Preliminary methodological note for: A Global-Scale Investigation of Firm-level Economic Recovery from Natural Disasters

Alina Gafanova[1], Arti Grover[2], Amir S. Jina[*1,3], Stephanie Lackner[4], and Ishan Nath[5]

[1]University of Chicago
[2]World Bank
[3]National Bureau of Economic Research
[4]IE University
[5]Princeton University

1 Introduction

This research project aims to to understand the mechanisms through which natural disasters can affect national economies in the long-term around the world. A major challenge in answering this question has been the lack of cross-disciplinary engagement between economics and the physical sciences that model disaster exposure. Using a novel combination of economic and earth science data and methods, we will explore the impacts of both tropical cyclones (i.e., hurricanes and typhoons) and earthquakes. Despite recent progress in demonstrating that these long-term economic effects exist (Hsiang and Jina, 2014), research has yet to fully identify the mechanisms that lead to them. We will focus on the effect of disasters on firm-level output which is one leading hypothesized mechanism. This question has relevance not only in terms of disaster response and economic policy in the present day, but also, in the case of tropical cyclones, will become more relevant as the frequency and distribution of these disasters may change with climate change (Emanuel, 2011; Patricola and Wehner, 2018; Vecchi et al., 2021).

This project, then, will examine the post-disaster trajectories of firms globally in order to understand 1) why firms' recovery from disasters is slow, and 2) if this slow recovery can account for longer-run growth effects on national economies. Using extensive firm-level data from dozens of countries combined with novel, interdisciplinary data on disaster exposure, we will examine firm dynamics after a disaster hits. The project will focus on earthquakes and hurricanes, which are global in scope and affect roughly half of the countries on Earth. Progress on this research topic has typically been difficult, as economists and other social scientists were often consumers of earth science data that was ill-suited to answering societal questions. In this project, the construction of ground shaking maps and wind speeds is done in such a way so as to capture the "social exposure" related to the disasters. This stands in contrast to the way in which these hazards are measured by earth scientists, which focuses on the physical characteristics with no regard to how people will be affected by the hazard.

Earthquakes and tropical cyclones affect around half of the countries in the world, making this a truly global research question. Out of approximately 200 countries, 101 are affected by tropical cyclones and

*Corresponding author: amirjina@uchicago.edu

41 are affected by severe earthquakes (over 4.5 on the Richter scale). The level of economic destruction caused by these two phenomena provides a rich trove of data to answer our research questions using the novel modeling methods developed by the research team. Each category of disasters will likely have different post-disaster dynamics. For earthquakes, we use several decades of global exogenous natural hazard data at high spatial resolutions for earthquake shaking and hurricane wind speeds (Lackner, 2018), to calculate firm-level hazard exposure. Earthquake data consists of the universe of global relevant ground-shaking for almost 5 decades at about 1km spatial resolutions from Lackner (2018). This unprecedented level of details will allow us to look beyond merely Richter Scale measures of single events and examine the considerable spatial heterogeneity in damage that an earthquake is known to cause. Hurricane wind exposures are at a $0.1° \times 0.1°$global grid (Hsiang and Jina, 2014) and extreme rainfall data (Bakkensen et al., 2018) at $0.25° \times 0.25°$resolution (Hersbach et al., 2020).

After the construction of these exposure datasets, the next major step will be to merge these together with the firm data. For firm data, in addition to manufacturing and service firm micro-data for 17 countries collected and assembled by one of the project researchers (Nath, 2020), we will also use manufacturing census data from 11 countries from (Goswami et al., 2019), and continue to expand the firm data as available. The primary outcomes that we will explore fall into three categories: firm productivity (e.g., output, sales); firm expenditures and investments (e.g., capital, labor force); firm survival (e.g., firm age, entry and exit of firms). A major aspect of this data construction will be to standardize the firm datasets, all collected idiosyncratically at the national level, across each country.

Finally, we will empirically estimate the causal relationship between disasters and firm recovery, using statistical and econometric techniques that control for unobserved differences across firms and across locations, and trends through time. We will establish a set of empirical facts about how disaster recovery manifests at the firm-level and interpret the economic and policy implications of these facts through the lens of macroeconomic models of firm dynamics and business cycle recoveries. For instance, we plan to analyze how disasters affect firm entry and exit, within-firm labor productivity, allocative efficiency across firms and industries, the composition of entering and exiting firms, and the innovative investment decisions of surviving firms. Do losses during disasters and subsequent recovery trajectories differ across larger or smaller firms, more or less productive firms, more or less labor or capital-intensive firms, or firms in different industries? Do the effects of disasters differ across countries by level of income, by experience with a given disaster type, or by size of the country?

This research makes four main contributions. First, it contributes to the research on the economic outcomes of environment, disasters, and climate change by exploring mechanisms in a literature that has often focused on aggregate measures of output. Historically, economists have believed that "disasters are good for business." This is due to an assumption that outdated, destroyed capital would be replaced and a building boom would ensue, as well as research on human-made disasters (e.g., war-time bombings in (Davis and Weinstein, 2002) and (Miguel and Roland, 2011)). Although observations and anecdotal evidence suggests recovery is actually slow, the economic literature has only recently begun to demonstrate that the prevailing theory – and the government policies that it informs – does not accurately reflect the reality. While early empirical evidence on natural disasters also seems to confirm the view that "disasters are good for business" (e.g., Skidmore and Toya, 2002; Toya and Skidmore, 2007; Hallegatte and Dumas, 2009; Noy, 2009; Cavallo et al., 2010), these papers suffer from a number of limitations that make their conclusions questionable. Notably, they used coarse, nationally-aggregated outcome variables and imprecise measures of hazard exposure, and their measures of disaster severity——usually reported monetary damages——were often endogenous. Additionally, disaster damage data are largely self-reported, and are thus both more accurate and more frequently reported in wealthier areas (Gall et al., 2009). The resulting correlation between wealth and disasters has often been misinterpreted as causal. Moreover, disasters of different types were grouped together and physical disaster intensity—e.g., windspeed or ground-shaking—was ignored.

Second, it relates to the literature on misallocation and economic growth (e.g., Hsieh and Klenow, 2009), as well as to research on the macroeconomic effect of consumption disasters, financial crises and other large shocks (e.g., Barro, 2006; Cerra and Saxena, 2008; Nakamura et al., 2013). Limited evidence on misallocation due to environmental shocks exists. While some studies have shown increased exit of firms after a single hurricane (Basker and Miranda, 2014), distortion to labor markets after a disaster (Belasen and Polachek, 2008, 2009), or distortionary spending (Deryugina, 2017) that results from hurricanes, no study to our knowledge has systematically examined firm microdata across multiple countries and disaster types. Internationally, hurricanes have been shown to distort financial flows (Yang, 2008), which may also account for changes to investment and allocative efficiency within a country. Hsiang and Jina (2015) posit that such shocks may also act as differential depreciation rates across locations, thus leading to smaller or slower growing firms in exposed areas.

Third, we advance the literature on the use of objective measures of environmental shocks using physics and earth science methods combined with sub-national economic analysis using rich microdata. For example, we will reconstruct every tropical cyclone that occurred since 1950 in the countries of our analysis. Country-level studies have demonstrated that these climate-related hazards have potentially large and long-term effects on economic growth (Hsiang and Jina, 2014; Strobl, 2011), but few studies have used these combined with detailed firm microdata.

Fourth, and perhaps most importantly, it contributes to the knowledge base of post-disaster impacts and their policy responses. While prior research has estimated significant effects of disasters in aggregate, it rarely identifies mechanisms through which those effects manifest. Understanding mechanisms is particularly important as they guide policy responses in order to help society cope with the longer-run effects of disasters. This is especially important in the case of tropical cyclones, as we expect the amplification of these effects as climate change alters the frequency or intensity of disasters (Nordhaus, 2010; Emanuel, 2011). These results are likely to be particularly salient in lower income countries, where governments are less able to provide general insurance and safety net policies that might mitigate the worst effects of disasters and climate change (UN and World Bank, 2010).

2 Data

2.1 Firm-level Data

To investigate the channels through which natural disasters affect the economy and for how long these effects persist, we focus on granular firm-level panel data. This data often exists in a form of a representative annual survey, such as the Manufacturing Industry Survey in Indonesia (Statistik Industri) or the Economic Census collected by the General Statistics Office in Vietnam. These surveys usually contain data on number of employees, capital, incurred costs, income, profits, and other firm information about establishment year and location. Depending on the dataset, these variables may be aggregate or broken into subcategories (e.g., capital can be reported as just capital or have separate values for land, machinery, buildings).

We prioritize accessing the firm-level data for countries that were regularly affected by either tropical cyclones, earthquakes or both. Other criteria for choosing datasets are the quality of the dataset, frequency of the survey, and data accessibility. An ideal dataset would cover all the firms in the economy and would contain data on labor, capital, output, income, investments and profits. Also, the ideal dataset would be the one from which we can deduce firms' entry into and exit from the economy.

2.2 Natural Disasters Data

Many previous studies that focus on natural disaster impacts use reported damages as a measurement of the severity of these events. A frequently used source for damage data is the Emergency Events Database (EM-DAT) (CRED, 2020). However, reported damages are often endogenous and positively correlated with GDP (Gall et al., 2009). Moreover, there may arise a selection bias concern since wealthier countries are likely to report natural disasters in a more complete manner. To overcome these biases, in this project we use several decades of global exogenous natural hazard data at high spatial resolutions for earthquakes (Lackner, 2018) and hurricanes (Hsiang and Jina, 2014; Boose et al., 2004). In particular, we use earthquake shaking and hurricane wind speeds as the physical hazard measures. The three crucial components our data provides are (i) exogeneity of the hazard exposure, (ii) spatially differentiated local exposure information, and (iii) measures that actually describe the physical phenomenon which is immediately responsible for causing damages.

2.2.1 Earthquakes Data

We employ a unique data set of global earthquake exposure, containing the universe of relevant earthquake ground shaking for almost five decades. Unlike data used in most previous literature, our data set is based on exogenous shaking data from thousands of earthquakes, instead of self-reports data, binary indicator data without detail on relevant economic exposure, or Richter scale magnitude. While this latter magnitude is also an exogenous measure, it describes the overall energy released by an earthquake and not the surface phenomenon of ground shaking. Importantly, magnitude does not account for spatial variation in exposure and it is essentially a bad proxy for overall surface shaking and, consequently, also for damages. Magnitude is therefore not well suited for use in economic assessments of earthquake damages.

Our surface shaking data set is based on USGS ShakeMaps of peak ground acceleration (PGA) and peak ground velocity (PGV) (Wald et al., 1999). These automatically generated maps provide a high spatial resolution of exposure and the data describes the actual hazard of concern: shaking on the surface. Similar as described in Lackner (2018), the individual ShakeMaps are collected from the USGS, overlapped with landsurface area to only consider ground shaking, and cleaned for outliers. After cleaning, the data set of ShakeMaps is representative of overall global earthquake ground shaking starting from the year 1973 (Lackner, 2018).

We will particularly focus on peak ground acceleration (PGA) as the primary ground motion measure, which is consistent with its use in earthquake engineering. Ground acceleration is the increase in velocity (measured in %g, or percent of accelaration due to gravity. 1g, or 100%g, is approximately $9.8 \mathrm{m/s}^2$). As secondary specification we will also utilise peak ground velocity (PGV). Ground velocity is how fast a point on the ground is shaking as a result of an earthquake (measured in cm/s).

2.2.2 Tropical Cyclones Data

Similarly to the magnitude of earthquakes, many frequently used measurements of tropical cyclones do not necessarily help measure the exposure of the economy to the disaster. Climate scientists typically care about the tropical cyclone itself, and many measures of intensity aim to summarize the entire cyclone. What matters for people and the economy, however, is local intensity, rather than intensity at the central part of the cyclone or overall energy as captured by the categorical description of the storm (i.e., the category 1-5 measures of the Saffir-Simpson scale). Therefore we need to reconstruct the entire exposure due to a cyclone rather than just a single summary measure. We use climate physics to reconstruct the wind speed and power dissipation of each cyclone and measure intensity, and weight these according to number of people or value of assets exposed.

The source of the data is the International Best Track Archive for Climate Stewardship (IBTrACS) (Knapp et al., 2010), which merges tropical cyclone reports from a number of agencies around the world. Data on the central eye air pressure of the cyclone, the cyclone's translational velocity, and the maximum sustained windspeed are reported at 6-hourly intervals. The variables that we need for our physical model are cyclone's path and maximum sustained wind speed (measured in knots). According to the IBTrACS documentation, Maximum Sustained Wind Speed (MSW) is the speed of the "highest surface winds occurring within the circulation of the system." These data are then used to calculate location-specific wind intensity at each point on the surface that experiences any tropical cyclone force winds, following Boose et al. (2004) and Hsiang and Jina (2014). The resulting dataset has a spatial resolution of $0.1° \times 0.1°$ and locations are linearly interpolated to hourly frequency.

3 Methodology

3.1 Gridded Exposure Data

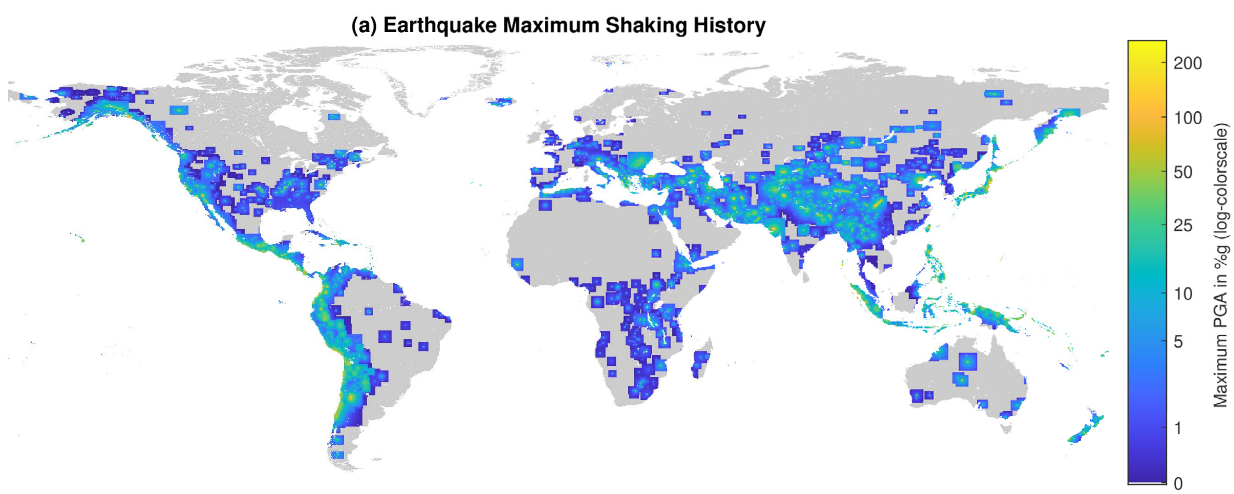


Figure 1: Maximum peak ground acceleration (PGA) in %g as calculated in Lackner (2018)

The earthquake raw data already provides the necessary physical hazard as gridded spatial data. We only minimally process and clean the USGS ShakeMaps according to Lackner (2018) to get our final spatial exposure maps. These data are shown in figure 1. We transform the raw cyclone data from IBTrACS to

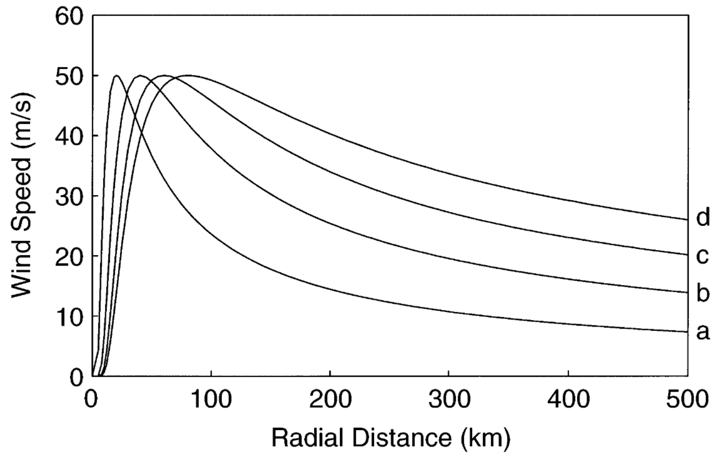


Figure 2: HURRECON model, reproduced from Boose et al. (2004). Estimated wind speed along a radial line outward from the storm center is a function of the radius of maximum winds (R_m), the wind speed at that radius (V_{rm}), and the scaling parameter B, which controls the shape of the curve. Figure shows four combinations of R_m and B: (a) 20 km, 1.5; (b) 40 km, 1.4;(c) 60 km, 1.3; and (d) 80 km, 1.2. Wind velocity curves are shown for an arbitrary value of V_{rm} =50 m/s

create a gridded spatial wind speed dataset. IBTrACS only reports data on the winds in the eye of the storm. We use a meteorological model to estimate local intensity in places that are not directly hit by the cyclone's eye. We use a model from Boose et al. (2004). The equation to estimate sustained wind velocity (V_s) at any point P in the northern hemisphere is the following:

$$V_s = F[V_m - S(1 - sinT)V_h/2] \times [(R_m/R)^B exp(1 - [R_m/R]^B)]^{\frac{1}{2}}, \quad (1)$$

where F is the scaling parameter for effects of friction (water = 1.0, land = 0.8), V_m is the maximum sustained wind velocity over water anywhere in the tropical cyclone, S is the scaling parameter for asymmetry due to forward motion of storm (1.0), T is the clockwise angle between the forward path of tropical cyclone and a radial line from tropical cyclone center to point P, V_h is the forward velocity of the tropical cyclone, R_m is the radius of maximum winds (20–80 km), R is the radial distance from the tropical cyclone center to point P, and B is the scaling parameter controlling the shape of the wind profile curve (1.2–1.5). This functional form is shown for different parameter values in Figure 2.

3.1.1 Exposure Summary Data

Table 1 reports relevant exposure measures of tropical cyclones and earthquakes for a set of countries that have high levels of exposure and available firm-level data. Earthquakes are summarized by the median of the highest PGA per earthquake for all earthquakes during the time period 1973-2018. Here, Max(PGA) is calculated on an event-level basis (maximum shaking during each earthquake). For this table, we drop all shaking events with $PGA < 1$ since those events are generally too small to cause any damage and it also prevents certain data quality issues. For tropical cyclones, we report median maximum sustained wind velocity in the storm's eye at the event-level (maximum over all the time that the cyclone was recorded). Given the spatial extent of a tropical cyclone, we report cyclones whose tracks lie within a distance of approximately 500 km extending from the coast of each country.

Table 1: Exposure to different disasters by country.

Country	N of Earthquakes	Median Max(PGA)	N of Tropical Cyclones	Median of MSW
Chile	724	7.3	0	-
Colombia	131	6.7	217	45.0
Côte d'Ivoire	1	1.5	0	-
El Salvador	143	3.3	188	33.5
Ethiopia	42	13.4	25	36.0
India	384	12.4	468	45.0
Indonesia	1700	7.1	1008	37.0
Japan	762	5.2	940	70.0
Mexico	546	7.6	1026	55.0
Moldova	7	3.0	0	-
Philippines	609	7.3	1005	63.5
USA	5146	4.5	863	55.0
Vietnam	18	2.6	527	50.0

Table Notes: N of earthquakes and median MPGA are calculated after dropping shaking records with PGA less than 1. Median MSW is for now calculated based on USA agencies only. Number of cyclones is based on all agencies. Only earthquakes in the country's boundaries are reported. Cyclones in 500km radius around the country are reported.

3.2 Spatial Data Aggregation

While our natural hazard data comes at a high spatial resolution, this is not necessarily the case for the firm-level data. Firm-level surveys usually don't report exact addresses for the plants. More often, they have second-level administrative unit identifiers. Also, those surveys are usually annual. To match the two different data sources - exposure data and firm data - we need to spatially aggregate the gridded hazard event data to the region-year level of the firm data. This section describes our approach to aggregating the earthquake shaking data and the cyclone wind speed data.

3.2.1 Earthquakes

From the raw data of PGA and PGV we will calculate several different admin-region exposure measures. We need to aggregate the original gridded data from the ShakeMaps to the region-year level of the firm data. The process will be the same for PGA and PGV and it will therefore only be explained for PGA to illustrate the methodology. The two main measures will be the "spatial average of maximum PGA during a year" (MPGA) and the "average number of strong earthquakes" (NE).

To calculate the spatial average (MPGA), we first determine the maximum value of PGA during a year for each gridcell in the boundaries of a region. We then calculate the area-weighted average of these maximum values in that year for that region. This process can be summarized with the following equation

$$MPGA_{r,year} = \frac{\sum_{cell \in r} \max_{t \in year}\{PGA_{cell,t}\}}{N_r}, \tag{2}$$

where r refers to the admin-region, N_r is the number of gridcells that fall within the boundaries of that admin region, and $PGA_{cell,t}$ is the PGA value experienced in the location of gridcell *cell* for an earthquake that happened in year t. We calculate different versions of MPGA, for example only considering populated/urban/rural areas, MPGA weighted by population instead of area, and restricting to the most affected $X\%$ area of a region.

The average number of strong earthquakes (NE) is calculated according to the following process. First, for each gridcell within an administrative boundary we determine the number of earthquakes within a year that exceeded a strength of 10% g at that location. In the second step we calculate the spatial average of that number. This process can be summarized with the following equation

$$NE_{r,year} = \frac{\sum_{cell \in r} \sum_{t \in year} \{1 \text{ if } PGA_{cell,t} \geq 10\% g\}}{N_r}. \tag{3}$$

3.2.2 Tropical Cyclones

Tropical cyclone spatial aggregation will be similar to earthquake spatial aggregation. Namely, once maximum wind speeds and power dissipation have been calculated at the cell-level at 0.1°resolution, values well be aggregated as follows:

$$MAXS_{r,year} = \frac{\sum_{cell \in r} \max_{t \in year} \{MAXS_{cell,t}\}}{N_r}, \tag{4}$$

where r refers to the admin-region, N_r is the number of gridcells that fall within the boundaries of that admin region, and $MAXS_{cell,t}$ is the maximum wind speed value experienced in the location of gridcell *cell* for a tropical cyclone that happened in year t.

3.3 Empirical Strategy

We will estimate a regression of the following type. Exact details may change as we begin to understand more about the theoretical implications of dynamics among the firms. Initially, this will be done for one country, but will be extended to other countries as they are added to the data. Versions will be run allowing for country-level heterogeneity while pooling data across countries. We will estimate this equation separately for each type of disaster. Below is an example that we will run initially for the Indonesia data:

$$ln(y_{it}) = \sum_{l=0}^{L} \beta_l D_{i,t-l} + \alpha_i + \gamma_t + \varepsilon_{it}, \tag{5}$$

where y_{it} is an outcome of a firm i in year t. $D_{i,t-l}$ is a measure of disaster's intensity aggregated at a region-year level, lagged L times. A region in our project is most frequently a second-level administrative unit (ADM2). α_i is plant/firm fixed effect, γ_t is year fixed effect. We cluster standard errors ε_{it} at the plant/firm and region-by-year level.

4 Case Study of Indonesia and Earthquakes

4.1 Data Summary

We start our project by focusing on Indonesia. Figures 3 and 4 show the spatial distributions of the two disaster types we study in this project: cyclones and earthquakes. In the case of earthquakes, we plot the mean of the annual MPGA across years. For cyclones we visualize historic cyclone tracks in the region around Indonesia. The cones of high wind speeds are much wider and overlap in many cases with the land mass of Indonesia. However, for the purposes of this note, we focus largely on earthquake exposure in Indonesia, since the country is more exposed to them.

Figure 3: Earthquake Shaking Intensity in Indonesia

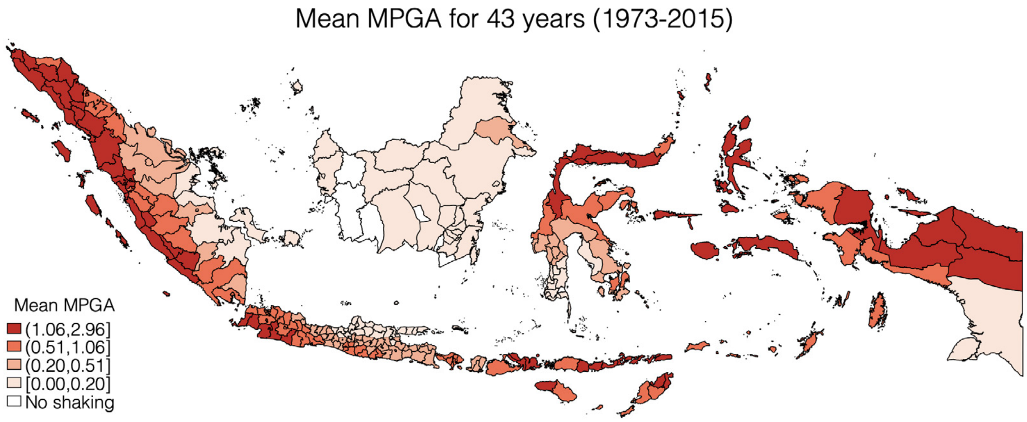
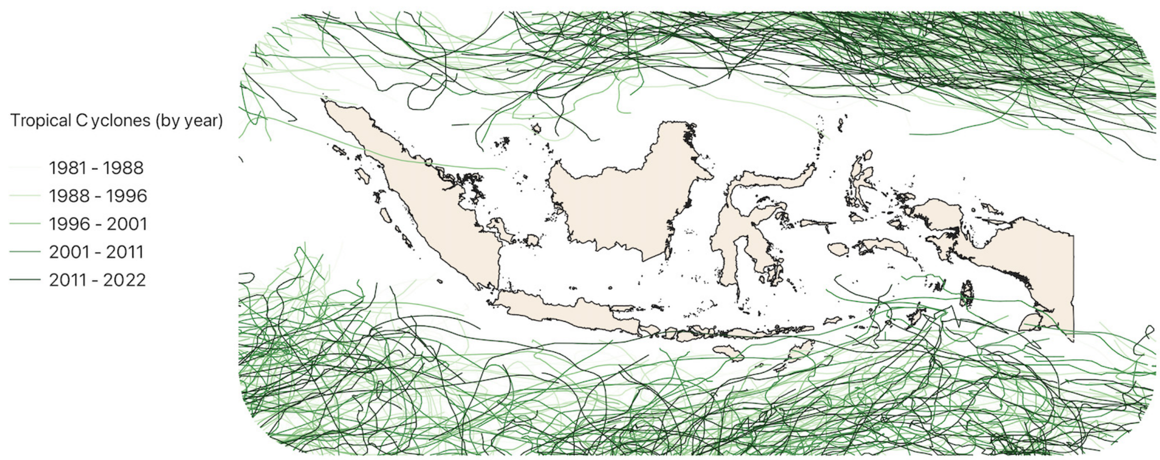


Figure 4: Tropical Cyclones around Indonesia



Firm-level data on Indonesia comes from a Manufacturing Industry Survey (Statistik Industri) collected by the Central Bureau of Statistics (Badan Pusat Statistik, or BPS). This survey is conducted annually, covering all the firms with twenty or more workers. We possess annual data for the period 1988-2015. Table 2 contains summary statistics for the most important variables we use in the analysis.

We present two key variables in Figure 5 to show how the economic activity is distributed spatially. These maps are produced using data for the year 2000 but the distribution of activity from other years is in general consistent with this picture. In terms of labor and output, the most important regions are Java with the capital Jakarta, Sumatra, Sulawesi and Kalimantan. We can see that regions that experience shaking and economically important regions overlap.

Table 2: Indonesia: Summary Statistics for Firm Data

	mean	min	p10	p50	p90	max	count
Labor	195.6	10.0	22.0	45.0	410.0	57384.0	468732
Output (real, th)	79966.6	2.0	424.8	3698.5	114685.7	1.3e+08	469155
VA (real, th)	32569.7	-3.8e+06	182.8	1299.9	36790.6	60023324.0	469177
Materials (real, th)	40171.5	0.0	77.5	1590.9	55574.8	69266568.0	469165
Capital (real, th)	305807.7	-0.1	0.0	721.1	25646.7	1.1e+10	461446
VA/Labor (real, th)	101393.9	-2.0e+06	5701.2	24549.0	158158.5	6.0e+08	468708
Wage (real, th)	3481.6	0.0	96.1	481.5	6694.2	4549636.5	468936
Avg Wage (real, th)	14.1	0.0	3.0	10.1	25.8	19413.5	468467

Table Notes: All values are in local currency (Indonesian Rupiah)

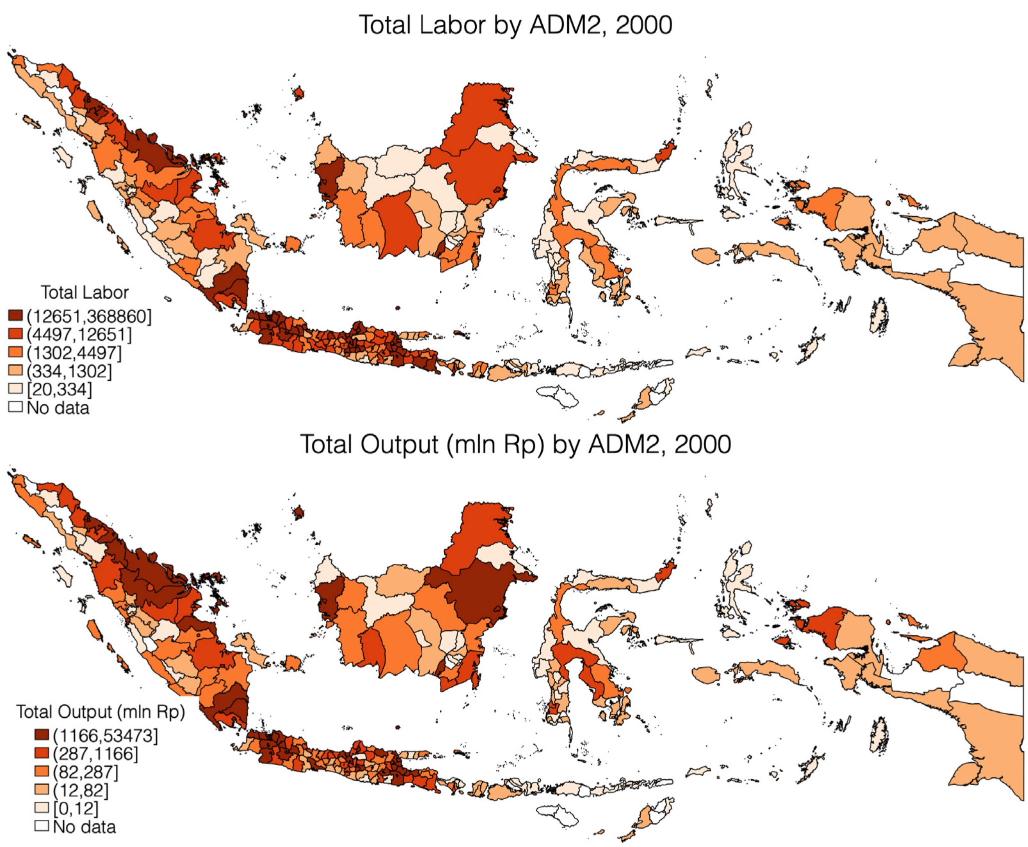


Figure 5

4.2 Suggestive Descriptive Statistics

Figure 6 shows the distributions of nominal output of the same set of firms one year before and one year after an earthquake occurs. Here, we simply plot the raw data without controls. We draw two conclusions from this figure. First, methodologically, we see that it is likely important to estimate changes at specific moments of the distribution of the firms. Second, we see this pattern as suggestive evidence for an increase in output following an earthquake. In the next subsection we show whether this relationship persists when we estimate our baseline regression.

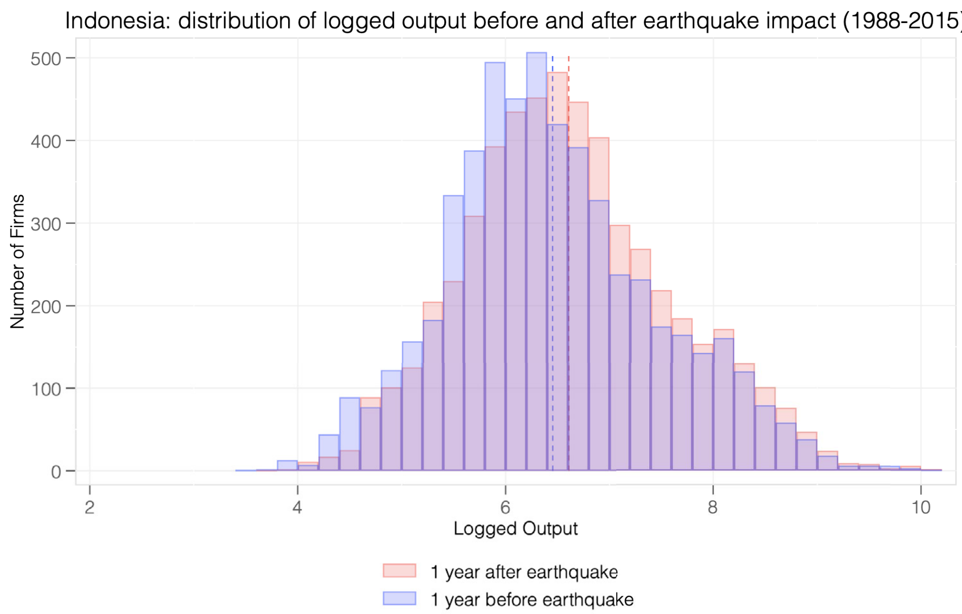


Figure 6: Distribution of log(Output) of firms one year before and one year after an earthquake.

Moreover, since we want to study exits of firms due to natural disasters, on Figure 7 we plot distributions of "years in survey" (that is, the number of years for which a firm is included in the manufacturing survey) for firms that were ever hit by disasters against those that were never hit. We see two spikes - there were many new firms included at the start of the survey and after a census (firms that are 10 years old). From this plot we see that firms hit by earthquakes are considerably older. There can be several explanations for this. First, as we show earlier, the most seismically active regions overlap with the most economically important regions. Thus, these regions may have a lot of older and larger firms. Second, this may imply that younger firms are more likely to exit after an earthquake than older firms. Third, trivially, it may be the case that younger firms only entered the survey and were not in a survey long enough to experience the earthquake. We aim to study which explanation is correct in the next steps of our analysis.

4.3 Preliminary Results

As a preliminary exercise, we estimate the equation 5 for shaking intensity and average number of earthquakes with five lags. We report the results in Table 3. Each column represents different dependent variables. Panel A shows results for the intensity of earthquakes in PGA. Panel B shows results for the same variables for the number of strong earthquakes within a year. In Panel A column (1), we report results for logged output.

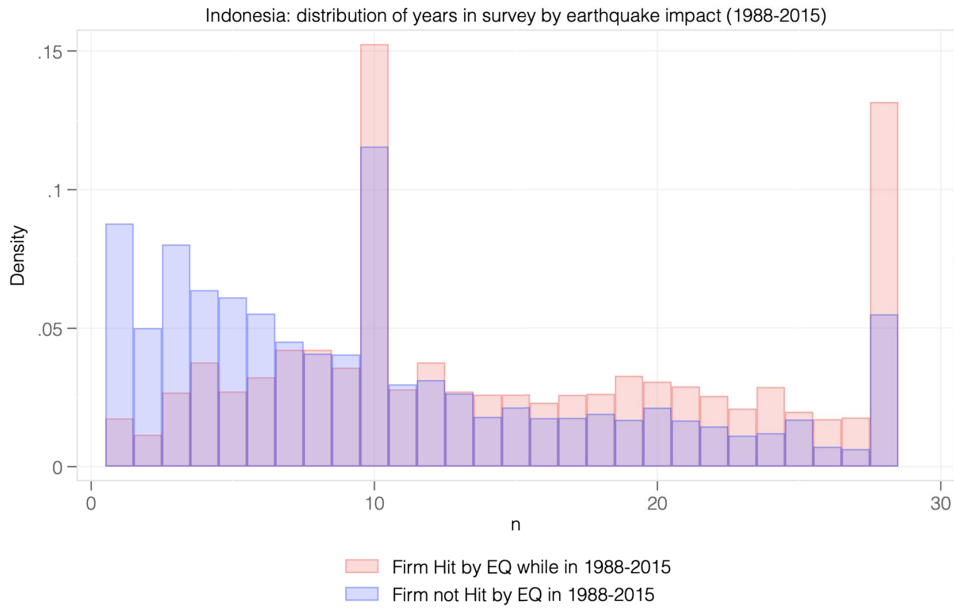


Figure 7: Distributions of the number of years for which a firm is included in the manufacturing survey for firms that were ever hit by disasters against those that were never hit.

Based on this equation, an increase of MPGA by 1%g is associated with 0.16% decrease in a total output in the same year, but there is no persistence of the result in the medium-run. Even though all estimates for lags 1 to 5 have negative signs, they are all not statistically significant. Based on the results in panel B, a 1 unit increase in the average number of strong earthquakes (NE) is associated with 4.5% decrease in a total output in the same year. The results persist, there is a decrease of 3% and 4.1% two and three years later.

Next, we focus on logged value-added in column (2). Table 3 panel A has negative signs for all estimates though none are statistically significant. However, in panel B, a 1 unit increase in NE corresponds to $3-4\%$ decrease in value added the same year, two years later and three years later. Column (3) shows the estimation results for logged net investment. An increase of MPGA by 1%g corresponds to a 0.6% decrease in net investment in 2 years. The results are consistent with panel B, where a 1 unit increase in NE is associated with 9.7% decrease in net investment in 2 years. In column (4) we show the results for logged labor productivity. Panel A in table 3 for this variable has negative signs for all estimates but none are statistically significant. In contrast, a 1 unit increase in NE corresponds to a 3.2% decrease in labor productivity the same year. The effect persists, and is of similar magnitude 2 and 3 years after. Lastly, column (5), shows results for the raw input. The pattern is unclear for PGA, whereas a 1 unit increase in NE corresponds to $3-5\%$ decrease in raw input materials the same year, two years later and three years later.

Table 3: Effects of Shaking Intensity on Firms' Outcomes

	(1) Log(Output)	(2) Log(VA)	(3) Log(Net Inv.)	(4) Log($\frac{VA}{Labor}$)	(5) Log(Input)
	Panel A: Effects of Shaking Intensity on Firms' Outcomes				
Median Peak Ground Acceleration (MPGA)					
t=0	-0.00161*	-0.00116	0.00123	-0.00112	-0.00119
	(0.000739)	(0.000786)	(0.00210)	(0.000749)	(0.000797)
t=-1	-0.000465	-0.000331	-0.00351	-0.000392	-0.000803
	(0.000836)	(0.000863)	(0.00227)	(0.000935)	(0.000968)
t=-2	-0.000356	-0.00112	-0.00684**	-0.00131	0.000165
	(0.000771)	(0.000808)	(0.00209)	(0.000748)	(0.000843)
t=-3	-0.00110	-0.00159	-0.00350	-0.00124	-0.000530
	(0.000828)	(0.000864)	(0.00211)	(0.000805)	(0.000895)
t=-4	-0.000808	-0.00128	0.00243	-0.00115	-0.000240
	(0.000960)	(0.000999)	(0.00208)	(0.000947)	(0.00102)
t=-5	-0.000107	-0.000895	-0.000975	-0.000492	0.000285
	(0.000927)	(0.000968)	(0.00193)	(0.00102)	(0.00103)
	Panel B: Effects of Strong Earthquakes on Firms' Outcomes				
Number of Earthquakes (NE)					
t=0	-0.0450***	-0.0390**	0.0353	-0.0315*	-0.0482**
	(0.0123)	(0.0130)	(0.0498)	(0.0129)	(0.0164)
t=-1	-0.00982	-0.00331	-0.0192	0.00543	-0.0211
	(0.0196)	(0.0219)	(0.0595)	(0.0236)	(0.0237)
t=-2	-0.0308*	-0.0417**	-0.0969*	-0.0279*	-0.0344*
	(0.0142)	(0.0149)	(0.0449)	(0.0139)	(0.0162)
t=-3	-0.0417*	-0.0377*	0.0427	-0.0318*	-0.0485*
	(0.0171)	(0.0169)	(0.0500)	(0.0152)	(0.0189)
t=-4	-0.0358	-0.0381	0.0797	-0.0307	-0.0275
	(0.0239)	(0.0233)	(0.0464)	(0.0215)	(0.0282)
t=-5	-0.0311	-0.0288	-0.0300	-0.0234	-0.0223
	(0.0218)	(0.0224)	(0.0446)	(0.0220)	(0.0244)
N	465736	465728	81893	465728	447328
Plant FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.854	0.830	0.840	0.672	0.818

Standard errors in parentheses

Plant and year fixed effects are included in each specification. All variables are real values.

Errors are clustered on both plant-level and region-by-year level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5 Case Study of Vietnam

5.1 Data Summary

The next country that we explore is Vietnam. We know that Vietnam is severely impacted by tropical cyclones, called typhoons in the Pacific basin, so this preliminary analysis focuses on them. The left part of Figure 8 shows locations of cyclone tracks making landfall and passing to within 500km of Vietnam as reported in the IBTrACS dataset. The right part of Figure 8 shows the annual average intensity of wind speeds that were reconstructed from the IBTrACS dataset using the methods of Boose et al. (2004).

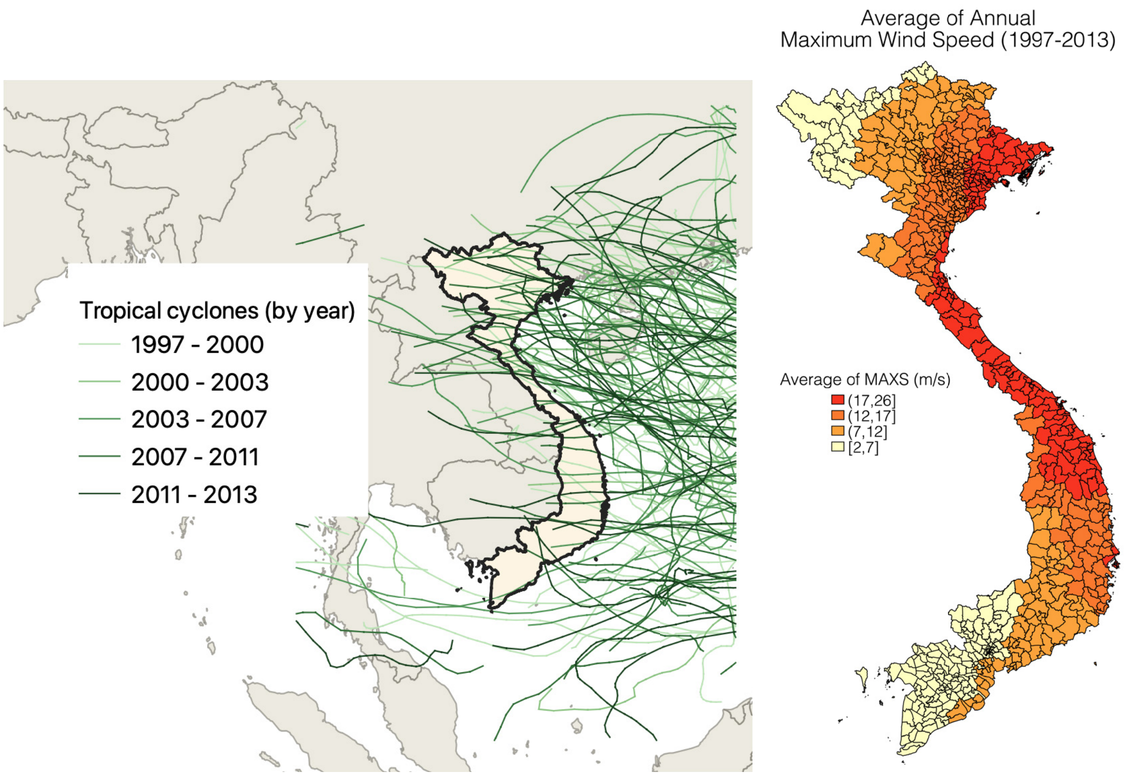


Figure 8: Left: Tropical cyclones (typhoon) tracks making landfall or passing to within 500km of Vietnam for 1997-2013. Right: Average intensity of tropical cyclones.

Firm data comes from an annual economic census provided by General Statistics Office of Vietnam and contains data on all registered firms for the years 2007-2013.[1] Table 4 contains summary statistics of the main variables we use in our analyses. The number of observations for value added, input materials and labor productivity (based on VA) is indeed lower.

We plot several variables to show the spatial distribution of economic activity in Figure **??**. The left subplot shows the number of unique firms throughout all the years of the survey. The center and right subplots show total labor and sales on a district (ADM2) level, respectively. The main economic clusters are located around Hanoi in the North and Ho Chi Minh City in the South. Even though labor and sales maps are for 2010 only, the maps from other years show similar clustering.

[1]One limitation of the data is that value added and input materials are not reported for 2008-09.

Table 4: Vietnam: Summary Statistics for Firm Data

	mean	min	p10	p50	p90	max	count
Labor	34.1	0.0	2.0	7.0	44.0	101235.0	1947996
Sales	12052991.2	0.0	37359.9	725714.0	10896637.0	1.5e+11	1828111
VA	1580461.8	-5.4e+09	0.0	52895.4	920474.1	2.7e+10	1446836
Materials	9993809.9	0.0	15957.2	500858.5	9352151.0	1.3e+11	1441573
Capital	5029.4	-1.5e+07	0.0	163.9	2120.6	1.1e+08	1803571
VA / Labor	24283.4	24.6	886.5	8921.6	53597.4	6717872.5	1230674
Labor Cost	29869438.0	0.0	21357.7	97151.2	944540.2	6.4e+12	1941442
Wage	635418.2	0.0	20520.1	88272.0	637297.6	5.7e+09	1941436
Avg Wage	15642.5	0.0	4643.9	12982.1	23557.5	1.8e+08	1941436

Table Notes: All values are in real local currency (Vietnamese Dong). All values are in thousands, except labor and VA/Labor

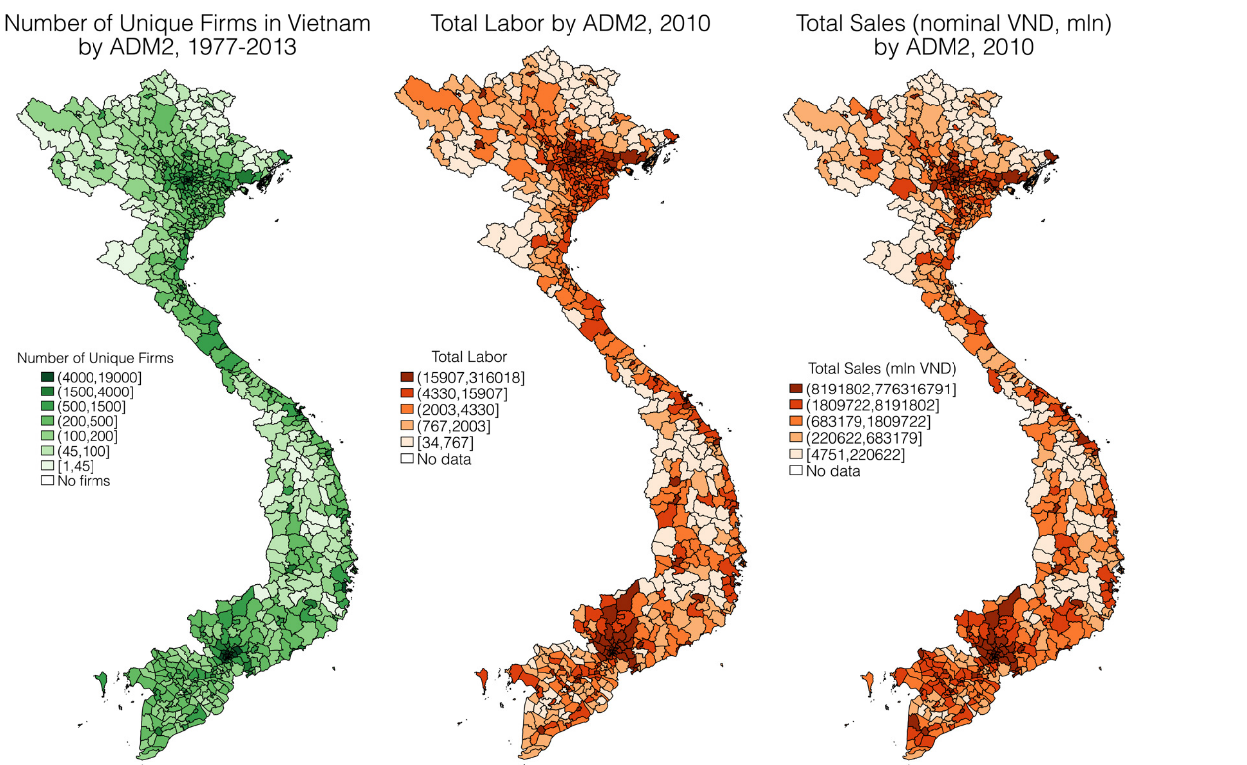


Figure 9: Spatial distribution of firm characteristics in Vietnam. Left: Number of unique firms. Middle: Total labor in 2010. Right: Total sales of firms averaged over ADM2 regions in 2010.

5.2 Preliminary Results

As a preliminary exercise for Vietnam, we estimate equation 5 for the spatial average of maximum annual wind speed (MAXS) for each region, measured here in m/s. In Table 5 we report the preliminary results. We take a subsample of the dataset in which firms do not have any missing values for the following variables: sales, VA, labor cost, wages, labor. For a storm to be classified as a tropical cyclone (i.e., category 1 on Saffir-Simpson scale), the maximum sustained winds should be over 33 m/s. To give more sense to the estimates, we can approximately say that a change of MAXS from 0 to 33 is equal to change from no storms to experiencing a typhoon-force wind speed in every part of the district.

Then, an increase from no storms to a tropical cyclone (33 m/s) in an average district is associated with an increase of sales by 2.9% (0.00087 * 100% *33m/s), a decrease of profits by 2.9%, an increase of labor cost by 2.2%, a decrease of average wage by 0.84%, an increase of labor by 1.02% and a decrease of productivity by 3.9%. Importantly, decrease in profits, average wage and productivity persist for several years.

Table 5: Effects of tropical cyclones on firm's outcomes

	(1) log(Sales)	(2) log(VA)	(3) log(Labor Cost)	(4) log(Avg Wage)	(5) log(L)	(6) log(VA/L)
Maximum wind speed (MAXS) (m/s)						
t=0	0.000365	0.00119**	-0.000201	0.000238	0.000118	0.00107**
	(0.000266)	(0.000439)	(0.000214)	(0.000137)	(0.000126)	(0.000395)
t=-1	0.000870**	-0.000871*	0.000671***	-0.000257*	0.000311**	-0.00118**
	(0.000267)	(0.000379)	(0.000201)	(0.000131)	(0.000115)	(0.000359)
t=-2	0.000668**	-0.00156**	0.00183***	0.000190	0.000785***	-0.00234***
	(0.000230)	(0.000512)	(0.000296)	(0.000135)	(0.000111)	(0.000526)
t=-3	-0.000380	-0.00123***	0.000607**	-0.000581***	0.000306**	-0.00153***
	(0.000197)	(0.000343)	(0.000194)	(0.000110)	(0.0000957)	(0.000339)
t=-4	-0.000426*	-0.0000357	0.000988***	-0.000853***	0.000474***	-0.000510
	(0.000205)	(0.000539)	(0.000276)	(0.000127)	(0.000112)	(0.000559)
t=-5	-0.0000434	0.0000922	0.000924***	-0.000141	-0.0000500	0.000142
	(0.000176)	(0.000409)	(0.000200)	(0.000118)	(0.0000852)	(0.000403)
N	1111650	1111650	1111650	1111650	1111650	1111650
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.861	0.774	0.797	0.669	0.893	0.623

Standard errors in parentheses
Plant and year fixed effects are included in each specification. All variables are real values.
Errors are clustered on both plant-level and region-by-year level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6 Timeline

The next steps are as follows: First, we will extend the tropical cyclone analysis to Indonesian data. Second, we will collect firm-level data on a set of countries based on disaster exposure and standardize the obtained data across countries. Third, we will produce disaster exposure data for the set of these countries. Fourth, we will conduct aggregated analysis for all the available countries. We expect to have regression results available for multiple countries by October 2022, with a working paper publicly available by that date. Results for tropical cyclones will include discussions and projections of changing impacts under climate change.

7 References

Bakkensen, L. A., D.-S. R. Park, and R. S. R. Sarkar (2018). Climate costs of tropical cyclone losses also depend on rain. Environmental Research Letters 13(7), 074034.

Barro, R. J. (2006). Rare disasters and asset markets in the twentieth century. The Quarterly Journal of Economics 121(3), 823–866.

Basker, E. and J. Miranda (2014). Taken by storm: Business survival in the aftermath of hurricane katrina. US Census Bureau Center for Economic Studies Paper No. CES-WP-14-20.

Belasen, A. and S. Polachek (2008). How hurricanes affect wages and employment in local labor markets. The American Economic Review 98(2), 49–53.

Belasen, A. and S. Polachek (2009). How disasters affect local labor markets. Journal of Human Resources 44(1), 251–276.

Boose, E. R., M. I. Serrano, and D. R. Foster (2004). Landscape and regional impacts of hurricanes in puerto rico. Ecological Monographs 74(2), 335–352.

Cavallo, E., S. Galiani, I. Noy, and J. Pantano (2010). Catastrophic natural disasters and economic growth. Inter-American Development Bank.

Cerra, V. and S. C. Saxena (2008). Growth dynamics: the myth of economic recovery. The American Economic Review 98(1), 439–457.

CRED, E. (2020). The international disaster database: centre for research on the epidemiology of disasters.

Davis, D. R. and D. E. Weinstein (2002). Bones, bombs, and break points: the geography of economic activity. American economic review 92(5), 1269–1289.

Deryugina, T. (2017). The fiscal cost of hurricanes: Disaster aid versus social insurance. American Economic Journal: Economic Policy 9(3), 168–98.

Emanuel, K. (2011). Global warming effects on us hurricane damage. Weather, Climate, and Society 3(4), 261–268.

Gall, M., K. A. Borden, and S. L. Cutter (2009). When do losses count? six fallacies of natural hazards loss data. Bulletin of the American Meteorological Society 90(6), 799–810.

Goswami, A. G., D. Medvedev, and E. Olafsen (2019). High-growth firms: Facts, fiction, and policy options for emerging economies. World Bank Publications.

Hallegatte, S. and P. Dumas (2009). Can natural disasters have positive consequences? investigating the role of embodied technical change. Ecological Economics 68(3), 777–786.

Hersbach, H., B. Bell, P. Berrisford, S. Hirahara, A. Horányi, J. Muñoz-Sabater, J. Nicolas, C. Peubey, R. Radu, D. Schepers, et al. (2020). The era5 global reanalysis. Quarterly Journal of the Royal Meteorological Society 146(730), 1999–2049.

Hsiang, S. M. and A. S. Jina (2014). The causal effect of environmental catastrophe on long-run economic growth: Evidence from 6,700 cyclones. Technical report, National Bureau of Economic Research.

Hsiang, S. M. and A. S. Jina (2015). Geography, depreciation, and growth. American Economic Review: Papers & Proceedings.

Hsieh, C.-T. and P. J. Klenow (2009). Misallocation and manufacturing tfp in china and india. The Quarterly journal of economics 124(4), 1403–1448.

Knapp, K. R., M. C. Kruk, D. H. Levinson, H. J. Diamond, and C. J. Neumann (2010). The international best track archive for climate stewardship (ibtracs) unifying tropical cyclone data. Bulletin of the American Meteorological Society 91(3), 363–376.

Lackner, S. (2018). Earthquakes on the surface: earthquake location and area based on more than 14500 shakemaps. Natural Hazards and Earth System Sciences 18(6), 1665–1679.

Miguel, E. and G. Roland (2011). The long-run impact of bombing vietnam. Journal of Development Economics 96(1), 1–15.

Nakamura, E., J. Steinsson, R. Barro, and J. Ursúa (2013). Crises and recoveries in an empirical model of consumption disasters. American Economic Journal: Macroeconomics 5(3), 35–74.

Nath, I. B. (2020). The food problem and the aggregate productivity consequences of climate change. Technical report, National Bureau of Economic Research.

Nordhaus, W. D. (2010). The economics of hurricanes and implications of global warming. Climate Change Econ. 1, 1–20.

Noy, I. (2009). The macroeconomic consequences of disasters. Journal of Development economics 88(2), 221–231.

Patricola, C. M. and M. F. Wehner (2018). Anthropogenic influences on major tropical cyclone events. Nature 563(7731), 339–346.

Skidmore, M. and H. Toya (2002, October). Do natural disasters promote long-run growth? Economic Inquiry 40(4), 664–687.

Strobl, E. (2011). The economic growth impact of hurricanes: Evidence from u.s. coastal counties. Review fo Economics and Statistics.

Toya, H. and M. Skidmore (2007, Jan). Economic development and the impacts of natural disasters. Economics Letters 94(1), 20–25.

UN and World Bank (2010). Natural hazards, unnatural disasters: The economics of effective prevention. World Bank.

Vecchi, G. A., C. Landsea, W. Zhang, G. Villarini, and T. Knutson (2021). Changes in atlantic major hurricane frequency since the late-19th century. Nature communications 12(1), 1–9.

Wald, D. J., V. Quitoriano, T. H. Heaton, H. Kanamori, C. W. Scrivner, and C. B. Worden (1999). Trinet "shakemaps": Rapid generation of peak ground motion and intensity maps for earthquakes in southern california. Earthquake Spectra 15(3), 537–555.

Yang, D. (2008). Coping with disaster: The impact of hurricanes on international financial flows, 1970-2002. The BE Journal of Economic Analysis & Policy 8(1).