a local level in Indonesia.

Lastly, in contrast to many other studies, the paper does not rely on the EM-DAT (Sapir and Below, 2014) database. As discussed in Felbermayr and Gröschl (2014), the quality of the EM-DAT database is correlated with a country's GDP as the data, especially on damages, is drawn from insurance data, which again is overrepresented in richer countries. For an analysis of relatively poorer countries or of regions within countries, as is the case in rural Indonesia, this would serve as a limitation. Similar

to other recent studies, which rely more on physical exposure metrics of disasters (for instance Felbermayr et al., 2022; Kunze, 2021; Friedt and Toner-Rodgers, 2022), this paper uses in addition to district-specific labor market shocks, an earthquake metric based on highly local interpolated earthquake intensities to better proxy potential damages, even in rural regions of the country.

The article is structured as follows: in Section 2 more context on the FDI and disaster environment in Indonesia is presented. Section 3 outlines what the expected outcomes of the studies are from a theoretical point of view based on literature. Section 4 presents the data and its limitations, whereas Section 5 shows the empirical strategy. Then, in Section 6 the results are presented divided into direct and indirect effects of earthquake exposure, followed by a conclusion in Section 7.

2 Indonesia's Foreign Investment and Disaster Environment

The subsequent paragraphs will introduce the foreign investment environment in Indonesia, but it also provides an outlook about how prone many Indonesian regions are to disaster risk.

2.1. Foreign Investment into Indonesia

In general, FDI inflow into Indonesia contributes to a similar extent to the GDP as in neighboring South-East Asian countries. In the considered period between 2003 and 2019, FDI inflows increased steadily up to 2014 and making up to 2.8% of GDP, before seeing a substantial decline in 2016 down to 0.5% and has since gradually recovered back 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 a withdrawal of some multinational companies (UNCTAD, 2017). The extent and evolution is similar to the shares found for instance in the Philippines or Thailand (The World Bank, 2022a)¹. In terms of the FDI origin, the most of it is sourced from the Asian region, whereby more than 60% originate from Japan and Singapore alone (OECD, 2020).

Despite Indonesia opening up increasingly since the 1980s to foreign investment, the country is still more restrictive than many other ASEAN countries (OECD, 2020, chapter 3). These restrictions rest upon so-called Presidential Decrees, which regulate FDI inflow and can range from requiring additional forms of licensing for FDI product inflow up to banning entirely some products. Especially the agricultural and service sector remain closed off from foreign investment (OECD, 2020). As mentioned in OECD (2020) this stricter FDI regulation tends to harm consumers, yet recently such FDI protectionist policies have also been found to improve local labor market outcomes in the case of Indonesia (Genthner and Kis-Katos, n.d.). In terms of geographic allocation, initially most FDI inflow

¹Yet up to 2012 the shares of FDI inflows have been on average 1.5% lower than in the entire East Asian and Pacific region once high income countries are excluded (notably Singapore)

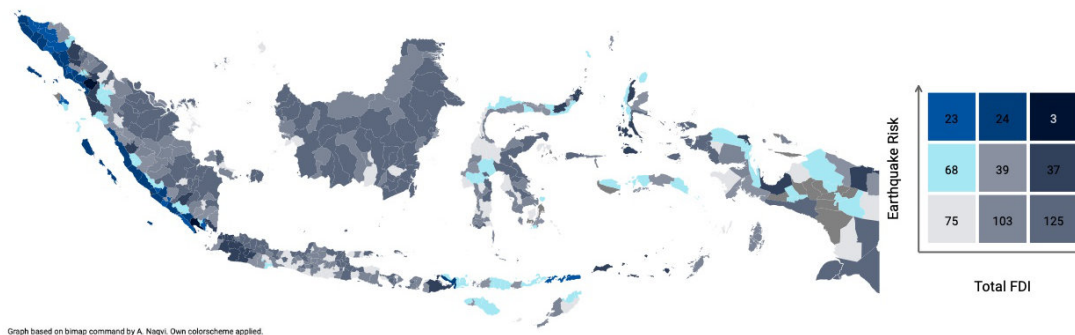


FIGURE 1: Indonesia's Investment and Risk Environment

Notes: The graph is based on FDI inflows aggregated over all available 17 years. Earthquake risk is based on 250-year return hazard of earthquakes. Composition is based on percentiles. In total 14 districts are non matched and excluded. Figure tends to mildly overestimate FDI in 51 districts.

has been attributed to the province of Indonesia's capital Jakarta, DKI Jakarta. Since 2003, the share of FDI inflow allocated towards this province dropped from 60% in 2003 to around 15% in 2019, whereas the spatially proximate province of West Java has seen persistent increase in FDI inflows, making up around 20% of all FDI inflow in 2019. Overall, FDI inflows are spatially relatively clustered, which is illustrated in Figure 1 where darker gray areas are areas with higher FDI inflows aggregated over time. The graph plots in colors, which regions are at high risk² (in blue) and receive a lot of FDI (in darker gray). One can see that high FDI areas are especially around the main island of Jakarta.

Sector-wise, Figure 2³ illustrates when and to which sectors most FDI has been allocated within Indonesia over the years. The largest inflow in FDI can be attributed to the manufacturing sector. According to OECD (2020) greenfield investments are predominantly found in manufacturing, whilst the agriculture and service sector see larger shares of M&A. Manufacturing itself has seen a decline in the total share of FDI inflows recently, because foreign firms face problems in recruiting workers (OECD, 2020). Dividing the absolute values from Figure 2 into relative shares in Figure 7, one can see that the major part of FDI received is in manufacturing making up on average over all years 43% of FDI inflows received, followed by services on average 30% and mining, quarrying and utilities (around 15%) even though mining has recently seen a rise in FDI received. Agricultural FDI is really low, likely due to the foreign investment regulation environment, mentioned above.

Recapitulating, FDI inflows into Indonesia are predominantly found in manufacturing sector and stem from predominantly other Asian regions. Compared to other country peers, the Indonesian FDI market is rather restrictive, while the allocation of FDI in Indonesia is clustered around few economic centers. Overall, foreign firms have been found to contribute to higher output in general in Indonesia, yet they have mixed effects on local labor markets, despite paying their employees better wages than

²Measured by the z-standardized historic risk of 250-year return period in *Peak Ground Acceleration* units, a metric to evaluate earthquake intensity.

³The code is adapted based on code by A.Naqvi (2020) on [Medium](#) (accessed: 18/10/2022)

local domestic firms (OECD, 2020). The above points taken together allow to generalize that FDI does seem to play a noteworthy role for Indonesia’s economy. In terms of operational risks for foreign firms, disaster risks of all kind play a key role which is why this environment will be presented next.

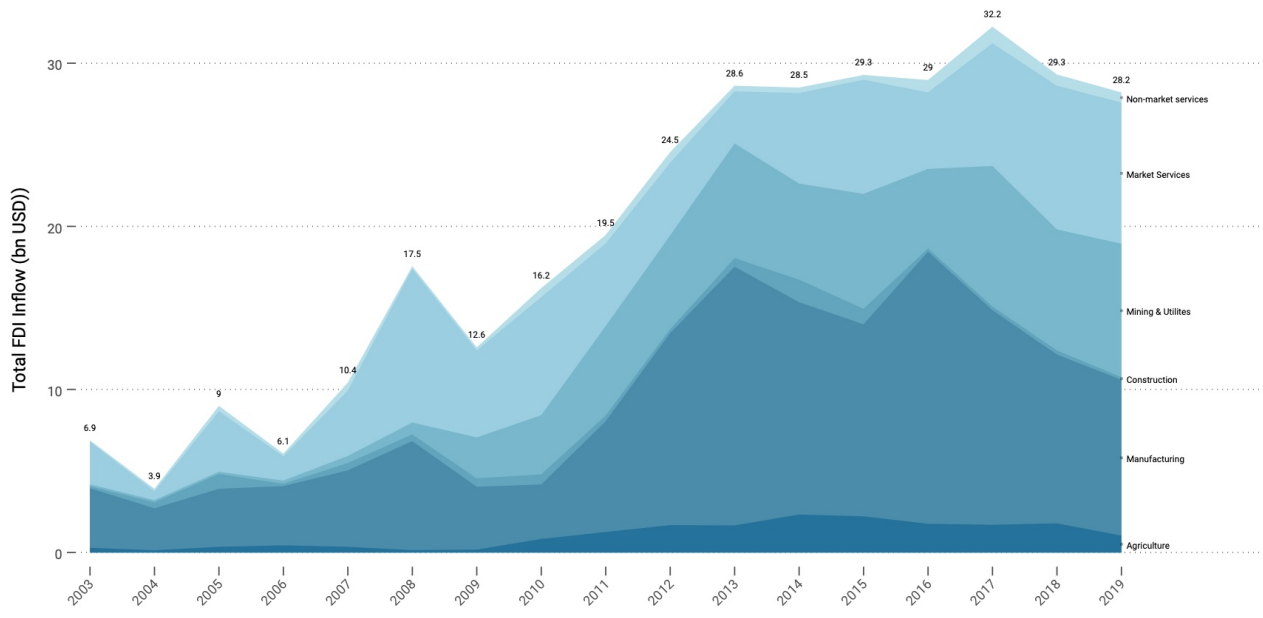


FIGURE 2: Development of FDI inflows over time by sector

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

2.2. Disaster Environment in Indonesia

Indonesia is located between several tectonic plates, notably the Australian and Eurasian plate and many more local tectonic fault systems. This makes Indonesia one of the most seismic active regions in the world. Indonesia received tragic notoriety due to the 2004 Tsunami, following a tectonic shift, which killed thousands of people in Indonesia as well as in nearby countries. Being located in proximity to the equator, Indonesia is also prone to large rainfall shocks and the associated hydrological disasters such as landslides or flood events. Finally, in parts also due to climate change, storms and cyclones are likely to become more frequent in Indonesia, even though its location in proximity to the equator makes at least cyclone exposure only a matter for the most southern and most northern regions of the country. Taking a look at Figure 3, in terms of destruction, earthquakes and their associated tsunamis are responsible for more than half of all damage recorded. They are also the most deadly disaster type in Indonesia. If one takes the victim number, people loosing their livelihood and income, as a measure, floods tend to be slightly more devastating than earthquakes. Overall, their destructiveness and deadliness provides justification, why this paper focuses specifically on earthquake exposure. Following the often used EM-DAT database (Sapir and Below, 2014) between 2003 and 2019, in

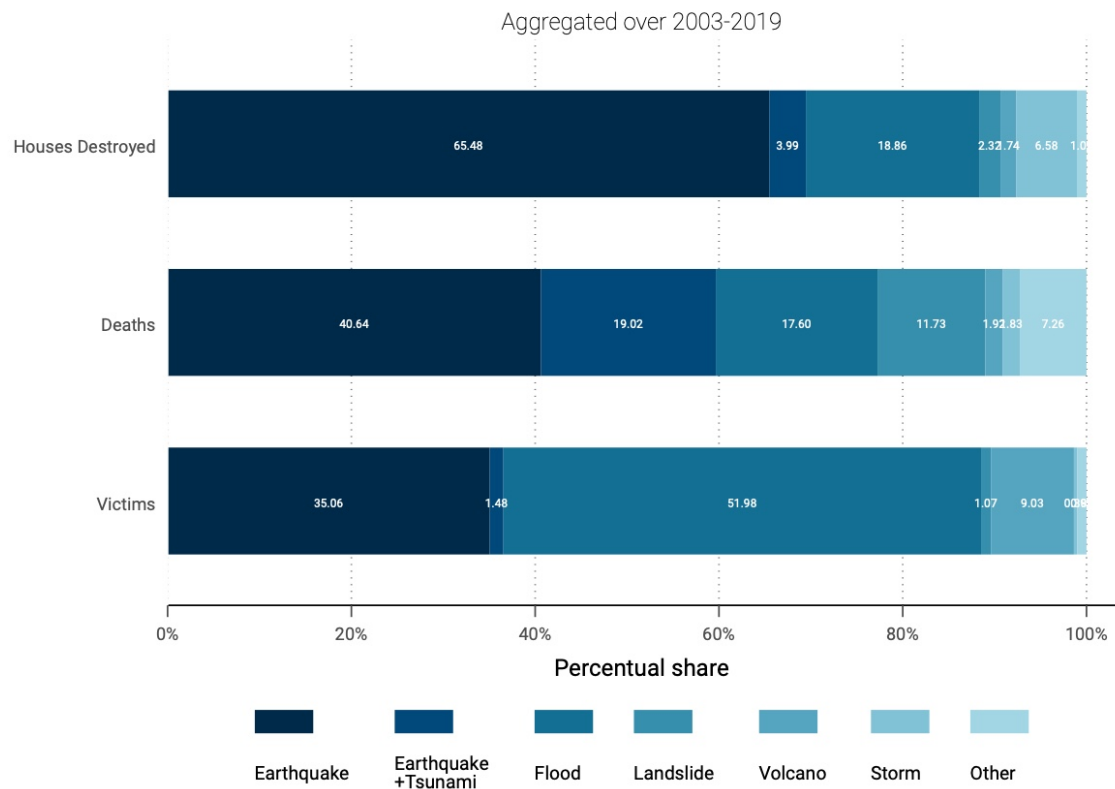


FIGURE 3: Overview on Disaster Relevance

Notes: Source: United Nations Office for Disaster Risk Reduction (UNDRR) (2022). 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.

Indonesia alone 71 geophysical events⁴ (earthquakes and the related tsunamis as well as volcano eruptions), 154 hydrological events (floods and landslides) and five major storms took place, which caused at least 25 billion USD in damages and killing almost 200 000 people, not even counting the thousands of people losing their livelihood. While spatially centered amongst certain regions depending on the proximity to tectonic ruptures, a location above sea level and the proximity to rivers and oceans, such disasters also induce large risks in business decisions for domestic but also foreign investors. The Indonesian National Meteorological Organization (*Badan Meteorologi, Klimatologi dan Geofisika*) monitors disaster risks and communicates them to stakeholders in order to deal with those risks and provide public accessible information regarding disaster risk (Global Assessment Report on Disaster Risk Reduction (UNDRR), 2020). Most other systems and institutions with the purpose to monitor hazards and streamline disaster reporting across districts have been developed following the tragic tsunami of 2004. In terms of post-disaster communication, the Indonesian National Board for Disaster Management (*Badan Nasional Penanggulangan Bencana*) manages the ex-ante prevention but also the coordination of the disaster response. There have been shortcomings in the past with regard to

⁴In this paper more earthquakes are recorded as a different earthquake measure is used, which might approximate better structurally damage on buildings locally.

post-disaster funding and aid disbursements, whereby in parts it took time to obtain aid post-disaster due to administrative procedures (Global Assessment Report on Disaster Risk Reduction (UNDRR), 2020, p.23). Such problems have been identified and are recently addressed with new policies.

Despite measures for disaster preparedness, disaster risk remains to portray a major operational risks of foreign firms, which motivates the research question of this paper: if and how does disaster risk, expressly disaster occurrence, impact post-disaster foreign investment flows. Before approaching this question, an expectation of potential results based on previous literature will be presented.

3 Theoretical Motivation

In order to build an expectation on how foreign investment flows react on a local level to exposure to disasters, it is useful to think about different channels through which disasters might impact the revenue of foreign firms. Disasters might affect a firm's production through direct channels (labor market variations, capital destruction or disruptions in production capabilities e.g. power cuts/road destruction) or indirect effects (e.g. supply chain disruptions or spatial spillovers), as for instance described in Antonioli, Marzucchi, and Modica (2021).

As a direct impact channel the labor market variation could describe the reduction in labor force due to the local workers' deaths, which, excluding inward migration, would increase wages, which is a higher cost factor for firms. Kirchberger (2017) finds that due to limited sectoral mobility opportunities, wages rise in agriculture in Indonesia following an earthquake. For a US case, Groen, Kutzbach, and Polivka (2020) show that following hurricane Katrina wages rose due to a general reduction in labor supply, combined with more labor demand in sectors connected to rebuilding such as manufacturing and construction. Another way labor could disrupt production is by workers not being able to show up to work as they might deal with personal tragedies. If labor input is reduced and/or wages rise, the production function would directly be impacted and output as well as firm profit would be reduced. The effect would be largest in labor-intensive sectors, where workers are immobile, such as the primary sector. In any case, this would serve as a disincentive to invest as long as labor markets are disrupted.

Capital is another mechanism by which disasters might impact FDI. The destruction of physical capital will require firms to replace destroyed capital, financed potentially by creating more debt. Whether the replacement of destroyed capital has a positive or negative effect on investment depends on which storyline one believes in: Cole et al. (2019), for instance, suggest that plants affected by the 1995 Kobe earthquake saw a rise in productivity after the disaster, suggesting the idea of *constructive destruction*, the idea that less productive old capital is replaced by more productive new capital. Other storylines find, for instance, a long-term negative effect on general economic growth (e.g. Hsiang and Jina (2014) for hurricanes or Mitra, Endengle, and Choi (2022) on Sub-Saharan Africa). Elliott et al. (2019) find in their study on consequences of typhoons on Chinese manufacturing plants an increase in debt and

reduction in liquidity in the aftermath, which would serve as additional obstacles for firm recovery. In Indonesia, Brucal and Mathews (2021) suggest a decline in output per worker for domestic but also foreign manufacturing plants after the experience of a flood. So the expected effects resulting from the capital channel depend on the belief in the "*constructive destruction hypothesis*". In other words, if one believes that less productive and older capital is more likely destroyed by disasters. This is a common theory and for instance discussed in connection with economic growth by Felbermayr et al. (2022) and Hsiang and Jina (2014). The ex-ante assumption of this paper is that nonetheless the capital channel will contribute negatively to foreign investment flows as investments decisions are postponed until the reconstruction of destroyed production capital is completed.

A final remark on direct effects should come from other disruptions in production capabilities. Electricity blackouts or destroyed infrastructure might also prolong the experienced production disruption. Without electricity or roads to transport goods on, firms, foreign or not, will not be adequately able to do business as usual. Using a modelling approach to assess the repercussions of earthquakes and floods in Turkey, Hallegatte, Jooste, and Mcisaac (2022) show amongst other findings that destroyed infrastructure capital has a direct effect on non-infrastructure capital and thereby directly affects the productivity of other capital. Applied work by Rentschler et al. (2021) also shows for the case of firms in Tanzania that infrastructure disruptions are indeed a key challenge for firms, even if they are located in regions not directly affected. So especially infrastructure disruption might further impair recovery from disasters until being re-build, which would suggest a spatial diffusion effect of the disaster.

Indirect effects in this paper refer to the spatial and sectoral channel: From a spatial point of view, disasters might make areas, previously popular to invest in, less attractive, which would augment the negative consequences of a disaster. Such a within-country reallocation pattern following disasters is for instance found by Friedt and Toner-Rodgers (2022). The sectoral channel refers to the idea that a disaster event might also interrupt either the supply of goods as input factors or change the domestic demand for produced goods and provided services, which would represent indirect sectoral effects. From a *supply side* perspective, Rentschler et al. (2021) find evidence that for domestic firms in Tanzania disruptions in supply chains make up to 50% of found effects. Firms seem to cope with that by extending their supply network over space. In contrast to this paper, my study will focus more on the effect on multinational firm behavior on an aggregate level. Negative supply chain effects are also found for Chinese firms after an earthquake (Huang et al., 2022) and for an earthquake in Japan (Carvalho et al., 2021). From a *demand* perspective, Elliott et al. (2019) puts forward a reallocation in sales but also in purchases from domestic buyers to foreign buyers or suppliers following typhoon exposure in China. Concerning multinational companies, Kato and Okubo (2022) show in a theoretical framework that multinational firms tend to leave the host country after disasters when the cost of using domestic intermediate inputs rises. They might, however, remain if the domestic inputs are essential for the international production of the foreign firms. In order to remain in the country it is also important that the foreign firm can substitute the reduction of intermediate inputs temporarily through low trade costs.

A final remark should go to one of the points brought forward by Oh, Shin, and Oetzel (2021). Frequent exposure to disaster risk, amongst other factors, might lead multinational companies to start adapting to the risk rather than trying to avoid the risk. So risk expectation also plays a role.

Considering the stated effects on foreign firms production in Indonesia, it is likely that in the time shortly after disasters foreign investment flows will be reduced, once because critical infrastructure might be damaged, labor market situations might have been worsened for the firms and capital might be destroyed and needs to be rebuilt. The deterioration of the labor market conditions and the destruction of capital are reflected in the way this study creates the treatment dummy: it takes both as necessary conditions, so a disaster treatment is only then defined if the labor market is affected and there are records of potentially damaging earthquakes. In the long run, however, assuming that trade costs are small enough for foreign firms and they are well enough integrated into domestic supply chains, these foreign investment flows will return to pre-disaster levels, once the destroyed capital is recovered.

4 Data

The paper is based on a balanced panel of Indonesia's 514 *districts*⁵, the second administrative level, for 17 years of which 422 are included in the analysis. In the process, not all districts could be matched over time and not for all districts data is available.

4.1. FDI Inflow Data

The key dependent variables for the purpose of this paper are the FDI flows between 2003 and 2019, before the beginning of the Cov-Sars-2 pandemic. Data on FDI inflows is obtained from 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, yet excluding investments through mergers or acquisitions. It is measured in per 1000 USD terms. In total, 24 sectors for investment are registered and are later assigned an industry code using the ISIC Revision 3 classification. There are a few limitations due to changes in the recording of investment in the period considered along with some minor issues, which are discussed below in [subsection 4.4](#). In order to be able to connect the data later, the investment information by district has been geocoded by using the second level administrative shapefile from OCHA's Regional Office for Asia and the Pacific (2021), whereby the assigned geographic coordinate refers to the centroid of each district polygon. A key concern is the frequent changes of names and divisions of districts, especially due to the decentralization policy becoming effective in 2001 (OECD, 2020, chapter 7). To avoid that FDI values are assigned to the wrong districts, all observations have been

⁵Indonesia 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.

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.

4.2. *Disaster Exposure*

Following the recent literature on disaster related studies such as Felbermayr et al. (2022) and Kunze (2021) or Friedt and Toner-Rodgers (2022) issues arise if one solely relies on recorded victims or damage data as for instance within the commonly used EM-DAT database (Sapir and Below, 2014). Problems emerging range from reporting bias to endogeneity bias, as EM-DAT relies on insurance data, which is more likely available in more advantaged areas (Felbermayr and Gröschl, 2014). Therefore, solely relying on damage and victim data is insufficient to account for a disaster's severity. This paper creates a dummy for the intensity of a disaster based on the following idea:

$$\text{Total Earthquake Shock} = \text{Capital Shock} \times \text{Labor Market Shock}$$

The total shock follows the idea that foreign firms might re-evaluate their investment if they cannot produce. This could be due to the fact that either productive capital of a firm or infrastructure is destroyed and needs to be rebuilt (capital shock) or to the fact that too many workers refrain from work to cope with the aftermath of the disaster (labor market shock). In the following paragraphs, the data will be presented how the capital shock and labor market shock are defined and how the data is obtained.

4.2.1. *Defining the Capital Shock*

As mentioned beforehand, relying on insurance data is likely biased if one considers the impact of disaster occurrence, which is why recently more often physical intensities of disasters are used. The capital shock is defined as the average recorded earthquake intensity in each economic center within a district within a year exceeding a level, which potentially causes at least minor damage. The shock will be on a district-level as this corresponds to the level of observation of the FDI flow data. In order to create such a metric one needs data on earthquake intensities over time, an identification of economic centers and a proxy for intensity, which might proxy physical damage.

First, to obtain information on earthquake intensities over time data is drawn from the US Geological Survey (2020) for the years 2003 to 2019⁶ between 6° and -11° geographic latitude and between 95° to 142° longitude. For each year, all available ShakeMaps, which are maps depicting the range of earthquakes along with their ground motion movement, have been obtained. However, only events with recorded earthquake intensity exceeding a potential damage threshold, moment magnitude of

⁶And for robustness also earthquakes from 1995 to 2002 are considered to create a dummy for pre-2003 treatments.

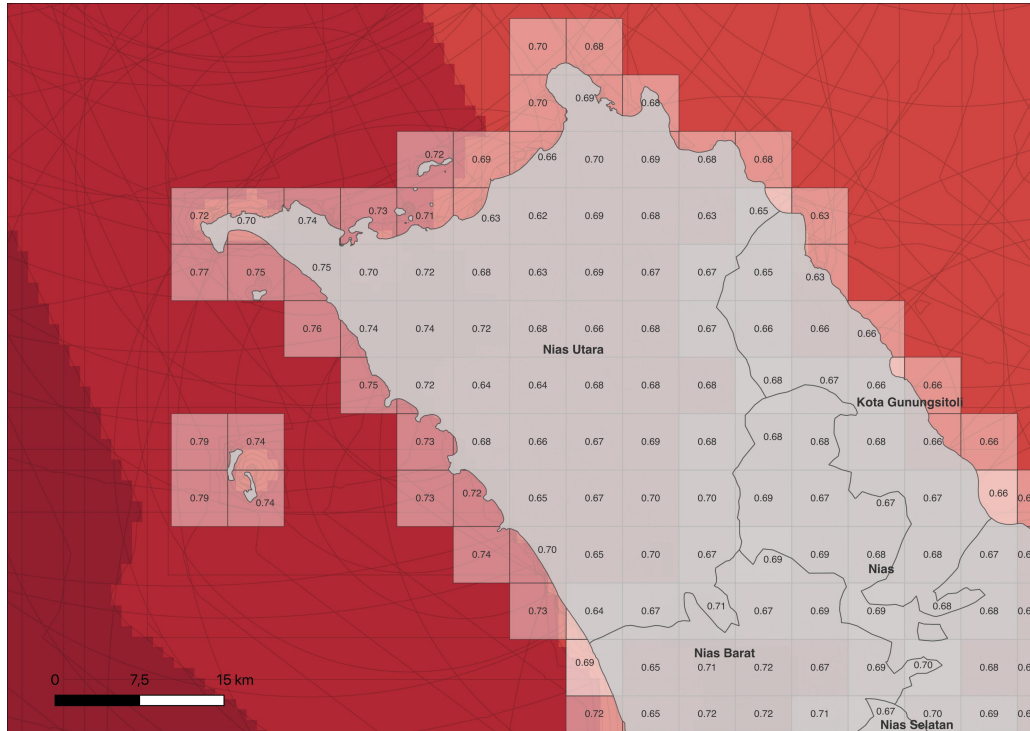


FIGURE 4: Example of a District Exposure in 2005

Notes: The figure shows the exposure of the Nias district to the earthquakes taking place in 2005. It is overlaid with the 5x5km grid. The red background color indicates the discrete proxied 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 gridcell. The map is created in Quantum GIS.

five, are included⁷, which corresponds to moderate earthquake size. In total, 897 earthquakes have been included. In order to assign earthquake intensity to a distinct district for each year all available earthquakes are converted into 1x1 km pixels, whereby each pixel contains relevant earthquake information. In the next step, the pixels are joined with a 5x5 km grid of Indonesia, whereby the respective grid cells are assigned the highest recorded value of the 1x1 km earthquake intensity values⁸. The measure used for intensity, is the *peak ground acceleration*, the speed of movements of the ground. So each 5x5 km grid cell now contains the highest recorded ground motion within that year for each given year. Furthermore, as grid cells are based on a shapefile of Indonesia, each cell also contains information on the district in which it is located. An example of how values are assigned to the grid cells is provided in Figure 4. The figure shows the 5x5 km grids of five districts on Indonesia's West coast in 2005 and their corresponding mean recorded intensity.

⁷Moment magnitude measures the size of an earthquake at its origin. It is similar to the well-known Richter Scale, but is more accurate for most types of earthquakes USGS (2022a)

⁸It is important to understand, the differences in earthquakes metrics used: the selection of the earthquake included in the study uses the magnitude measure, the "size" of an earthquake. For this, only earthquakes of at least moderate size are included. Then, the intensity used is derived from a model based on the size of the earthquake and is called *peak ground acceleration*, a metric measuring the speed of ground movements at a certain point. Albeit, the speed itself says little about the damage caused, which is why the final metric obtained is the *Modified Mercalli Intensity scale*. It is a leveled scale ranging from 0 to 10, whereby every intensity exceeding level V causes light to moderate damage to buildings (USGS, 2022a).

Second, after having obtained a metric for local earthquake intensities in each given year one needs to identify the economic center in each district. Thus, each grid cell is assigned the highest value of nighttime light within the respective year using a homogenized nighttime light series from 2000 to 2019 by Chen et al. (2021). The reason for adding nighttime light data is twofold: firstly, while GDP metrics are available especially in rural regions, they tend to fall short to accurately depict economic development, which is why nighttime light has been used in the past to improve this concern (see e.g. Sutton, Elvidge, and Ghosh, 2007; Hu and Yao, 2019). Secondly, using the nighttime light within each grid cell one can identify economic centers within each district. So for each district and year using the 5x5 km grid cells the economic center is identified as the most illuminated grid cells within each district⁹. This is done as earthquakes can be highly local events, whereas FDI tends to be allocated in economic centers. For the most underdeveloped regions, when even nighttime light might be an insufficient proxy, economic centers are classified using gridded population density based on population density measure of 2000, 2005, 2010 and 2015 by the Center for International Earth Science Information Network - CIESIN and NASA Socioeconomic Data and Applications Center (SEDAC) (2018).

Finally, after identifying economic centers and their associated earthquake intensity the data is collapsed on a district-year level using the mean intensity over all grid cells identifying an economic center. This is necessary as the FDI inflow data is also on a district-year level. In a final step, the intensity values are converted into a metric called *Modified Mercalli Intensity* scale. This scale categorizes the intensity into a scale from zero to ten, whereby everything above level five starts to damage buildings (based on USGS (2022b) and conversion shown in Table 5) and serves as a better proxy of the potential damage created. In the Appendix H it is assessed, whether the identification of economic centers with nighttime-light is accurate and whether the use of only the mean intensity by economic center instead of the highest intensity by district biases the results. One is left with the metric for the capital shock: a district is considered to be exposed to a capital shock, if within a year the economic center of a district, identified by the highest nighttime light or population density quantiles, has been exposed to a ground motion which is likely to have caused at least minor damage.

4.2.2. Defining the Labor Shock

The labor market shock is defined as the share of the local population being directly affected by an earthquake event. In order to compute that shock, one requires two data sources, the amount of people affected and the population of each district within a given year, and a definition of "being affected". Data for the affected population on a district level is drawn from the United Nations Office for Disaster Risk Reduction (UNDRR) (2022) Desinventar database, which in the case of Indonesia is updated by the Indonesian National Board for Disaster Management. In contrast to the commonly used EM-DAT

⁹Grid cells of the highest quantile of nighttime light intensity within a district-year

database of Sapir and Below (2014), the Desinventar data provides district-specific instead of event-specific data for the entire time horizon. The definition of who is "affected" by an event combines multiple variables from that dataset. For this study, "being affected" refers to the sum of people either permanently, being dead, or temporarily affected, because they are directly or indirectly¹⁰ affected by the disaster. In both cases, individuals drop out of the labor force. Instead of solely considering victims of earthquakes, the data also includes data on earthquake induced tsunami. These victims are also included as tsunami can specifically be attributed to a related earthquake event.

After having obtained the number of people affected by an earthquake event, it needs to be weighted by the local population to better proxy the disruption in local labor markets. Thus, the victim data is complemented by data of lagged population by district within a year from the INDO-DAPOER data frame of the The World Bank (2022b)¹¹.

TABLE 1: Overview of 20 Most Affected Provinces (by Intensity)

<i>Province</i>	<i># of affected districts</i>	<i>Year</i>	<i>MMI overall</i>	<i>MMI urban</i>	<i>Deaths</i>	<i>Victims</i>	<i>Affected¹⁾</i>
Prov. Nanggroe Aceh Darussalam	5	2004	8	7.8	128 728	279 556	2 830
Prov. Nusa Tenggara Timur	1	2004	9	8	33	265	169 275
Prov. Nanggroe Aceh Darussalam	1	2005	9	9	37	53 541	0
Prov. Jawa Tengah	1	2006	7	6	1 045	713 788	18 127
Prov. D I Yogyakarta	4	2006	7.75	7	4 688	1 328 641	18 109
Prov. Sumatera Barat	2	2007	7	7	13	91 477	283
Prov. Nanggroe Aceh Darussalam	1	2013	7	6	35	48 563	2 418
Prov. Nanggroe Aceh Darussalam	1	2016	8	8	101	85 256	17 683
Prov. Sulawesi Tengah	2	2018	9	9	4 125	135 306	3 311
Prov. Maluku	2	2019	7	6.5	29	202 267	1 546

Notes: The data is based on US Geological Survey (2020) and United Nations Office for Disaster Risk Reduction (UNDRR) (2022). Victims are the number of persons directly affected by the event (e.g. lost home or all crops etc.), whereas affected persons suffer secondary effects e.g. deficiencies in public services.

4.2.3. Other Disasters

As disasters are common in Indonesia, also data on other disaster categories in terms of victims from Desinventar is included. The purpose is to isolate the effect earthquakes have on FDI inflows and to not accidentally account for the effect of simultaneously appearing disasters. As the other disaster types only serve as control, solely victim data is used, which would correspond broadly to the labor market channel of the earthquake treatment dummy. Then, using data on victims of all other disaster categories included (volcanic activity, landslides, tsunamis, flood, storm, drought, forest fire and tidal waves) a dummy is created to account for all non-earthquake related disasters within a given year and district. In the Appendix E furthermore data on precipitation is used to model capital shocks for flood events, as floods are the second-most devastating disaster types in Indonesia, but the data sources are

¹⁰Per UNDRR (2022) 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 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"

¹¹The population data is only available until 2014. All years after 2014 are imputed using the district-specific linear population trends

explained within the respective section.

4.2.4. Risk Measures

To control for district-specific and disaster-type-specific risk measures, dummies are created to serve as proxy for disaster risk. These dummies are based on probabilistic risk maps¹² for earthquakes (UNDRR, 2017b; Cardona et al., n.d.), floods (UNDRR, 2017a; Cardona et al., n.d.), landslides (International Centre for Geohazards and Smebye, 2018; International Centre for Geohazards / NGI and Smebye, 2018), tsunamis (International Centre for Geohazards / NGI and Lovholt, 2009) and forest fires (UNEP/DEWA/GRID-Europe and Peduzzi, 2014). These maps have been created originally for the Global Assessment Report on Disaster Risk Reduction of 2015. For disaster categories not covered, the main disaster data from Desinventar (United Nations Office for Disaster Risk Reduction (UNDRR), 2022) is used. For each disaster category (earthquake, landslides, volcanoes, tsunamis, floods, droughts, forest fires, storms and tidal waves) a dummy is calculated ranging from zero (no to little risk) to four (high risk). The computation of these risk measures is briefly explained in the heterogeneity section of the Section 6 and in-depth in Appendix I, where also validity checks on them are included. Only two of these indices are considered in the main analysis: the district-specific time-invariant earthquake risk as well as the district-specific time-invariant *composite hazard index*, an overall disaster risk metric, which is the sum of all individual disaster risk dummies, and which is based on a paper by Emrich et al. (2022).

4.3. Additional Data Sources

Another key data source used in this paper is the interregional Input-Output table of Indonesia using domestic transactions over 34 Provinces and 17 Business Fields from 2016 (Badan Pusat Statistik, 2021a). This data is used to create linkage variables between provinces and sectors.

In order to account for economic activity in each district, the same data series on nighttime light as for the economic center identification is used (Chen et al., 2021). As the nighttime light values are defined on a 5x5 km grid level, a mean is created by district and the value is negative hyperbolic sine transformed. The variable shall proxy economic development, especially for rural areas where GDP measures tend to fall short. Similarly, as used in the labor shock, the amount of total population is drawn from the INDO-DAPOER database of The World Bank (2022b). Investment might be attracted to areas with higher population due to more available work force and usually better developed infrastructure. Thus, the total amount of population is included in logs as a control of a district's attractiveness to FDI¹³. From this database also data on sectoral GDP including oil and gas in million IDR (domestic currency) at a constant price (2008), the total of people in the labor force, the morbidity rate

¹²These maps show which areas would be effected by an event of a given return period.

¹³As mentioned before, the population variable is imputed after 2014 with district specific linear trends.

in percent and the poverty rate in percent is drawn. The data, mostly based on data from Indonesia's Statistical Office, is not available for all the years and is only used as extended controls. The sectoral GDP variables are included to compute the share of manufacturing production within each district and year. As Figure 2 has shown, the vast majority of FDI inflow is allocated in the manufacturing sector. As a high production in manufacturing might incentivize FDI inflows through local production networks, it is included as extended control. To create the control for each district, first the total GDP is calculated as the sum over all sectoral GDP values and based on that the share of manufacturing GDP over total district GDP is calculated. The sectoral GDP values are only available from 2010 onwards. All values before 2010 use the shares computed for 2010. The total people in the labor force is similar to the total population included to account for labor market potential. Morbidity rate and poverty rate are used as alternative proxies for economic development. The underlying assumption is that poverty and morbidity are signs of lower economic strength of a district, which might discourage foreign investment.

The main data source of FDI inflows provided by Indonesian Investment Co-ordinating Board (BKPM) (2021) includes also information on domestic investment flows. These values are also included in some specifications as extended control. Domestic investment increases the attractiveness for foreign investment and facilitate greenfield investment, if they help for instance to create local supply chain networks for the foreign multinational company.

Data on foreign aid comes from AidData GeoQuery (Goodman et al., 2019) and contains the amount of World Bank ODA by district. Foreign Aid will be used in an extended control to baseline regression under the presumption that the presence of foreign aid might attract foreign investment, if for instance public infrastructure is improved.

Then a variable to Bartik-like control¹⁴ for share of migrants within a district is created. Information on migration data on people being foreign born is drawn from the Population Census of 2000 of Indonesia acquired from the IPUMS (Minnesota Population Center, 2020) and is interacted with the five-year migrant stocks recorded in the UN Economic and Social Affairs (Population Division) (2019)¹⁵. The population census data is available on a district level and thereby has again been geocoded, which is why it is possible to recover a rough proxy for the initial share of foreign born people within each district in 2000. This share can then be interacted with the changes in Indonesian migrant stocks over time, to obtain a variable for relative migrant growth within each district¹⁶. The final Bartik control

¹⁴The name Bartik-control refers to the principle of a Bartik-Shift share instrument common in the migration but also in the trade literature. A common application is to instrument migration, which is endogenous due to omitted variables, with an interaction of the initial composition of migrants with the change over time. It is only "Bartik-like" as the extent of migration data is limited and the control is not used as an instrument.

¹⁵Migrant stocks are available for the years 2000, 2005, 2010 and 2015. The calculation in migrant growth therefore covers four periods (2000-2005,...) in which the value of the growth rate is assumed to be the same. This means if the migrant stock growth is calculated to be 2% in 2003, then it is also assumed to be the same in 2004 and will change from 2005 on.

¹⁶In the methodology of the Bartik shift-share, the "share" refers to the weights of migrants in each district in 2000 from the Census data and the "shift" refers to the changes over five year in absolute migrant stocks in Indonesia.

is then standardized using z-scoring. A control for migration is included as in literature it has been discussed that migration and FDI are strongly correlated (see for instance Javorcik et al., 2011; Kugler and Rapoport, 2007). All additional controls for robustness checks are described in the respective sections.

4.4. Overview and Discussion on Data

An overview of the data is provided in Table 2. Following the vast majority of literature on the effects of natural disasters on economic growth, it does not come as a surprise that 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 and is addressed empirically by using matching methods as robustness in Appendix B. The selection-into-treatment issue is one of the most common issues in the disaster literature as the same argument can be made for other disaster categories also (for instance, districts with rivers are more prone to flood events). In terms of systematic differences across districts, the paper will for once include the differential controls in an extended baseline model as well as in decomposing effects based on historic risk measures. Apart from the selection into treatment, two other data limitations are noteworthy.

Firstly, the dependent variable for FDI inflow 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 in the data set. Thus, there is a likelihood that the FDI data does not sufficiently reflect FDI inflows into Indonesia. According to OECD (2020) the data covers investment realizations by foreign capital investment companies, including those below 10% share and with joint ventures of local partners. This practice is likely to inflate the FDI inflow recorded. Hereby it is also noteworthy that foreign share ownership is not recorded, which is why the evolution of the BKPM data might differ from the official nationwide statistics. Compared to national aggregated total FDI inflows, it seems that the used data source underestimates FDI inflow received in agriculture and the service sector by around 4-6% (OECD, 2020). Yet, it is the only data available on a second-administrative level.

Secondly, the final treatment sample is rather small. While considering initially 896 earthquake models, the final dataset contains only 207 urban centers exposed to an earthquake potentially being damaging to capital¹⁷. This is not surprising as stronger earthquakes are relatively rare, while they might predominantly affect large shares of less inhabited land. The final conditioned treatment sample (ex-

¹⁷Precisely, only earthquakes with the Modified Mercalli Intensity above level V are considered damaging. The metric has been obtained by converting the speed of ground motion (peak ground acceleration) to a bounded scale from 0 to 10 (Mercalli Intensity Scale).

TABLE 2: Descriptive Statistics

	(1)	(2)	(3)	(4)
	Full sample	Control	Treated (MMI6+)	Difference (3)-(2)
<i>Dep. Variable</i>				
Arcsin (FDI inflows) in 1000 USD	5.70 (5.379)	5.82 (5.458)	4.87 (4.726)	***
<i>Main controls</i>				
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)	***
<i>Risk Measures</i>				
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)	***
<i>Additional Controls</i>				
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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

cluding treatment reversal and any other disaster exposure than earthquakes) is even smaller, causing the treatment group to be rather small. Next, the empirical strategy is introduced and it is discussed if and how it might address some above-mentioned concerns.

5 Empirical Strategy

The paper investigates the impact of earthquake exposure from three different sides: first, it takes a temporal perspective to see how foreign firms respond to a disaster shock. Secondly, for spatial aspects, the paper investigates if 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.

5.1. Estimation Strategy

5.1.1. The temporal perspective

For the temporal perspective, a dynamic difference-in-differences approach is used of the following form:

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

The dependent variable f_{ijt} is 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 4. The dummy equals 1 if at least a single person is 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 condition is fulfilled the dummy equals zero¹⁸. In Equation 1 also the four forwards and four lags around the treatment year of any earthquake between 2003 and 2019 are included to add pre-trends and post-treatment periods. 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. ω 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 which are treated more than once, which is assessed in the robustness section with an estimator as suggested by Chaisemartin and D’Haultfoeuille (2022) allowing for treatment reversal. Furthermore, in order to isolate the effect of earthquakes onto FDI without contagion through other disasters, a dummy is created to control for simultaneously occurring other disaster types. This dummy equals 1 if more than 20 people are affected by any other disaster type than earthquake or earthquake induced tsunamis. Data on the affected people is taken from the Desinventar database. 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 . In Appendix I, this condition is excluded and the arbitrary cut-off of 20 people affected for this dummy is changed.

¹⁸Admittedly, compared to the calculation of the total shock in Section 4, having a binary dummy as a final results does not fully exploit the complexity of the shock calculation. The described calculation of the shock, using the labor and the capital channel individually, is used in the Appendix D for the classification of extreme outlier events as well as in the Appendix G to test for the bias induced by the used shock definition.

5.1.2. 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:

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

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.

5.1.3. The sector-network perspective

For analyzing the sectoral outcomes, the paper follows broadly the approach by Acemoglu, Akcigit, and Kerr (2016). Using multi-regional input-output tables for Indonesian provinces from 2015 (Badan Pusat Statistik, 2021b), up- and downward linkages are calculated¹⁹. Upstream linkages are used to show the impact of a supply-side shock to foreign investment, whereas downstream linkage shocks correspond to the demand-side shock. Before presenting the estimation strategy, it is important to understand the shock used in this approach varies from the one in the temporal and spatial approach. The methodology still relies on the dummy variable D used beforehand being one if at least a person is affected within a district and the economic center being exposed to an earthquake with damage potential. Yet two extensions are included: the sectoral dimension is added and the input-output data is on province-level only, so the shock needs to be aggregated and account for the sector dimension. To incorporate both the new within-sector shock $Shock_{sijt}$ in sector s , province j and year t over district i is defined as

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

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. As alternative this weight is also computed using employment shares and using a time-variant version of the weight. The interaction of district-sector weight and dummy of exposure will be then aggregated on a province level. The total shock corresponds to the share of sector GDP affected within a year and province. For instance, if

¹⁹The I-O table is sector-wise aggregated to match the corresponding FDI sectors and converted to the Leontief inverse matrix

only one district is affected within a province, but it makes up 80% of the production within a year, then the shock variable will be 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 way:

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

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 words, the up- and downstream shocks are linkage-weighted sectoral shocks occurring in other sectors than 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 log of population by province lagged by one year. Equation 3 compares the effect of within sector-province shocks to those provinces within the same sector which are not or 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. An extension of Equation 3 is a division of the linkage shocks into within-province supply chain shocks and shock resulting by supply and demand outside the province of interest. This should be considered as local production networks might be more tightly connected than nation-wide production networks. In order to test for local production network effects, a final regression conducted

follows the following form:

$$\begin{aligned}
 f_{jst} = & \gamma f_{j,s,t-1} + \beta_1 Shock_{j,s,t-1} + \beta_1^{up} Upstream_{j,s,t-1}^{Prov} + \beta_2^{up} Upstream_{j,s,t-1}^{RoI} \\
 & + \beta_1^{down} Downstream_{j,s,t-1}^{Prov} + \beta_2^{down} Downstream_{j,s,t-1}^{RoI} \\
 & + \Gamma X_{j,t-1} + \epsilon_{jst}
 \end{aligned} \tag{4}$$

Hereby, the *Upstream* and *Downstream* measures of Equation 3 are each divided into the within-province linkages, the two variables *Up-/ Downstream^{Prov}* and the rest of Indonesia linkages *Up-/Downstream^{RoI}*. This is done to see if effects of a supply-chain shock substantially vary depending on the spatial origin of the earthquake: either originated within the province of interest itself or originated in distant provinces of Indonesia.

5.2. 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 treatment as after all Table 2 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.

Reverse causality is not a major threat here as the direction of the effect of disasters on FDI is one-sided. 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 to 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 are impacted by 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. Then, in Appendix B bias through (temporal) SUTVA is tested using a methodology by Imai and Kim (2019), whereby pre-existing trends in the outcome variable as well as trends in the controls are used for building matched control groups. Finally, all models mentioned above ignore the staggered adoption design of treatment, which according to Goodman-Bacon (2021) might lead to biased estimated due to negative weighting of estimates. In the robustness section it will be assessed to which 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 Chaisemartin and D'Haultfoeuille (2020). The issue of violation of SUTVA, which indeed is a main concern for this paper, is extensively discussed in Appendix B.

To conclude, one needs to keep in mind that this paper mainly considers earthquakes. Indonesia, however, is exposed to a multiplicity of natural disasters. These disaster types are often intertwined: cyclones might bring damage in the form of a storm together with heavy rainfalls or an earthquake in the

ocean might trigger a tsunami causing additional damage. To account for this matter, in [Appendix F](#) it is at least discussed how classes of natural disasters (such as climatological events as a whole) impact FDI inflows as a robustness check. Hereby, especially floods as second most devastating disaster category in Indonesia are considered individually in [Appendix E](#).

6 Results

The section is divided into two main parts: first, the general impact of earthquake exposure as a direct channel on foreign investment is analyzed. Then, it is also tested if the results vary across different subgroups. Then, it is tested if proximity to disasters matter and if so, which role the sectoral level plays. For this channel, also the industrial linkages are considered, which represent the indirect channel through which earthquakes might impact foreign investment. Robustness checks are briefly summarized, whereas extensive descriptions are provided in the appendix.

6.1. Direct Temporal Effect of Earthquake Exposure

The key effect of experiencing an earthquake within an economic center of a district can be seen in [Figure 5](#). 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 5](#) use different specifications: the first is the unrestricted baseline model (dark blue connected line), which compares the impact of the disaster in affected districts with those not affected, controlling for lagged nighttime-light as economic proxy and lagged population as proxy for amount of people at risk as defined in [Equation 1](#). The model includes district-, time- and province-year fixed effects and is clustered at the district level. Furthermore, districts are excluded in which more than a single earthquake occurred and districts are excluded in which within the earthquake treatment year another disaster not linked to earthquakes (such as storms) took place as it would bias the estimates. The second model (lighter blue with dashed line) excludes additionally also districts in which in the five years prior to 2003 (the first year of observation) disasters occurred as one might have a carryover effect to the treatment period. Lastly, the final model adds domestic investment, the log of people in labor force, the manufacturing share as share of GDP, the morbidity and poverty rate as well as a proxy for migration as additional controls. An overview of the results can be found in [Table 6](#). 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% level²⁰. 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 measure, 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 intense industries. The extended controls in Column (3) show positive effects of domestic investments and higher man-

²⁰Conversion follows Bellemare and Wichman (2020) (equation 11) of arcsin-dummy conversion: $exp(\beta) - 1$

ufacturing share within districts. Migration and morbidity are insignificant, whereas higher poverty rate tends to decrease FDI inflows, which all follow the standard economic theory. If one is interested in a more disaggregated time category, the same regression as Column (1) is re-run on quarterly level data and shown in Figure 8. It is noteworthy that on the quarterly level the shock dummy excludes the capital shock within the treatment definition²¹ and considers solely, whether people are affected are not. So the dummy in Equation 1 take the value one if at least 15 houses are destroyed. This value appears arbitrary, but it has also been tested if results still hold using other thresholds. One can notice in the Figure 8 that the first significant drop in FDI inflows is observed three to four quarters after the disaster, while another drop can be seen seven to eight quarters after, which confirms the found reduction in the year following a disaster on an aggregated level.

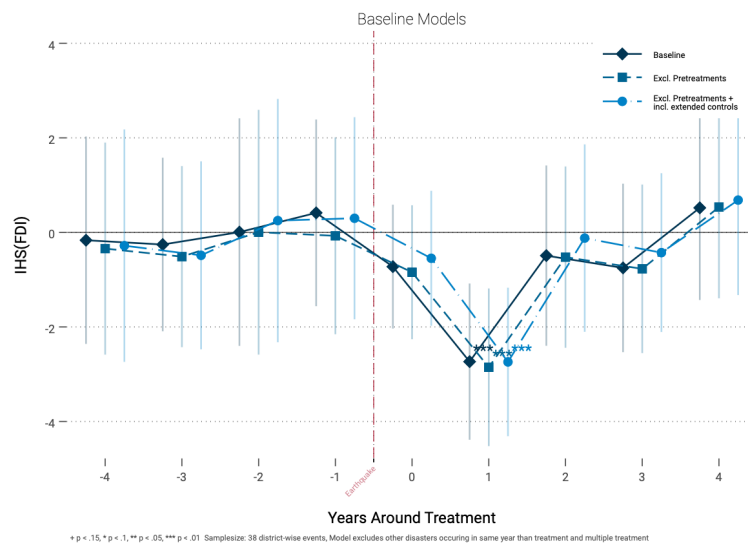


FIGURE 5: Dynamic Treatment Graph of Exposure to Earthquake

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(nighttime-light) and logged and lagged population as core controls. The corresponding R^2 is approximately 0.68 and the estimates are based on district-clustered error-terms.

6.1.1. 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 and here briefly summarized:

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

²¹The reason is that during the assignment on grid cell level data is lost in areas where multiple earthquakes occurred (overlapping intensities).

this issue is entirely ignored, which might lead to wrong estimates. [Figure 9](#) 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 the one of the baseline specification in their extent and significance. More information is provided in [Appendix B](#). By using the DiD_t estimator of Chaisemartin and D’Haultfoeuille (2020) within this section it is also evaluated, if results of the baseline estimation still hold if one allows for treatment reversal. In this case, also districts with multiple treatments are included in the regression model. The results seem to be comparable. Finally, it is tested how results change if one allows for dynamic carryover effects of the dependent variable in addition to treatment reversal, meaning that past FDI inflows might impact future inflows even after an earthquake treatment. Using a matching approach combined with a difference-in-difference strategy based on Kim, Wang, and Imai (2018), it is still found that in the two years following a disaster FDI is substantially reduced. So overall, the results appear to be robust to econometric specifications.

Lastly, it is tested if specific outlier events drive the results. [Figure 10](#) shows in the left panel the mean estimates of the baseline regression and in gray the estimates excluding each time a distinct event. So from all available earthquake events, one earthquake event is dropped at a time and then the baseline regression is re-run to investigate how the estimated coefficients fluctuate. While the β coefficients tend to vary to a certain extent, taking the mean variation of the coefficients (right panel) one can notice that on average the coefficient does not vary more than 0.005 point estimate from the baseline regression if in each iteration one singular event is excluded. Overall, this brief test confirms that the results are also valid once individual events are excluded.

6.1.2. *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 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 non-existent. Similarly, the response in FDI flows might depend on the stock previously invested. The more one has invested in a region, the higher is the individual cost of an earthquake. Therefore, the effects might vary depending on initial capital stock invested. These two channels, the risk expectation and capital stock, are investigated in this subsection. But first it needs to be clarified, how the model distinguishes for disaster risk and investment stock.

In order to divide the sample into the relative risk likelihood, the five maps for risk measures mentioned in [Section 4](#) are used. In short, these maps are merged with Indonesia’s 5x5km grid to obtain five grids for Indonesia for the five disaster categories (earthquake, flood, landslides, forest fires and tsunamis).

As the different probabilistic hazard maps refer to different return periods or even to different types of measures, they are not directly comparable to each other. Thus, for each of the five disaster grids, each grid cell is standardized using z-scores within the respective "risk value"²² to the nation-wide "risk values" of all grid-cells of Indonesia. Then event-type specific z-scores for each grid cell are averaged to obtain a mean z-score for the entire district as the FDI data is on district level. For the other disaster categories for which no hazard maps are available (volcanoes, storms, droughts and tidal waves) district-specific z-scores are directly computed²³ using data from the Desinventar database. Following Emrich et al. (2022) the event-specific z-scores are converted into dummies ranging from one (no to low risk) to four (high risk). The computation of the dummies is done in the following way: the disaster-specific dummy equals 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 dummies are then aggregated using the formula:

$$CHI_i = \sum_{c=1}^9 x_{ic}$$

So x_{ic} is the recoded standardized risk score for district i and disaster category c stands for all nine disaster categories. The composite hazard index reflects the district time invariant index for multi-hazard disaster risk, which is used in Column (1) and (2) of Table 3 to divide the sample into above and below median composite hazard. Column (3) and (4) use the dummy for time-invariant earthquake risk (which is already included in computing the composite hazard index) to divide the sample into above and below median earthquake risk.

Next, to divide the sample into how much has been invested initially, 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 on FDI stock.

Table 3 presents the effects of the analysis in Column (1)-(4) based on either overall risk or on earthquake risk and in Column (5) and (6) it is based on initial FDI stock. The results show that for Column (1) and Column (3), so for the risk measures, 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

²²The "risk value" refers to different measures in the different maps. It might refer to the mean frequency of event occurrence within the 5x5 km grid or to the amount of pixels affected within a 5x5 km grid if extreme events take place. It is important that within the event type the metric is consistent across the entire 5x5km grid.

²³The calculation by event-type is based on the total number of events within the 17 years within a district in comparison to the mean amount of events taking place nation-wide of that disaster type within the 17 years.

treatment year and year after. These effects are not found for above median risk districts or after period 1 past disaster. 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 has been 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 confirm the hypothesis that higher initial investment might cause stronger response to shocks than if less has been invested.

TABLE 3: Dynamic Difference-in-Differences: Heterogeneity

	Composite Hazard		Earthquake Risk		Initial FDI Stock (2003)	
	(1)	(2)	(3)	(4)	(5)	(6)
	Below Median	Above Median	Below Median	Above Median	Below Median	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> ²	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 on district level.

6.2. Indirect Effects in (Sector) Space

After having investigated the repercussions of earthquake events over time and different subgroups, it is analyzed what are the indirect impacts onto FDI, meaning what are the effects of shocks in proximity and through network linkages.

Table 4 presents the impact on FDI inflows based on 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 on the treatment dummy and use only the labor market or the capital shocks, but do not combine them as done in Column (1). So the treatment dummy in Column (2) considers only districts where at least one person either died or is directly affected as treated, independently if an economic center is exposed to a physically intense earthquake or not. One can note in Column (2) that 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 substantially 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 on a 10% level. These effects tend to persist even up to two periods after the disaster. Column (3) in contrast to Column (2) only regards districts, where the economic centers are physically exposed to a damaging earthquake, independently on the number of persons affected. 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. Additional tests on distance to affected regions, especially distance to an event of each economic center are shown in [Appendix C](#). There it is based on empirical evidence conjectured that distance of economic centers to disaster districts do appear to matter, with the proximity having larger effects on FDI inflow. 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. Besides proximity to a disaster area what might matter more is the fact how well foreign firms are integrated in local supply chains as, for instance, brought forward by Kato and Okubo (2022). The following paragraphs will present evidence that indeed it appears that for well-integrated sectors earthquake exposure does appear to have heterogeneous effects.

Before focusing on the linkage approach, [Figure 11](#) shows the results of [Equation 1](#) if one extends the model on district level over ISIC Revision 3 classified sectors. On a district level in the year after the earthquake (right panel) one can observe negative effects for all sectors. Manufacturing, utilities and transport, storage and communications tend to be the most affected sectors. The least affected is mining and construction. Nonetheless, all the found effects are comparable to the baseline aggregated estimates. In the next step, the methodology of [Equation 3](#) is used.

[Figure 6](#) visualizes the impact of sectoral shocks on FDI in different sectors following a shock on a province level through direct and indirect effects. To be precise, what is measured are two different effects. Once there is the sector-province specific effect of a disaster shock. In other words, what is measured is the repercussion of a 1% increase in affected sectoral GDP stock within a province and a year onto the same sector's FDI inflows into this province. To illustrate this, imagine some districts of a province are affected by an earthquake in a given year. If these affected districts account for 60% of the province's GDP in a distinct sector, the shock variable measures how does FDI inflow into the

TABLE 4: 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> ²	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 at least any person is 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.

sector change if one percent more of the sector GDP is affected. The effects of higher shock exposure can be found in the first column of the upper panel in [Figure 6a](#) converted into a percental change. Only cells are filled in which the p-value of the coefficient is below the 10% threshold. 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. As one might notice, the results are substantially different to the ones on a district-level shock, which are strongly negative. Four potential reasons might explain the difference: first, the shock used is on another scale (one percent GDP shock vs. dummy if an economic center within a district is exposed to an earthquake). The second reason could be 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

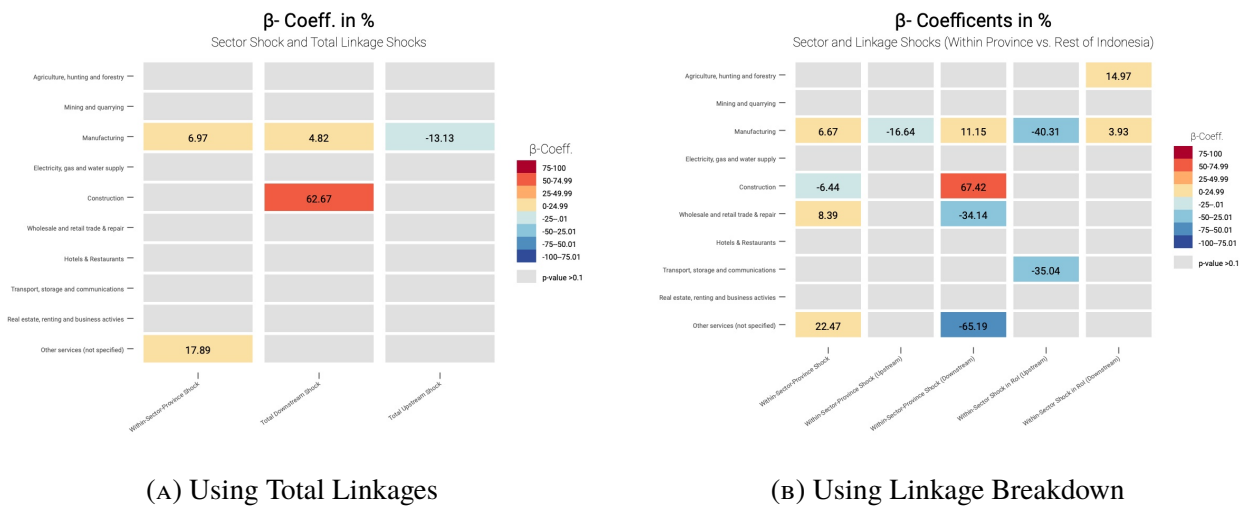


FIGURE 6: Effect on Sectoral FDI via linkages

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 and Equation 4. All earthquake events are included and each regression includes lagged and logged nighttime-light and population values as core controls.

aggravating the negative effects on a district level, which is discussed in the next paragraph. The other two columns in the panel of Figure 6 show the consequences of a one percent increased shock through sectoral GDP weighted up- and downward linkage values (the sum of rows or columns in the Leontief inverse matrix). So in simple terms, one considers how much a 1% increase in indirect supply and demand side shocks changes FDI inflow in the affected sector.²⁴ The second column upper panel in Figure 6a indicates that downstream-demand side shocks lead to 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%. Taken together, the tables reveal that the most concerned sector following an earthquake on a province level tends to be manufacturing. The shock is not unilaterally negative for sectoral FDI. It rather appears that it matters through which channels the shock touches FDI, whereby especially supply-chain disruptions are problematic for foreign investment. One should keep in mind while interpreting the results as shown in Figure 2 that due to the used data source the manufacturing sector tends to be the industry with the least non-zero FDI inflow data.

The right panel of Figure 6b investigates an additional channel: not only does it regard up- and downward linkaged shocks, but also considers the origin of the linkage by differing between within-province linkages and rest-of-the country linkages. It follows the estimation of Equation 4. The working hy-

²⁴The shock itself, is nothing more than a double interaction term: first, a province-sector shock is computed ("how much of a province's industry is affected by an earthquake in a given year") using district GDP weights over total GDP by sector within a province and is interacted with district shock dummies. Second, the relative province-sector shocks are interacted with the relevance the province and the sector have within the supply chain for the sector-province of interest.

pothesis is that shocks will matter more within province networks, assuming more local production networks. Again, the first column shows the effect of a within-sector-province shock. Here more significant effects are found in comparison to the previous ones. This is likely due to more within regressor correlation. 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 inflow 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. So they benefit solely if there are shocks requiring more construction work originating on the demand side. The next columns are divided into within-province linkage effects and the linkage effects with the rest of the country (assuming a closed economy case). For a one percentage supply-chain shock, 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 in the linkage weighted demand side.

A one percent increase might weight more in the regression models for the rest-of-the-world shocks as mentioned before the shock here is an interaction term of the province-sector specific shock and the province-sector specific linkage value. **Table 7** shows the descriptive statistics of the shocks and one can notice that the mean of shocks within province-sector are in linkages 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 regression²⁵.

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 sides tend to benefit the manufacturing and construction sector as it is likely that the demand for intermediate goods for instance for reconstruction might increase. For wholesale and trade as well as other services sector, one sees a reduction as it is likely that direct demand for these services is reduced. Shocks occurring upstream reduce in general FDI inflow as it might cause production interruption, which is generally bad for business.

²⁵Note also that the maximum impact is for downstream larger than 100. This is because the total downstream linkage for particular sector-provinces is larger than 1. Interacted with the shocks it is possible that the absolute value thereby exceeds 100. It is only the case for two observations.

6.2.1. Robustness

In order to validate the found effects in space and sector several robustness checks are run.

First, it is tested 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 paper. In contrast, it seems that the closer an economic center is located to an affected district the larger 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 parts 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, includes productivity per worker already. These different channels captured are the most likely reasons for the differences. Both regression results are similar to the extent that upstream shocks tend to impact FDI negative, whereas downstream shocks have a positive sign on FDI, generally speaking.

6.2.2. Limitations

Although being used often in post-disaster analysis, multi-regional IO tables suffer extensively from the fact that they are static. The linkage values here are used from 2016. Yet, a disaster might change supply-and demand networks within a country, which is ignored in this setting. 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 consider also, 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). For this setting, IO shall nonetheless serve the purpose of the paper as the focus is more on the general effects onto FDI inflows than on production-network shifts.

6.3. Additional Robustness Checks

In addition to the previous mentioned robustness checks, it is also tested if 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 G](#) shows how reliable the shock metric is by modifying individually the components of the shock variable (the capital shock and the labor shock). Individually taken the shocks seem to also matter and the physical capital shock proxy indeed tends to increase damage with increasing strength. In terms of controls, nighttime-light overall tends to sufficiently proxy GDP in the case of Indonesia ([Appendix H](#)) 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 of the official disaster management office as well as the often used EM-DAT database.

A last remark refers to additional checks on other disaster types. [Appendix D](#) to [Appendix F](#) test for extreme events in earthquakes, but also for floods and show general effects using other disaster categories such as storms or hurricanes. Extreme district-events vary from the baseline results, likely due to a stronger selection into treatment as the ex-ante risk in these districts is larger. 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 than for earthquakes are found, 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, thus the results on disaster category-wise should be taken with caution in its extent.

7 Conclusion

Previous literature dealing with the impact of natural disasters on foreign investment are mostly based on cross-country studies or on firm level data. Only few papers focus on the impact of FDI within a country. This study contributes to literature by answering questions on temporal, sectoral and to a limited extent on spatial dynamics of FDI inflows following the occurrence of earthquakes exposure in Indonesia's economic centers between 2003 and 2019. For this reason, a shock variable is created as the union of physical intensity and the percentage of people affected to account for the effects of earthquakes through a labor or a capital channel. 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 an ex-ante lower risk as the disaster might be less anticipated as well as in districts with 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 it seems 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, the paper finds that the strongest effects are found for manufacturing, which is also the sector which receives 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. Most sectoral effects are found within-province linkages, which would explain why in the case of bordering districts being affected the effects aggravate the reduction in FDI inflow; the within-province supply-side for intermediate goods are impacted. Construction seems to be one of the sectors benefiting from earthquake events, especially if it takes place within the same sector or downstream in the supply chain. Thus, overall one might carefully claim that the found negative effects in FDI inflows are caused by intermediate disruptions in the supply of goods, being necessary for production, which predominantly play a role within regional production networks. This storyline 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 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), this study observes a rebound effect for FDI in the years following a disaster.

This differences in long-term effects in literature also contours one of the limitation of this paper: its external validity. Countries are globally unequally affected by disasters, specifically now through climate risk. On a smaller scale, there is a similar heterogeneity of disaster exposure within countries and even within districts of the countries. 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 case.

While this study seems abstract from a distance, talking about financial flows into regions and how they are changing following disasters, there are true 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 neither substantially reallocate nor 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 for 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,

which take bottleneck productions into account as for instance described in Hallegatte (2008). Also, the findings of the reduction in flows should be complemented with extensive analysis on a firm level response as for instance discussed in Brucal and Mathews (2021), yet with a stronger emphasis on the production network of the foreign firm along with location specific risk metrics for each disaster category. Lastly, future research should take a perspective of multi-hazard disaster risk as climate change makes connected disasters more likely (e.g. flood and extreme rainfall induced landslides). Papers with a focus on single disaster types tend to fall short in accounting for the complexity of repercussions of disasters such as compound events. However, on a local level differing between different disaster categories matters as disaster risk might be unequally distributed within sub-national districts. In this study, this is only contoured by including besides earthquakes additionally earthquake induced tsunamis (yet excluding earthquake induced landslides).

In recent years, the literature on disaster risk has seen its 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, local communities, but also foreign firms to 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 side to develop the best strategies for adaptation against disasters in order to minimize the loss of capital, to 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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8 Tables

TABLE 5: Conversion of PGA to MMI

Intensity Level (MMI)	I	II-III	IV	V	VI	VII	VIII	IX	X-XII
Acceleration (%g) PGA	<.17	.17-1.4	1.4-3.9	3.9-9.2	9.2-18	18-34	34-65	65-124	>124
Potential Damage	None	None	None	Very light	Light	Moderate	Moderate/Heavy	Heavy	Very Heavy
Perceived Shaking	Not felt	Weak	Light	Moderate	Strong	Very strong	Severe	Violent	Extreme

Formula taken from Wald et al. (1999) and table applied for instance in Gignoux and Menéndez (2016) with the extended expected damaged/shaking.

TABLE 6: Dynamic 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 \times 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 on district level.

TABLE 7: 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.

9 Figures

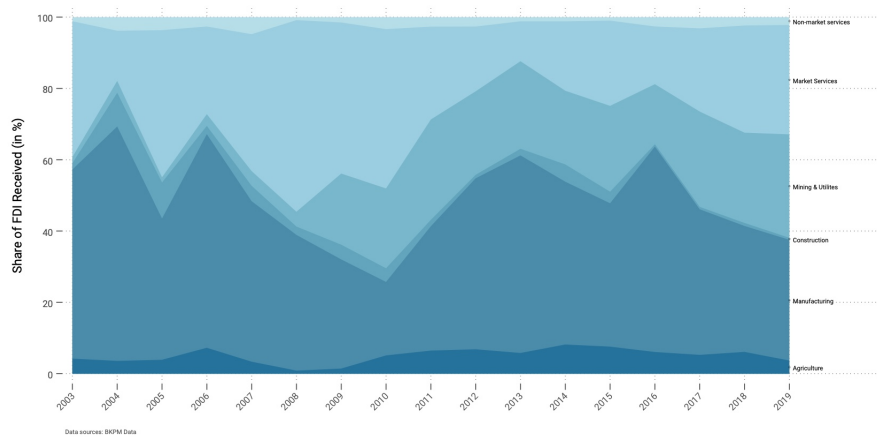


FIGURE 7: Sectoral FDI Flows over Time (relative terms)

Notes: Data is taken from Indonesian Investment Co-ordinating Board (BKPM) (2021). Calculations are the author's own. Figure shows the relative share of sectoral FDI flows broadly corresponding to the ISIC Rev. 3 level two.

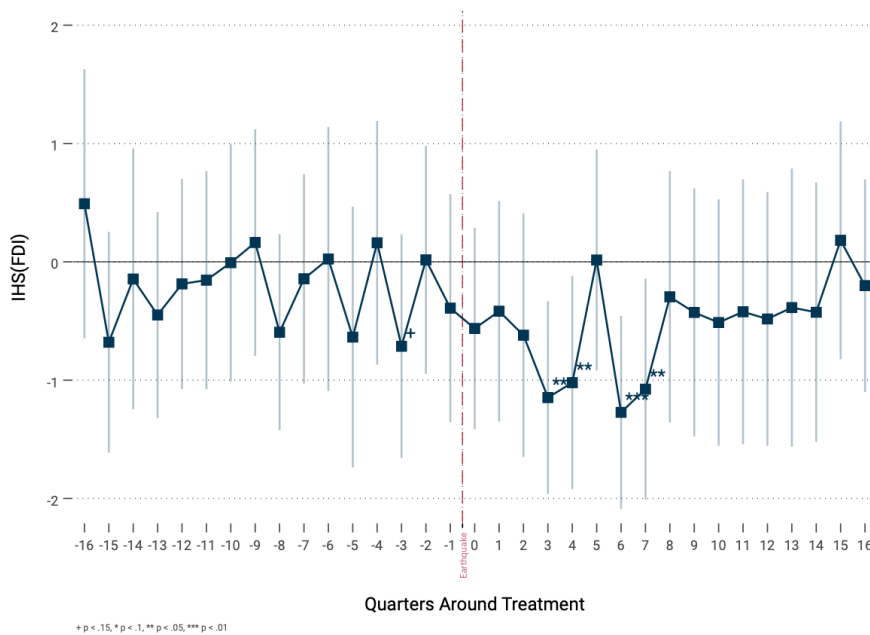


FIGURE 8: Impact on FDI inflows on Quarterly Levels

Notes: Figure shows the impact of earthquake exposure on quarterly FDI inflows. Treatment here is defined if at least 15 houses are destroyed (as no physical proxy of exposure is computed). The estimation follows Equation 1. Estimations based on 21 991 observations and includes lagged and logged annual nighttime light and population as core controls. The regression excludes multiple treated units and includes thereby 38 treated districts. Simultaneously occurring disasters are excluded. The R^2 is 0.58 and standard errors clustered on district level.

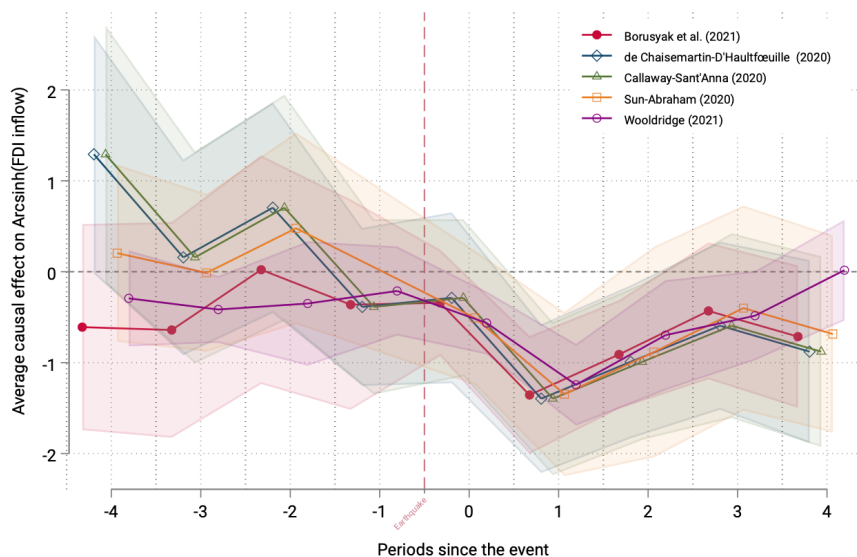


FIGURE 9: Comparison of different recent DiD estimators

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), Chaisemartin and D'Haultfœuille (2020), Borusyak, Jaravel, and Spiess (2021), and Wooldridge (2021). The chosen CI bandwidth is the 10% threshold.

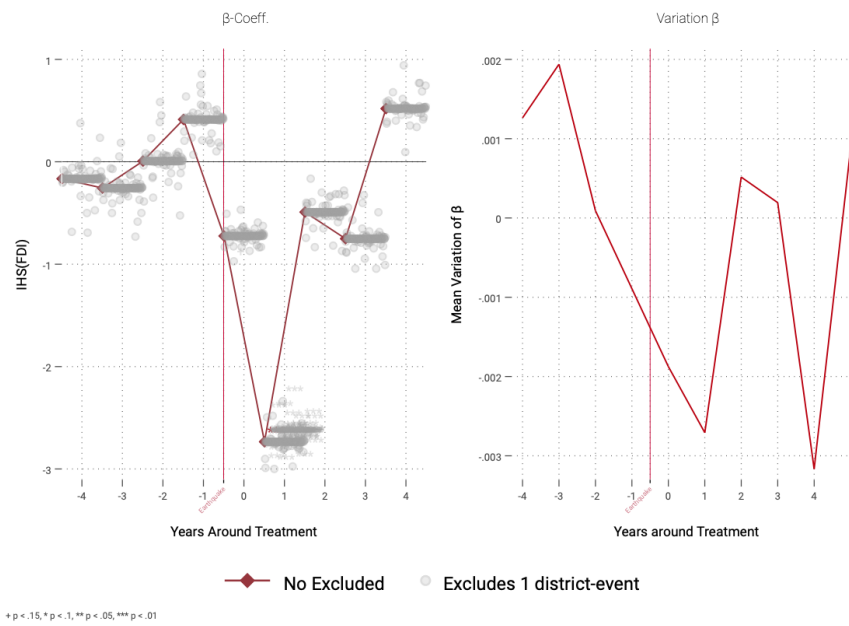


FIGURE 10: Leave-one-Out Exercise

Notes: The figure shows the specification of Equation 1 yet excludes one district-event at a time. The maximum deviation is around 0.5 within a given year. Multiple treatments are excluded. The left panel shows the point estimates excluding a single event every time. The gray bar indicates identical point estimates. In the right panel we see the mean variation of point estimates in each period.

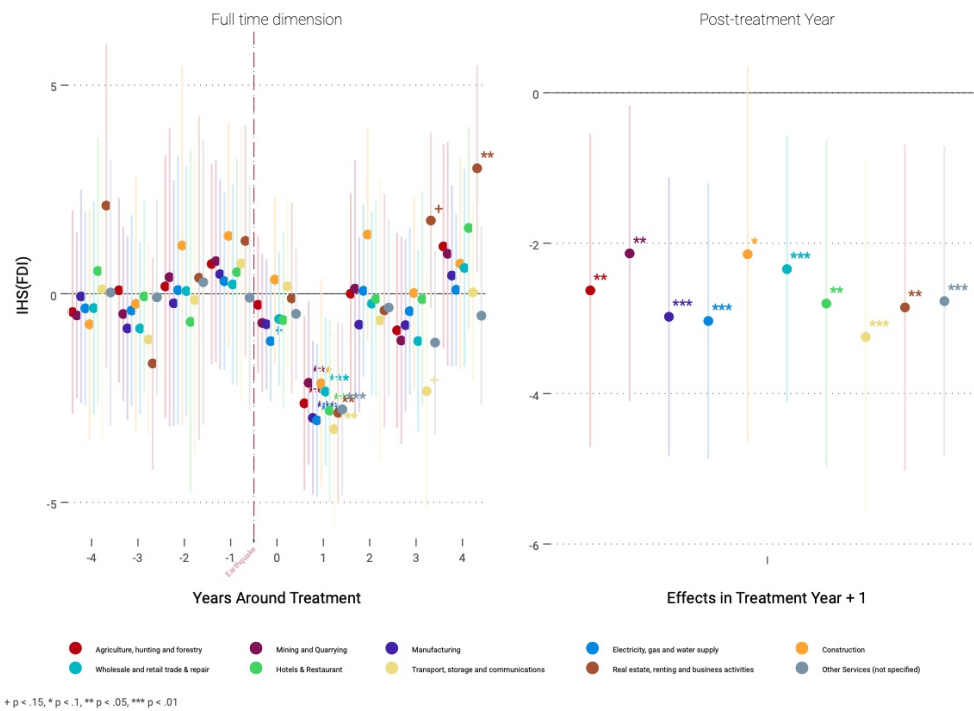


FIGURE 11: Effects on District-level

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.

Supplementary Material

A Indonesia's Decentralization Policy

Indonesia has decentralized many of their previous aggregated districts to smaller districts in the years following 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> ²	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 on their original 2003 names and identifiers. In other words, if a district is divided in the years following the years of 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, which have switched their name after 2003. The aggregation serves the purpose to not lose this data, yet it might be that thereby I overestimate the effects within these districts. Also, economic center identification might be inaccurate as it has been done on the 2015 identifiers. By excluding the 51 district from the analysis, one reduces also the treatment sample by 31 of the 127 earthquakes recorded. This motivates if and in how far these districts, if excluded, bias the main results of this paper. 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 exclude districts completely which have switched their name. The coefficients of the controls are comparable. Excluding this subsample will matter in case of extreme outlier events, precisely in occasions where there are ex-ante fewer observations in the treatment group as then each additional lost observation might substantially pull the regressions towards 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. Recently, nascent literature have risen highlighting issues with econometric specifications as used in this paper. This section shall cover four parts: first, the problem of the baseline method is introduced based on recent literature. Then, more recent empirical methods are applied to the baseline method to investigate the reliability of the baseline results. Then, an extension to these recent models is presented, which loosens the condition of only single treatments. Finally, a method is presented which is highly flexible and time-dynamic and allows for a more balanced control group.

Various problems can emerge with the method chosen: first, the treatment timing varies across groups of districts. If one would only consider those districts, which 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.

A key problem with the treatment definition used in the paper is that the methodology relies on the

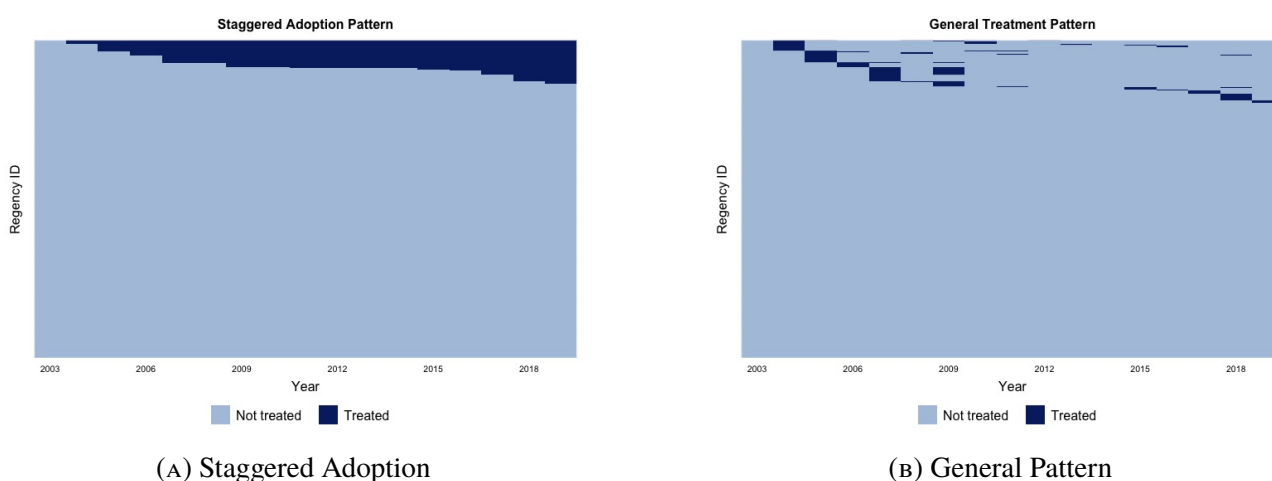


FIGURE B1: Different DGPs

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

strict exogeneity assumption. Following Xu (2022) and Imai and Kim (2019) strict exogeneity relies on four main assumptions, namely the absence of confounding variables which vary over time, the absence of lagged dependent variables, the absence of an effect of past outcomes onto the likelihood to be 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 effects, which is respected in this paper by differing between different timings since last treatment. It is not considered so far 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 existence is excluded by design in this study. So, to summarize, the carryover effects of past treatment onto current outcome and of past outcome onto 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.

Another problem arising in the chosen model is the weighting of different treated groups. In recent literature, many researchers have pointed out the problems resulting from ignoring the different treatment periods for different treated groups. It has been brought forward that a bias arises due to heterogeneous treatment effects post treatment as those observations with the highest variance tend to have the highest weights in the creation of post treatment average treatment effects of the treated (discussed for instance by Xu, 2022, Chaisemartin and D'Haultfœuille (2020), Goodman-Bacon (2021), Callaway and Sant'Anna (2021), Sun and Abraham (2021), Borusyak, Jaravel, and Spiess (2021)). The classic TWFE estimator thereby is a sum of the variance weighted average treatment effect of the treated for each treatment group (so for instance all districts exposed in year 2006) minus the change of the individual ATTs of each cohort (cp. Goodman-Bacon, 2021). The problem that earlier treated units remain as control for later treated ones, which would bias the estimates, portrays a challenge in this paper.

Many researchers have proposed estimation methods in the last years to deal with this bias. In this section the found results of this paper will be re-evaluated using two of such methods: firstly, for simplification excluding multiple treated units, so using only 94% of the full sample, several recent suggested methods are applied and compared taking varying group-specific heterogeneity into account. Then, to account for the general treatment pattern of the main sample, a panel matching procedure by Kim, Wang, and Imai (2018) is used. The advantages and problems are highlighted in the respective subsection.

A final remark refers to the strict exogeneity assumption of the outcome conditioned on treatment status. The stable unit treatment value assumption (SUTVA) requires in the picked models to hold, meaning that if district A is treated, district B next to it is not affected by A's treatment status. This assumption is violated in the case of spatial spillovers for instance. Given that foreign firms will not easily shift production to neighboring districts, it is not extremely likely that SUTVA is violated in

this study. This is assessed in the main part by considering spatial effects of proximate earthquake events onto a district of interest. There could be other unobserved effects such as labor market spatial spillovers or internal migration, which might have feedback effects onto FDI inflows. The potential SUTVA violation based on unobserved spatio-temporal spillovers will portray a key limitation of this paper, yet cannot be avoided due to the complexity of disaster propagation.

B.1. Dynamic Heterogeneous Treatment Effects

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

At first, [Figure 9²⁶](#) shows the comparison between a selection of different estimators from recent difference-in-difference literature (Sun and Abraham, 2021; Sant’Anna and Zhao, 2020; Chaisemartin and D’Haultfœuille, 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, which 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 Chaisemartin and D’Haultfœuille (2020) suggest to use weighted average of two difference in difference estimators: the first compares districts switching from being not exposed to an earthquake to experience an earthquake with districts which have not experienced any in both periods. The second estimation compares districts which have experienced an earthquake at both points in time with those which 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 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 Chaisemartin and D’Haultfœuille (2020) and the Sant’Anna and Zhao (2020) estimator. In terms of significance, all methods find a statistical significant reduction on FDI inflows in period 1 and 2 after disaster occurrence on a 10% level. The coefficient is similarly large as in the baseline regression. Overall, the found effects, reconfirm the baseline results of this paper.

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

²⁶The code is inspired by Borusyak (2022)

B.2. Allowing For Treatment Reversal

The paper by Chaisemartin and D’Haultfœuille (2020) proposes the DiDi_t estimator, which allows not only for dynamic effects²⁷, but also for treatment reversal. This allows the treated districts to switch back from being exposed to an earthquake to not exposed anymore. 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, which especially in the right panel for some replications the p-value is marginally above the 10% threshold. This subsection provides further evidence that even 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 than in the baseline results.

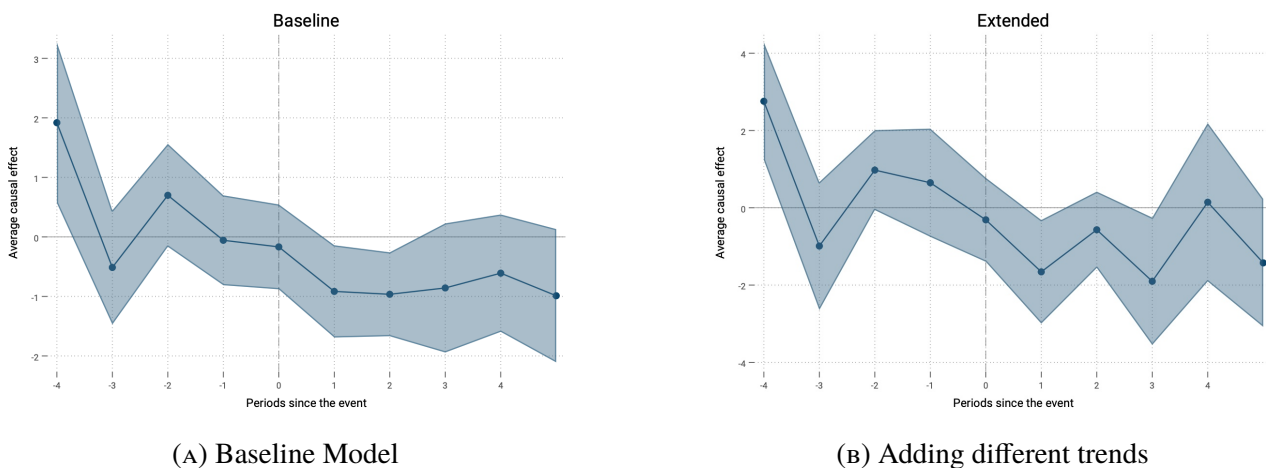


FIGURE B2: Allowing for Treatment Reversal

Notes: The graphs are based on Chaisemartin and D’Haultfœuille (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.

B.3. Adapting the Control Group and Allowing For Dynamic Carryover Effects

To loosen some rather restrictive assumptions of the strict exogeneity assumption in previously used methods, this subsection presents a method based solely on the sequential ignorability assumption. While the method of Chaisemartin and D’Haultfœuille (2020) allows for dynamic treatment effects (which is already loosening one restriction of the strict exogeneity assumption), the panel matching method by Kim, Wang, and Imai (2018) allows in addition also for carryover effects, notably sequential correlation of the dependent variable. In a first step, the idea, in short, is to build for each treated district a matched set of similar district based on a similar or equivalent treatment history (see Figure B3).

²⁷This 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)

In a second step, this matched set is refined across a set of covariates. Then the average treatment effect of the treated is computed by the difference between the treated set and the refined matched set and finally standard errors are computed based on block bootstrapping (see Kim, Wang, and Imai (2018) for a detailed explanation). A key advantage is that one can use the general treatment pattern as in Figure B1 Panel (b) due to the first step matching, one has a more balanced control group due to the second step refinement and finally one can account for carryover effects, which in this setting are likely to exist as districts with historically high FDI inflow are more likely to receive more FDI inflow in the future.

For the purpose of the analysis here, the robust sample of districts has been used (the ones which

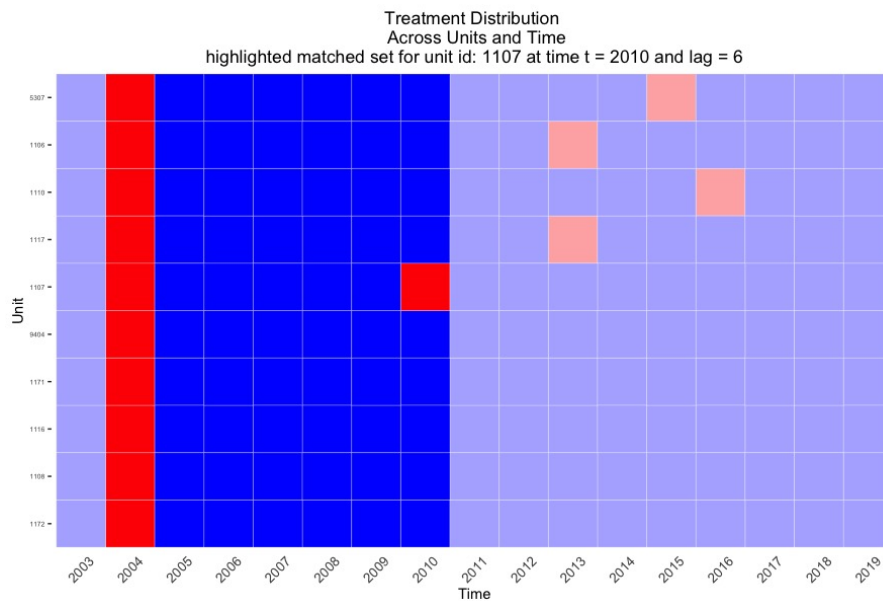
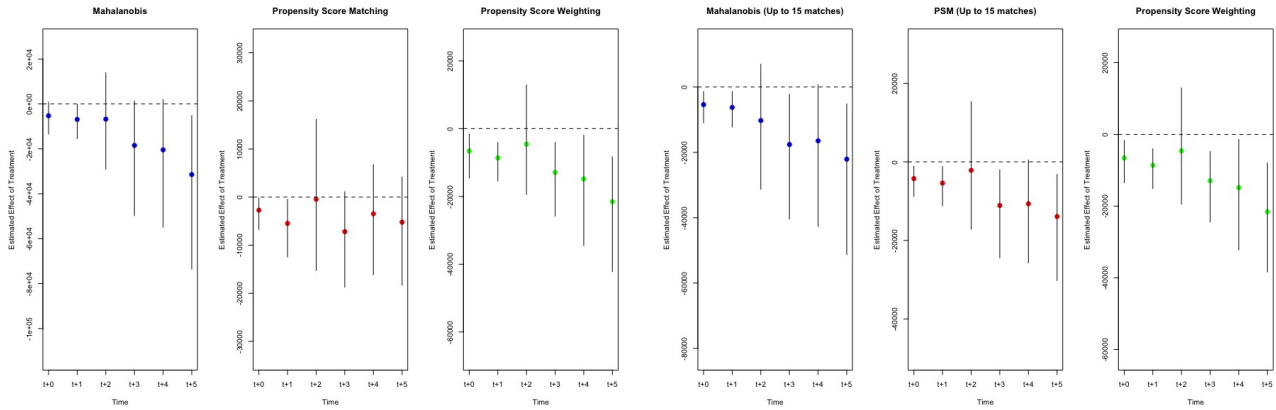


FIGURE B3: Example of Panel Matching

Notes: Figure is based on Kim, Wang, and Imai (2018) and result from a Mahalanobis matched set of observations.

did not split up) to avoid over-accounting of FDI inflow²⁸. For the matching in the first step, for each treated district 5 (Panel (a)) or 15 (Panel (b) Figure B4) similar districts in terms of treatment history are selected showing a similar or equivalent treatment history in the last six years. The refinement method uses different matching methods, whereby propensity score matching seems to be the best fitting in terms of co-variate balance. The covariates chosen for matching are the lags of the last four log GDP per capita, the composite risk index for a district and the lag of the last six FDI inflow levels. To compute standard errors 1000 bootstrap replications are used. Again, one finds that only short term effects in the first two years after a disaster appear to be significant. The found effect corresponds to an approximate 13 000 USD reduction in FDI inflows. In contrast to original findings, one observes also a longer term reduction in FDI inflows in comparison to control districts. The effects found correspond broadly to the effects found in this paper and in the other methods used (if an arcsin transformation

²⁸However, the results do not substantially change using the main dataset



(A) Using 5 matched control units

(B) Using 15 matched control units

FIGURE B4: Different matching approaches

Notes: The graphs are created from the associated package of Kim, Wang, and Imai (2018). Confidence intervals are based on a 10% level. Dependent variable is FDI inflow in 1000 USD in levels.

is used). Contrary to the baseline regressions, the dependent variable is used in levels and not transformed. The reason is simply that due to the matching procedure, the control group is matched on a similar history of FDI inflow. The results are similar even if the bucket of control observations is reduced in size or if lags are changed. Using a matching procedure for obtaining a better control group and allowing for dynamic carry-over effects, this section shows that at least the direction of the results tends to be comparable to what has been found in the main part of the paper.

Conclusion

The main strategy used in this paper ignores group specific ATTs. Ignoring such ATTs might lead to negative weighting and bias of the estimates. Concerning this study, this section has shown that in most setups similar negative short-run effects can be found, whether in models relying on strict exogeneity (or at least relaxed versions of it) or in case of panel matching based on sequential ignorability assumptions. A key assumption made for the analysis is assuming 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 still pose a threat for the SUTVA, which cannot be ruled out with certainty. Overall, the results of this section taken together tend to reconfirm the results of the baseline regression of this paper.

C Results: Reallocation Effects to Economic Centers

In the main paper, it has been tested what the impact of a district's FDI inflow is if a neighboring district is affected. Yet, FDI might be predominantly allocated towards 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 has been 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 main economic centers is re-validated with various statistical yearbooks. Then the distance of 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 is the impact onto 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, there are no significant effects found anymore. A key limitation of this model is the little amount of treated economic centers as 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> ²	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: Analysis of Extreme Outlier Events

D.1. Identification

The main specification regards all district-events in districts where a single event occurred over the course of time in order to have the largest possible treatment sample. As described in the data section, an earthquake event is classified as described beforehand as the interaction of two factors: first, the value of peak ground motion converted into the indexed Modified Mercalli Intensity (MMI) scale within classified economic centers of each district and secondly the share of local working population either dying from the earthquake event or being directly affected by it meaning for instance through loss of homes or livelihood. The product of these two factors is then converted into a dummy being zero if a

district is not treated within a given year and one if the product is larger than zero. Evidently, hereby it is only indirectly distinguished between the severity of the event as districts are only considered treated if the economic center of a district has been exposed to an earthquake with damage potential (MMI above 5). Yet, all districts are considered in which at least one person is affected. The baseline specification does not make use of the continuity of the total shock variable as it considers automatically all as treated if both shocks are unequal to zero. The precise definition of the total shock used in this study is as follows:

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

All indices refer to district i , province j and year t . In order to see if results change using only extreme outlier events, this section will describe the effects for extreme events, which are identified as using a ranking of continuous total shock variable. Hereby, the top 10 and top 20 of district-year events are compared to the results with the baseline, which regards all as treated. It can be expected effects to vary given the disaster intensity, especially following the 2004 Banda Aceh earthquake and tsunami²⁹. Disaster relief aid for instance might be stronger for disaster events with large media coverage causing arbitrary responses in FDI inflows.

D.2. *Effects on Temporal Level*

Figure D1 shows the impact of extreme events onto FDI inflows along with the baseline specifications of this paper. One can see that some pre-trend periods are significant, whereas for post-treatment periods it depends on which specification is used. The two panels differ in the amount of variables included: the left panel only accounts for lagged NTL data and population and is conditioned if no earthquake took place within the treated district five years prior to 2003. The left panel uses the same condition, yet adds lagged domestic investment, poverty, morbidity percentages, the Bartik like control for migration and manufacturing share. Given the small sample size of six to twelve affected districts it is likely that if two or three districts received larger inflows pre-treatment that suddenly these pre-treatment effects become strongly significant. Also, the top 10 and top 20 district-events see a dip in the year after the disaster, yet not significantly on standard levels. One also observes a similar recovery in the two years after the disaster in the left panel. In the right panel, one can see a huge rise in FDI inflows. This differential effect is likely due to correlations with included controls, especially domestic investment, poverty share and manufacturing share. One would have expected to see larger effects for extreme events, yet it is likely that in these regressions there is a stronger selection into treatment bias than in the case allowing for all events. Another explanation why the effects vary so widely between

²⁹Recall that for the labor channel also tsunami events are included if caused directly by an earthquake

Temporal Effect

Top 10 and 20 Districts

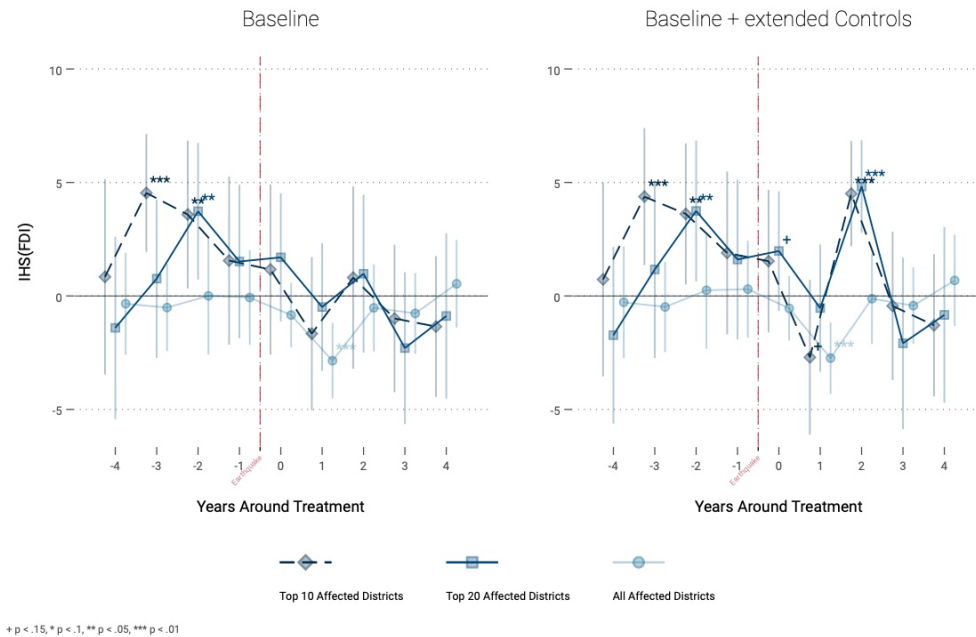


FIGURE D1: Extreme Events over Time

Notes: Estimations based on Equation 1. Classification of Top 10 and 20 events is using the definition of the total shock as interaction of the labor and the capital channel. The total value is ranked and here represented top 10 and top 20 are the most impacted districts by earthquakes following the described definition of a total shock in Section 4. The same estimation models as in the baseline regressions apply. Within the Top 10 most affected districts are affected by 6 events, the top 20 by 12 events and the full sample (as the baseline) by 47 earthquake events. All models exclude districts which are treated in the 5 years before 2003.

the baseline and the outlier regressions is that in these regressions other treated districts, namely all earthquake events which are not outlier events, are included in the control group, which would reduce the substantial difference between the treatment and the control group.

D.3. Effects on Sectoral Level

Figure D2 shows the differences of a one percent shock onto FDI inflows in a given year, whereby the shock being measured as percentage of affected GDP across districts within a province. One can see on the right that there are little to no effects on sectoral FDI inflows (at least using this metric) if all earthquake events are used. Only hotels and restaurants observe a reduction in FDI inflows in the year after. Both panels show the impact of a shock in the previous year onto current FDI inflows. In contrast, one can see negative impacts on FDI inflows for construction and wholesale and services after a 10% shock. Real estate is the only sector showing a statistical significant increase in FDI inflows in the year after the disaster event. An additional observation is that the confidence intervals appear to be substantially larger, likely due to the reduced sample size of treated units. While it is also tested how the impacts are through shocks in up- and downstream linkages, the results are not shown here as they are unreasonably large. The overall tendency is that one sees large increase in FDI inflows, especially in construction and transport and communication through within-sector-province shocks.

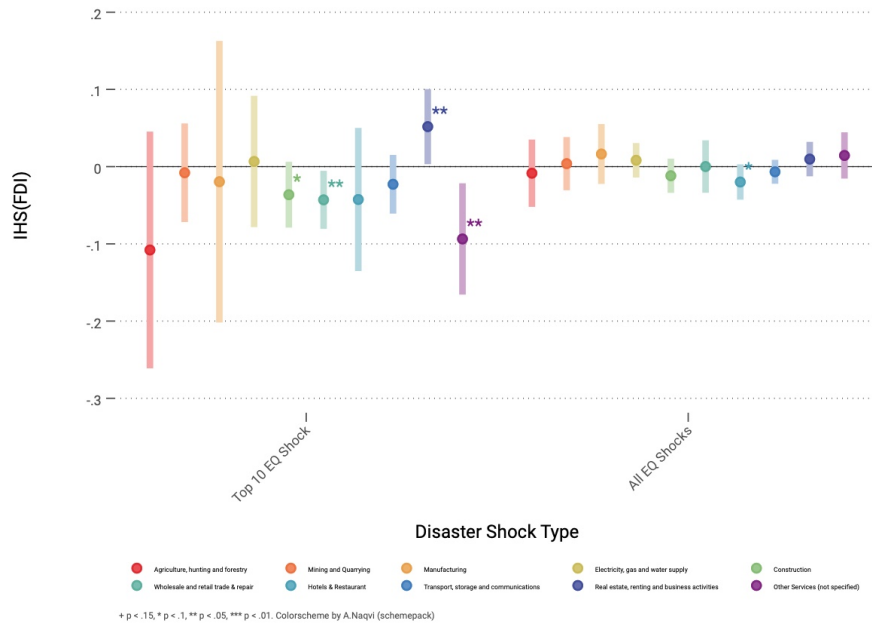


FIGURE D2: Extreme Events over Sectors

Notes: Graph shows the differential effects on sectoral level between the top 10 most affected districts (on the left) and the general baseline sample (on the right). The estimations are based on Equation 3 using the same econometric model, solely using the within-sector GDP shock. Fixed effects included are sector, year, and province FE. The same core controls are included as in the baseline. To weight the shock, district-sector specific GDP weights are used.

Overall, downstream shocks of exposure of a top 10 district-event cause huge increases in FDI inflows for transport and communication and also in agriculture. Upstream shocks have generally quite a negative impact especially onto construction, agriculture, manufacturing and transportation, yet a large positive effects on services. The large coefficients of some of these effects are due to the fact that a one percentage change in linked shocks weights heavier if the overall mean of shocks is lower than in the case where all events are included.

Generally, the results of the extreme events are different to the ones on general earthquake shocks. While it has been expected that the shocks might follow the pattern of the general case, the fact that they do not reveal the mechanisms behind changes in FDI inflows to be different for the extreme outlier events than for disaster events, which are deadly and damaging but not as extreme as the top ten district-year events.

E 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 of 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 in a similar way.

E.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. For this paper, extreme rainfall shocks are used 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 gridcells, 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 which can be brought forward with this methodology. Rainfall is an insufficient predictor of flood exposure, especially of riverine floods, as after all neighboring districts might be more affected from 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.

E.2. Effect on Temporal Level

Figure E1 shows the temporal effects of flood exposure. Panel (a) differs between the impact 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 a single 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_t estimator by Chaisemartin and D’Haultfœuille (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 also negative but not as obvious as for earthquakes since potentially floods have other mechanisms through which they affect foreign investment. An effect on a sectoral level is discussed next.

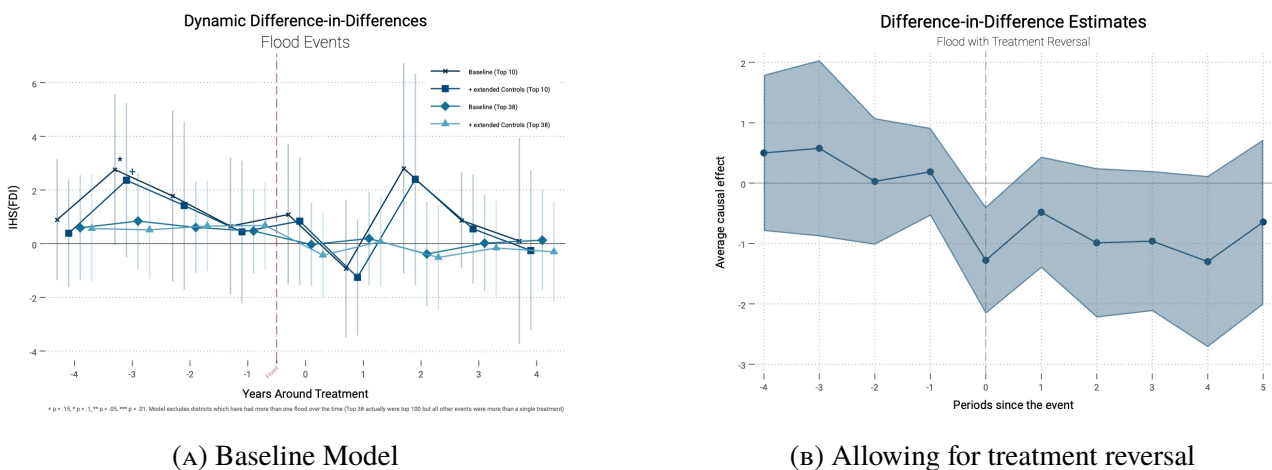


FIGURE E1: Temporal Effects on Flood

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 Chaisemartin and D’Haultfœuille (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.

E.3. Effect on Sectoral Level

Using the same methodology as for earthquakes, the regression model including linkages are re-run. Figure E2 shows the impact of a 1% GDP weighted shock within a province on FDI inflows once for extreme outlier events and once for weaker flood events.

The left panel shows the impact of a one percent GDP weighted shock within-sector if the shock is

caused by a flood event which belongs to the 10 strongest recorded over the 17 years. One can see mild positive effects of FDI in mining, but stronger effects for wholesale and services. Transport and communications see a large reduction in FDI inflows. The effects are somewhat opposing the direction of effects of top 10 earthquake events, likely because different districts are treated with ex-ante varying sectoral compositions. The right side shows the impact of a 1% shock through a weaker flood event. The effects are substantially smaller and only cause a small reduction in transport and communication and a minor increase for hotels and restaurants. In contrast, hotels and restaurants actually saw a minor decrease in FDI inflow following an earthquake event. The differences in sectoral effects between flood and earthquake can be attempted to be explained through the distribution of the respective disaster hazard across Indonesia. Not the same regions are affected by floods and earthquakes at the once, which causes the sectoral FDI results to change.

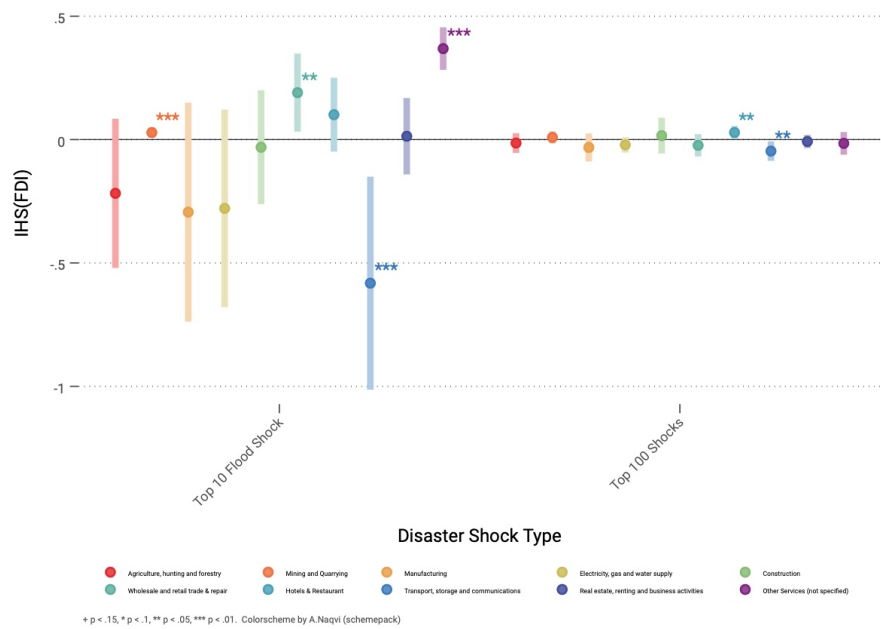


FIGURE E2: Impact of within-province sector shock

Notes: The figure shows the impact of within-sector shocks onto sectoral FDI inflows. It is based on Equation 3 and uses only the within-sector shock. The shock corresponds to a 1% of within-sector affected GDP. Both panels make use of the computation of the total shock as interaction of the labor and capital shock, by ranking the top 10 and top 100 district-events based on the product of the labor and capital shock. Fixed effects included are sector, year and province FE. The same core controls are included as in the baseline.

Figure E3 adds a network perspective by showing shocks through linkage effects once for extreme events (Panel (a)) and once for weaker events (Panel (b)). At the first sight, one can see weaker effects through linkages in panel (b). Panel (a) shows surprisingly that through floods for most sectors, downward linkage shocks cause FDI inflows to reduce in the year after the disaster. As an exception utilities show a significant rise in FDI inflows with a coefficient of 0.68. Upward linked shocks cause a reduction of FDI inflows only in the construction and mining sector, yet hotels see with see a substantial rise in FDI inflows. Within-sector strong negative effects are found for utilities and small positive

effects for mining and services.

In Panel (b) weaker flood within-sector shocks cause FDI inflows into transport to decline and to mildly increase into real estate. Moving on to downstream shocks, real estate and agriculture are the only ones seeing a reduction in FDI inflows, yet agriculture sees an FDI increase through upstream shocks. Here again it becomes clear that weak floods seem to take place in other regions than weaker earthquakes which explains the differences in effects on a sectoral level.

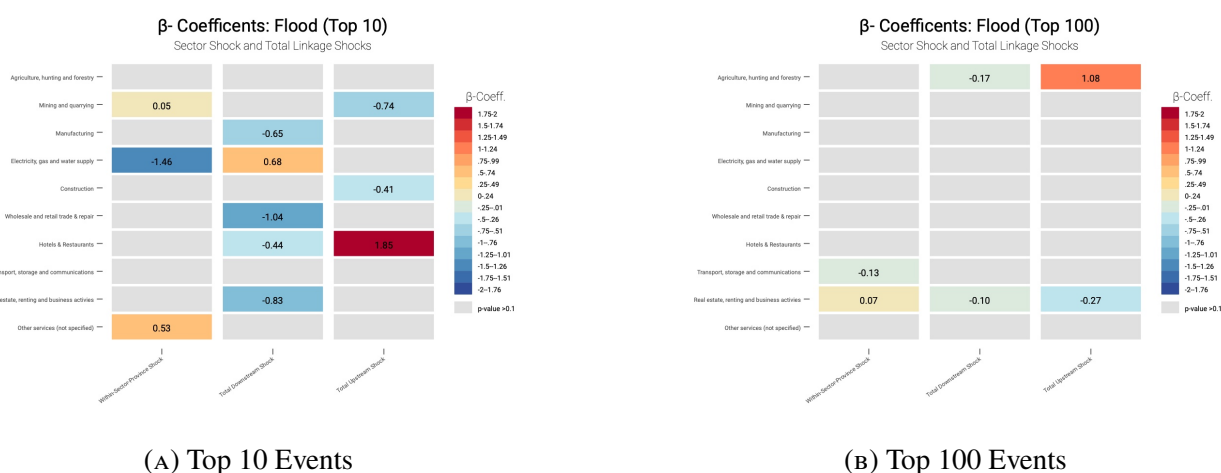


FIGURE E3: Linkage Effects on Flood

Notes: The two panels show the sectoral response of IHS-transformed FDI inflows based on a 1% flood-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. Grey fields are below the 10% significance threshold. Estimations are based on Equation 3 and Equation 4. The classification of top-events is based on the continuous function the total shock and each regression includes lagged and logged nighttime-light and population values as core controls.

E.4. Explanation of Differences

A key question arising from this section is why are the effects so different, especially in sector level, between earthquake and flood exposure. Temporally speaking, in both cases after disaster exposure FDI inflows seem to reduce either immediately or with a delay of a few years. Yet, the origin of the effects might be different.

First, it has been shown in the introduction that floods seem to have different effects on firms and population than earthquakes. Floods tend to affect more people in their daily lives, whereas earthquakes are more destructive and deadly. For firms, domestic or foreign, they might adapt differently to either shock. 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 into backup technologies, earthquakes and their associated tsunamis tend to cause more long-lasting damage to local economies, which would explain why the found effects vary.

Secondly, the expectation to disaster risk might vary between the two categories. Earthquakes are prone to occur in proximity to tectonic plates, whilst their associates tsunamis are more likely to affect low-land coastal regions. Floods also tend to originate in low-lands 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 strategy of foreign firms.

Lastly, as mentioned briefly before, the sectoral composition of affected districts might vary between

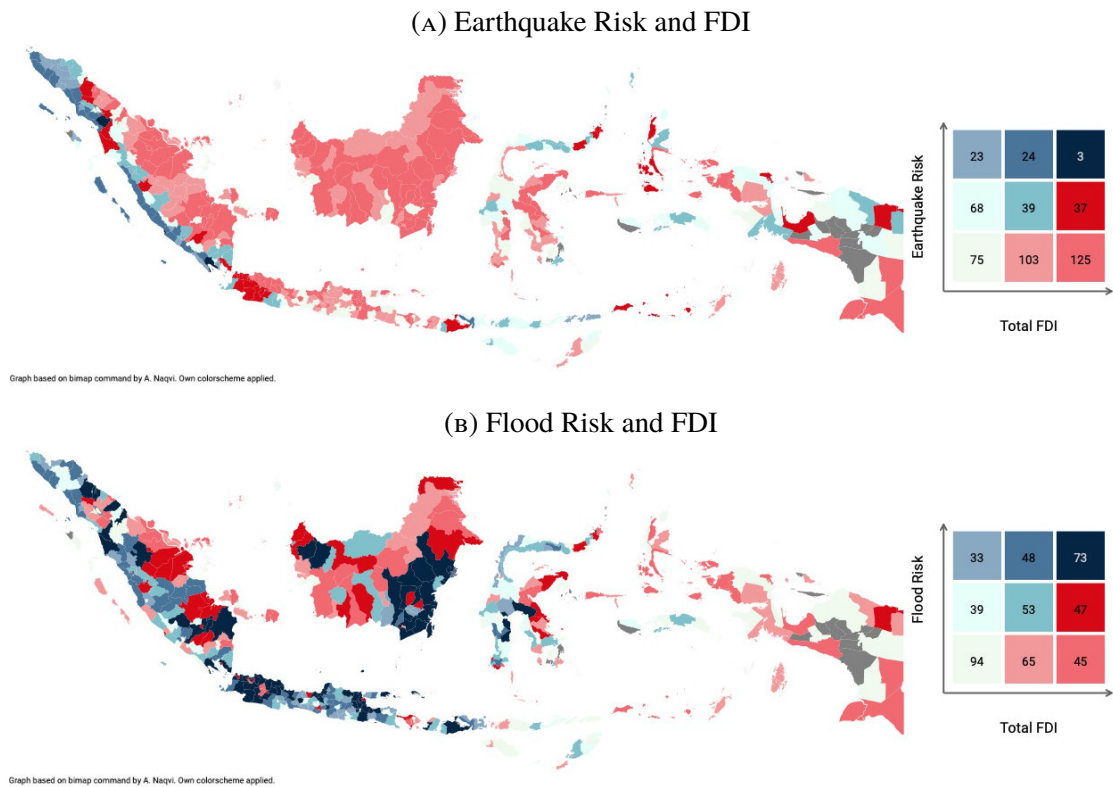


FIGURE E4: Spatial Distribution of Risk

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.

the two disaster categories. **Figure E4** plots in a bivariate map the FDI inflow against the calculated district-specific composite hazard index³⁰. 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 flood might cause different effects onto foreign firms than earthquakes, yet nonetheless it shows that also flood events do not contribute generally positively to FDI inflow, similar to earthquake events.

³⁰The 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

F Results: Impact of other Disaster Types

The paper predominantly focuses on the impact of earthquakes onto FDI as they represent the major threat for human and economic life in Indonesia. In the previous section it has been more in-depth investigated what the effects of floods onto FDI inflow by using another physical intensity proxy. This section will only outline the effects on FDI inflow, where disaster types are categorized into four major categories: geophysical disasters (earthquakes, tsunamis and volcanic activity), hydrological disasters (flood, landslides and tidal waves³¹), meteorological (storm and cyclone exposure) and lastly climatological disasters (drought and forest fires). All but geophysical events are described in literature to be directly related to climate change. There is, however, even for geophysical disasters a nascent literature which 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 in various disaster shocks onto 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 United Nations Office for Disaster Risk Reduction (UNDRR) (2022) database is used. A disaster is considered to be a disaster if at least a single person has died or been directly impacted by a disaster event. Admittedly this is a very strong assumption, but in this way the maximum amount 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 F1 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, that geophysical events cause a substantial reduction in FDI inflows in the aftermaths. For hydrological events, there is a huge fluctuation likely because the effects of landslides and floods are substantially different to each other. One can see that the FDI inflows fluctuate substantially in the years following an event. Similarly to this also meteorological events see little to no significant effect in the years following storm events, only for climatological events one finds 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.

³¹Waves caused for instance by tidal gauges

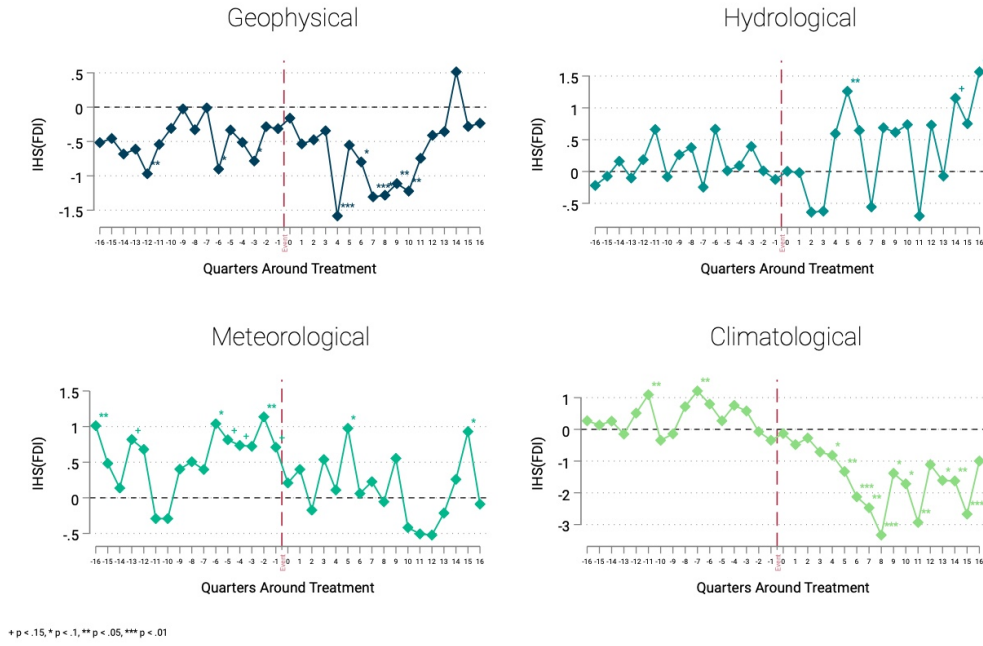


FIGURE F1: Overview on Different Disaster Types

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.

G 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. As briefly explained in the data section, the shock is defined as an interaction term of the following form:

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

All indices refer to district i , province j and year t . The Modified Mercalli Intensity scale values are obtained using the peak ground motion maps of the USGS ShakeMaps and converted towards a grid cell level. Each 5x5km grid cell contains a value of maximum ground acceleration within a given year. If multiple earthquakes take place within the same grid cell, they are overlaid and converted to the maximum value recorded. These values of peak ground acceleration are then converted onto the Modified Mercalli Intensity scale using the division by Wald et al. (1999) using the conversion shown in Table 5. Figure G1 illustrates the impact on the coefficients if one changes the individual parameters of the shock. On the left-panel one sees two suggested changes of the capital shock parameter. The dark blue line shows the impact of earthquakes exceeding the higher threshold as only

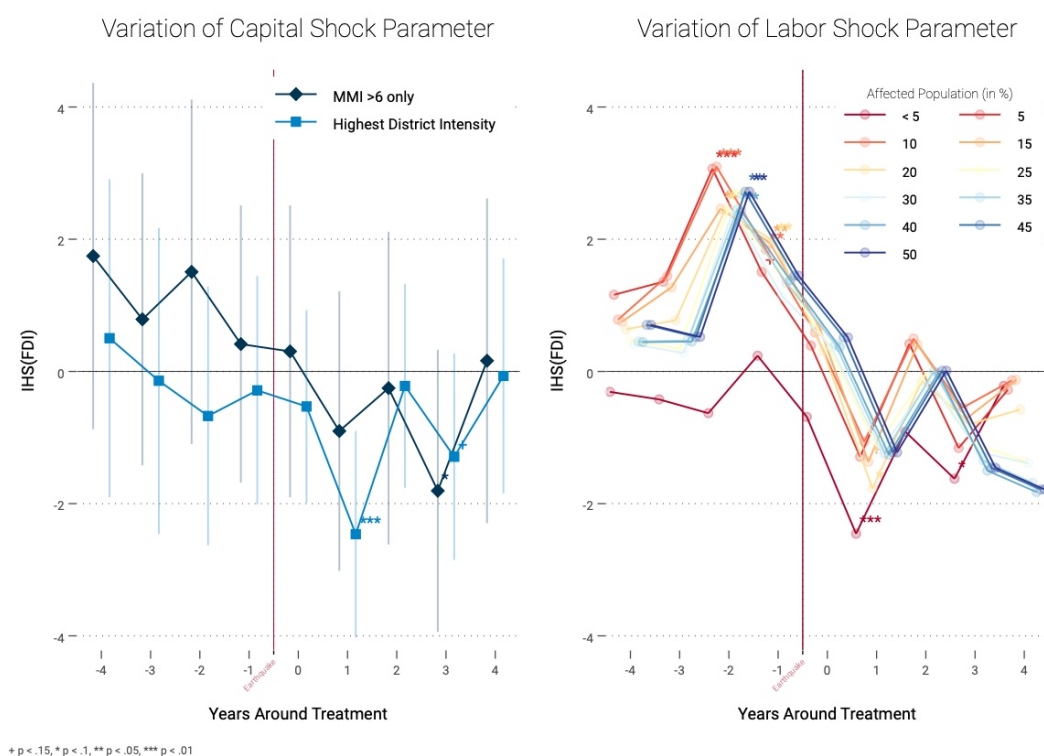


FIGURE G1: Variation of the Shock Parameter

Notes: The two panels show how the baseline results change, if one modifies either variables on the capital or the labor channel in the creation of the shock dummy variable. The left panel shows modifications in the definition of the capital channel: once only considering strong earthquake events (dark blue) and once defining earthquake intensity on district instead of economic-center level (light blue). The corresponding treated sample size is 30 for the high-intensity definition and 51 for district-wise definition. In the right panel, the labor channel is changed: instead of allowing for all affected people as in the baseline (in red), the threshold is increased in 5% steps. The treated sample size thereby drops from 55 to 30. All estimations follow the same strategy as the baseline regression, whereby the only thing changed is the shock dummy variable.

events above the Modified Mercalli Intensity six are included. **Table 5** illustrates that under MMI mild damage can be expected, while from seven or above one sees moderate damage to buildings. One would expect stronger effects, which is not the case. Despite significant effects are found three years after the disaster, the effects appear to be smaller than in the baseline specification. That could have multiple explanations: on the one hand, the smaller sample size might cause effects to be non-significant, especially as districts with stronger events might be even more systematically different to the ones in the baseline specification. On the other hand, districts with stronger events might postpone their investment decisions even for a longer period of time. In light blue in the left panel, one can see similar effects to the baseline. The difference here is that instead of using the highest value of ground motion within economic centers, the highest ground motion within a district is used, even if it might not take place within an economic center. The effects are largely comparable to the one of the baseline specification meaning that it might not matter as much as thought if the earthquake occurs within an economic center or in proximate rural areas.

The right panel shows how results change if one changes the threshold for affected population in the labor market channel. In the baseline model all events are regarded even if just a single person is affected,

which corresponds to the line in red. Increasing the number of affected people causes the coefficients to increasingly become insignificant. The direction of the coefficients remains. A key difference is that pre-trends become significant likely because the sample size drops with higher thresholds and thereby individual FDI inflow fluctuations tend to matter more. One needs to remember that the red line is closer to the median value of the distribution of affected people. Approximately in 80% of the labor shocks less than half of a percent of local population are affected. Therefore, all other values are already relatively extreme events.

In addition, the effects of the original shocks individually, the labor and the capital shock, excluding the interaction of the two is tested, yet not shown here. Both shocks individually show similar effects than the baseline specification with similar significance levels. So the shocks individually taken matter also.

H Results: Robustness of Controls

H.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 to check how much logarithmic nighttime-light in Indonesia correlates province-wise with logarithmic GDP. Data on GDP values³² over time is drawn from the INDO-DAPOER data frame of The World Bank (2022b). **Figure H1** 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 which are relatively weakly illuminated at night and thereby the correlation of GDP and nighttime light is low for these districts. The mean correlation on district level between NTL and GDP is with 0.6 sufficient high to say that nighttime light proxies GDP sufficiently well for this dataset. On 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 within this paper.

³²The GDP is based on 2008 constant values

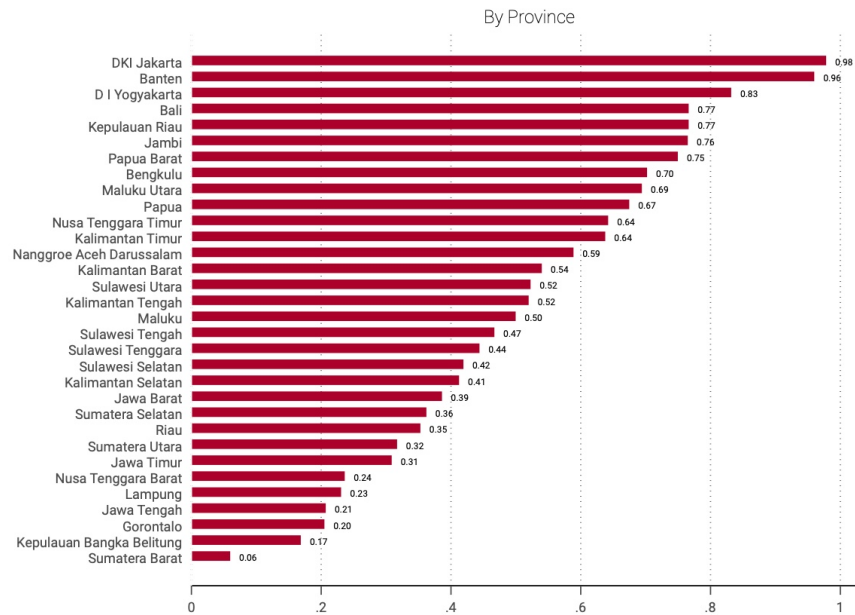


FIGURE H1: Correlation of Log(NTL) and Log(GDP)

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

H.2. Reliability of Economic Center Classification

Another test, which is important to be conducted, shall assess if the economic centers within each district are accurately matched. In order to do so, information on geographic coordinates of cities in Indonesia and their population are obtained from GeoNames (n.d.). The cities have been 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 H1 that most cities, indeed, fall into the fifth quintile. The cities in the first quintile are predominantly those which 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 classified in it. There is only a single exception: the city Depok. Analysis on 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 however does not. Thus, this outlier can be ignored as Depok is accounted for by the neighboring grid cell.

TABLE H1: 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.

H.3. Reliability of Disaster Effect Data

A key criticism to the paper could be brought forward if one does not believe in the main data source from United Nations Office for Disaster Risk Reduction (UNDRR) (2022). 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 occurrence and has since also their geodata portal (DiBI). In the following the Desinventar data will be compared 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 H2a shows the percentage of matched district-events between the two data sources. Differences in all categories but forest fire 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 accounted by BNPB, but in the data portal, where for this comparison data has been obtained, the author has 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 H2b 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 to make big claims based on that figure. First, it could be that EM-DAT only accounts for additional districts but for the same event, thus would have more or different districts included. It could also be that a certain percentage of matching errors results from switches in district names. While it is attempted that all district names are standardized and collapsed

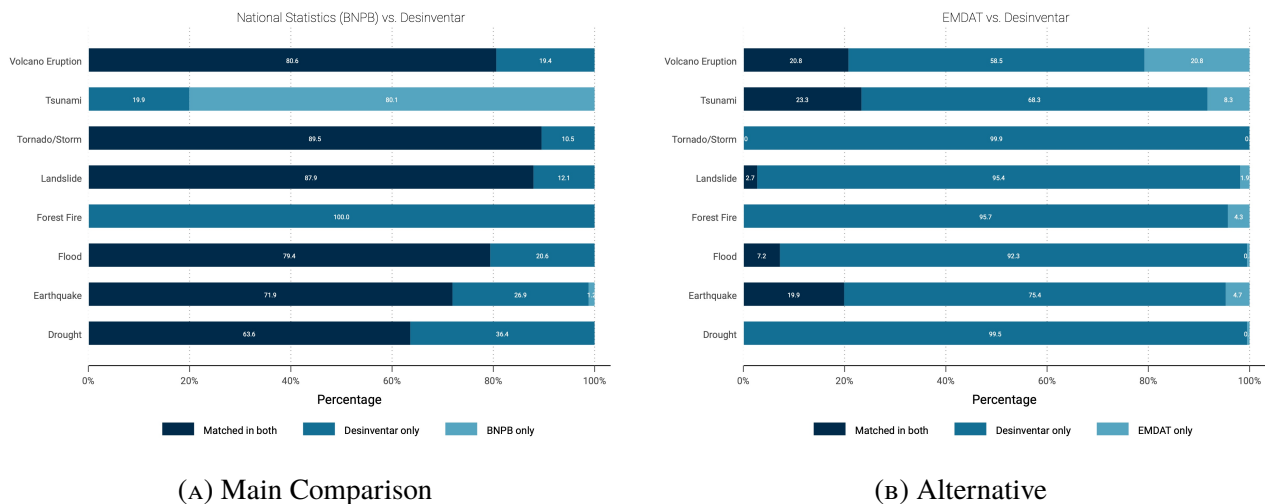


FIGURE H2: Comparison of Matched Results

Notes: Data is based on United Nations Office for Disaster Risk Reduction (UNDRR) (2022), 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.

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 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 for this study of using Desinventar over EM-DAT is the usage 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 into the usage and reliability of the damage statistics used in this paper.

I Method: Assessment of Hazard Risk Indices

1.1. 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 2015³³. These models show where different disasters are likely to take place based on historic data and probabilistic models. They serve the purpose to create event-specific risk indices, which can be combined to an overall *composite hazard*

³³Flood 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)

index.

In order to create risk indices one needs a comparable measure of risk exposure across disaster categories. The different probabilistic maps show, however, varying return periods, which is why just using the values of the hazard itself is not comparable. In order to create a comparable metric for the five categories (earthquake, flood, landslides, tsunami, and forest fires) the available hazard maps are merged with the previously used 5x5 km grid of Indonesia. So one obtains five grids of Indonesia, wherein each grid cell contains a mean positive value if it is at risk to be affected by the respective disaster type. Again, the values are not comparable across disaster types, but they are within disaster types. To make them also comparable across disaster categories they are standardized using z-scoring. So for each of the five categories, the mean value as well as the standard deviation of risk values over the entire country is computed and each grid cell is then assigned to their respective standardized value of risk³⁴. For robustness, this standardized value is also computed specifically on the subset of grid cells falling into economic centers, so only considering the z-score across economic centers of the country. Then to get a district-specific value, the grid cells are collapsed whereby the mean z-score by district is used. One ends up having the mean standardized risk score by district over all Indonesian districts by all five used disaster categories. They are now more comparable across disasters. In this study no hazard maps are included for volcanoes, storms, tidal waves and droughts, but their risk should be included nonetheless. Thus, they are standardized differently: Their z-score is based on the recorded number of events within a district drawing from the Desinventar database (United Nations Office for Disaster Risk Reduction (UNDRR), 2022). Here, the z-score is the district deviation in event occurrence from the average number of event occurrence in all districts over 17 years. Admittedly, it is not a perfect measure, but it shall serve as a rough proxy for risk likelihood. As robustness this method is also applied to the five categories, where hazard maps were available.

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.

³⁴Essentially, it is computed as $\frac{\Omega_g - \bar{\Omega}}{\sigma_{\Omega}}$ where Ω is varying mean risk value by gridcell g , $\bar{\Omega}$ is the mean risk value over the entire country and σ the corresponding standard deviation.

1.2. Assessing Validity of the Two Main Hazard Indices

The heterogeneity analysis in this work relies on the validity that the created composite hazard index as well as the dummy for earthquake risk 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 I1** shows the computed composite hazard scores by district. Note here that as the

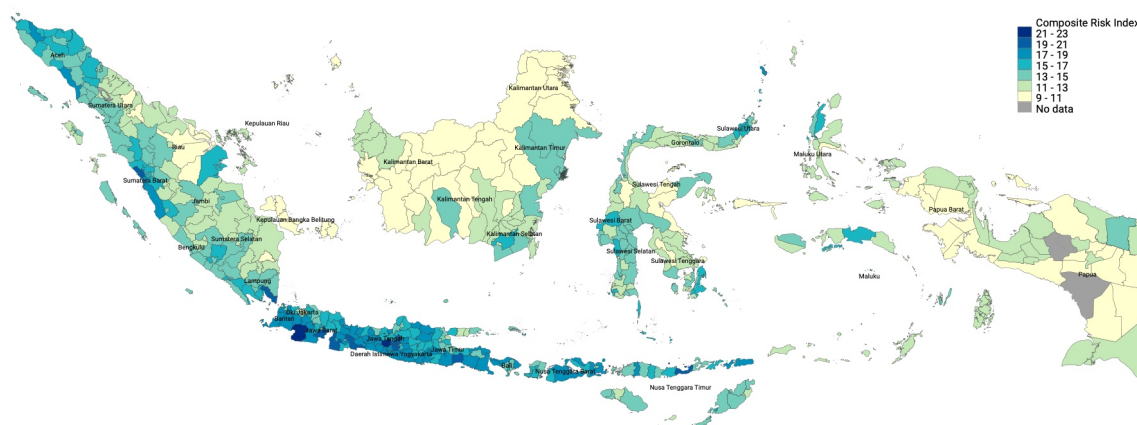


FIGURE I1: Visualization of the created CHI

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.

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 grey). 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. Taking the average composite hazard scores by province, one receives the following table:

TABLE I1: Overview of the Top 10 Provinces with Highest Composite Risk

Province	CHI Rank	Total CHI	Earthquake	Flood	Landslide	Fires	Tsunami	Volcano	Storm	Drought	Tidal Wave
Special Region of Yogyakarta	1	16.9	2	1.5	1.5	1	1	1.6	3	2.6	2.6
Central Java	2	16.4	1.9	1.7	1.7	1	1	1.4	3.1	3	1.6
West Java	3	16.3	2.5	1.7	1.7	1	1	1.1	2.6	3.1	1.6
West Nusa Tenggara	4	15.7	2.7	1.6	1.2	1	1	1.3	2	2.4	2.4
East Nusa Tenggara	5	15.4	2.9	1.4	1.2	1	1	1.3	2.2	2	2.5
Banten	6	15.4	3	1.8	1.3	1	1	1	2.2	2.7	1.5
Aceh	7	15	3.8	1.6	1.1	1	1	1	2	1.6	1.9
North Sulawesi	8	14.9	3	1.4	1.2	1	1	2.3	1.4	1.2	2.2
Bali	9	14.8	2	1.3	1.3	1	1	2.2	2	1.7	2.3
East Java	10	14.7	1.9	1.7	1.3	1.1	1	1.4	2.5	2.3	1.6

The table is generated using the definitions precised above. The hazard scores are meaned over all districts, as using the maximum value might overestimate the general risk within provinces.

As seen in **Table II** the most affected regions according to the self-computed risk metric are Yogyakarta, Central and West Java and West and East Nusa Tenggara. Comparing these results with an evaluation of disaster risk in Indonesia (Sett et al., 2022, p.39), all hazard hotspots of provinces (Aceh,

East Nusa Tenggara, East and Central Java and North Sulawesi) are included in the top 10 provinces, however only two of them in the top 5. The non-inclusion into the top 5 has multiple reasons: firstly, this paper considers a large variety of different disasters types including tidal waves, which are usually not considered in overall hazard maps. Each disaster category, independent of their destruction potential has an equal weight in this calculation, yet focusing on more destructive disasters such as earthquakes, Aceh ranks really high. Then, the composite hazard index calculated here is far from perfect. For instance, all provinces mentioned have no to low risk category for tsunami risk, which is not true as for instance the Java provinces and Aceh is at an increased risk for tsunami exposure. So for some measures the calculation might not be perfect. Lastly, for volcanoes, storms, droughts and tidal waves the calculation is based on observed frequency rather than probabilistic frequency. Thus, their respective risk scores are relatively high as in these provinces these event-types occurred between 2003 and 2019. Overall, the metric is not perfect, but for the purpose of the study it is sufficiently accurate to identify higher risk areas, notably using the aggregate composite hazard index.

Evaluating the Calculated Earthquake Hazard

In order to evaluate the accuracy of the earthquake hazard dummy, it is visually compared to a pre-existing map from UN OCHA Regional Office for Asia Pacific (OCHA-ROAP) (2011). The comparison is shown in Figure I2. One can see a similar pattern of earthquake risk. For the comparison,

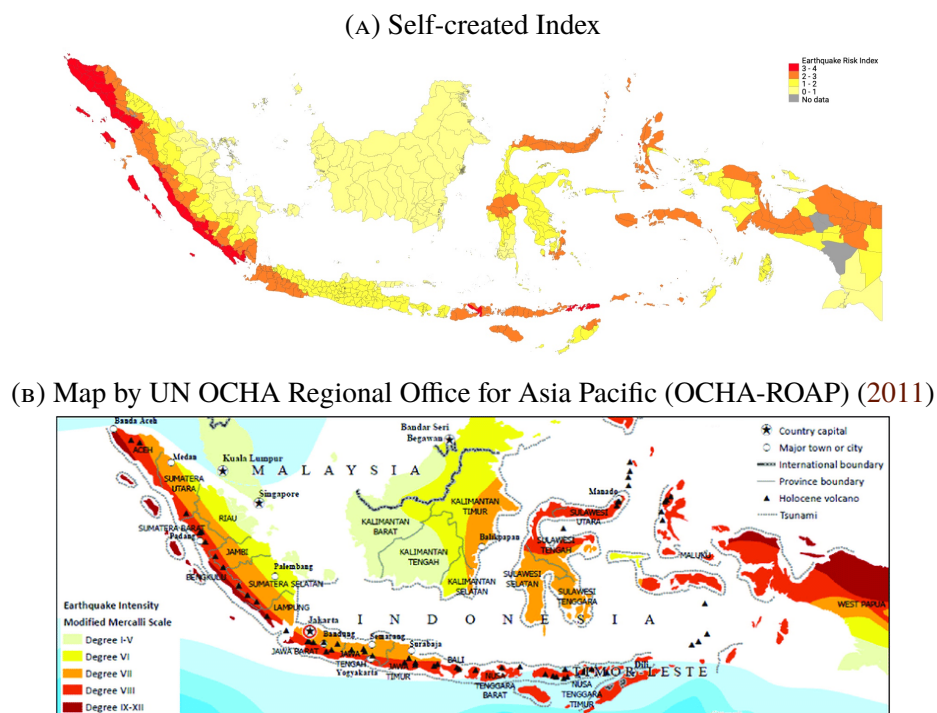


FIGURE I2: Visualization of the Earthquake Risk Metric

Notes: Graph (a) 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). The graph (b) is also included in Gignoux and Menéndez (2016) and also taken from there. It is based on data sources from: UN Cartographic Section, Global Discovery, Indonesia National Statistical Office, Smithsonian Institute, Pacific Disaster Center, UNISYS, Munich Reinsurance Group

it is important to keep in mind that the map in [Figure I2b](#) uses five categories, which refer to zones where the probability to exceed the intensity within the next 50 years is at least 20% as shown on the map. [Figure I2a](#), in contrast, only shows the dummies for risk based on the calculated hazard index and thereby considers the intensity only indirectly. Nonetheless, from a visual point of view, the distribution of risk is similar to the one used in this paper.

In order to see whether the results of the heterogeneity analysis change if another hazard metric is used, instead of z-scoring based on the hazard maps, a z-scoring using the number of events is used as mentioned. In comparison to the results in the heterogeneity analysis, the results do not change. It is also tested 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.

1.3. Assessing Validity of the Baseline Condition

Each of the baseline regressions are run under two conditions: if districts are treated, they are only treated once and no simultaneous disasters take place. In [Appendix B](#) it is assessed whether results change allowing for multiple treatments. The condition that no other disasters take place besides earthquakes or earthquake induced tsunamis serves the purpose to ensure that solely the effect of earthquakes on FDI is measured. For this purpose, a dummy is introduced, which sums up the number of other event-types within the district-year under the condition that due to the event at least 20 persons were directly affected. To test if the results change, if one uses another condition for including other events, [Figure I3](#) shows the effects on the baseline regression if one changes the number of people affected from 0 up to 90 in the left panel. The right panel shows the same regressions, but instead of applying a threshold of people affected, it uses the amount of people who died by other events. One can see that in both cases the coefficients vary, but not substantially. Finally, it is also tested if the results also hold if other events take place within the same year. Indeed, the direction of the results remains. The reason is that the condition solely changes the amount of observations in the control group and in parts the amount of observations in the treatment group. Yet, overall, one can say that the definition chosen and the dummy chosen to control for simultaneous other disaster events appear to be valid.



FIGURE I3: Analysis of Exclusion Condition

Notes: All regressions are run on the conditions that no other disaster occur simultaneously. These two panels show how the baseline results of Equation 1 change if one uses alternative definitions of this restriction. The data for other simultaneous occurring disasters is drawn from the Desinventar database (the main database for disasters in this paper).