Flash Flood Hazard: an Economic Analysis of Firms in Central America and the Caribbean

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Abstract

This paper studies the effect of nearby flash floods on firms' establishment performance in Central America and the Caribbean. To this end, I physically define flash flood occurrences from satellite rainfall data across countries and connect them with geo-located establishment survey data. I find that a flash flood significantly decreases sales and the number of employees but increases capital productivity. This decrease in output and employment is driven by establishments where financial market access is considered an obstacle to operations, whereas the increased capital productivity occurs in establishments where it is not. The construction sector is the only industry affected differently, with no negative effect on output or employment. Overall, my results suggest that flash floods negatively impact firms and that their increase in frequency and intensity due to global warming threatens economic development. Improving financial market access is an effective adaptation strategy to increase establishments' resilience. (JEL O12, Q54, R11)

Keywords— Natural Disaster, Firm Impact, Central America, Caribbean

1 Introduction

In July 2021, London was hit by intense storms, resulting in the flash flooding of many homes and businesses (Thames Water, 2021). This is not an isolated incident nor particular to the colloquially bad English weather. In the same month as the London Floods 2021, severe flash floods in Mexico, the USA, Costa Rica, Panama, and Colombia have been reported, with severe consequences to human life and economic prosperity.[1] In the future, such extreme rainfall flood events will likely become more prevalent. For instance, the latest IPCC Report states that direct flood damages are projected to increase non-linearly with global warming without adaptation (IPCC, 2023). However, it is a priori unclear how direct flood damage translates to overall economic impact and what role adaptation plays. With a limited capacity to adapt to climate change, especially in developing countries, studying how climate change affects the economy is necessary to guide policymakers (Mendelsohn, 2012). This study aims to shed some light on the impact of nearby flash flooding on establishments and its economic implications.

The earlier literature on the economic consequences of natural disasters has relied on cross-country models, where the results of the overall impact are somewhat mixed (Albala-Bertrand, 1993; Noy, 2009; Loayza et al., 2012; Cavallo et al., 2013). A frequent hypothesis is that the direct destruction of a hazard might stimulate economic activity through efficient re-organization or even creative destruction, allowing for a positive net impact (Miao and Popp, 2014). More recently, further negative channels of natural disaster impact on the aggregate level, such as higher interest rates, a decrease in the savings rate, and the spatial displacement of investments, challenge the notion of positive net impact (Friedt and Toner-Rodgers, 2022; Berlemann and Wenzel, 2018; Cantelmo et al., 2023) How an increase in direct flood damages will influence economic activity overall can therefore not be determined without considering the nature of a hazard's impact on local establishments. To the best of my knowledge, no study focuses on the firm impact of flash floods.[2]

Flash floods are caused by heavy rainfall in a short period of time, generally less than six hours, and are characterized by heavy torrents that sweep everything before them. Due to climate change, they are predicted to increase in frequency and severity in many parts of the world (Seneviratne et al., 2021). Since flash floods are triggered by episodes of extreme rainfall, they are particularly localized and can occur almost anywhere, even if the local climate is comparatively dry (Yin et al., 2023). In addition, it has been recognized that large regional units of analysis aggregate out the economic effects of natural hazards when the hazard impact is predominantly local in nature (Elliott et al., 2019). It follows that a precise geographical and temporal definition of the hazard is necessary to study the impact on firms.

[1]That is, focusing on the Americas only and according to FloodList, which aims at reporting on all the major flood events from around the world.

[2]Closely related to this study is Zhou and Botzen (2021), who focus on larger flood events, including river floods, as reported by disaster and flood databases.

The economic impact of a natural disaster can be divided into a direct and indirect part (Cavallo et al., 2011). The direct impacts refer to the directly caused destruction of assets when a natural hazard strikes. They commonly include the destruction of residential housing, establishments, infrastructure, and crops, but can also include health impacts.[3] The indirect impacts are the second-order effects of a natural hazard. In other words, they are due to changes in the behavior of economic agents, namely firms and households. Direct impacts are well understood, while there is large uncertainty in how natural disasters indirectly impact economic activity and growth (Botzen et al., 2019). Empirical evidence is necessary to reduce this uncertainty concerning indirect effects.

There are two main challenges in credibly analyzing the impact of flash floods empirically. First, since no data exists that adequately captures flash floods, one needs to physically derive their local occurrence to ensure comparability across regions without concerns of endogeneity.[4] An excellent example of this is the literature on tropical storms' economic effects, which has successfully produced physical measures to approximate local impacts (Strobl, 2012; Hsiang and Jina, 2014). The second challenge is with regard to the data on economic agents and identification. Sufficiently detailed micro-data of either firms or households do usually not provide locations or are unavailable for confidentiality reasons, especially for developing countries.

I attempt to overcome these challenges by employing remote-sensing rainfall data to detect potential flash flood events on a high spatial resolution and linking these to the Worldbank Enterprise Surveys for Central America and the Caribbean. I estimate the effect of flash floods on several measures of establishment performance while controlling for the local history of extreme rainfall events. The region of Central America and the Caribbean is particularly at risk and, therefore, well-suited to study flash flood impacts. Since the mid 20^{th} century, the magnitude and frequency of extreme precipitation events have increased significantly in the region (Seneviratne et al., 2021). Soil degradation is common, and urbanization is unregulated, exacerbating the risk for flash floods (Charvériat, 2000; Pinos and Quesada-Román, 2021). Further, many countries in the study region are lower- to middle-income, so the efficiency of adaptation and investments to increase resilience against natural hazards is crucial for further development (Marto et al., 2018; Cantelmo et al., 2023).

The contribution of this study is two-fold. Regarding the methodology, flash floods are detected based on an intensity-duration classification from Collalti et al. (2023), which provides a physical-

[3]For instances, Kousky (2016) summarizes the health impacts natural hazards have on children. These include malnutrition, diarrheal illness due to contaminated water, and various mental health problems.

[4]Recent studies that investigate the indirect effects of flood events use the Dartmouth Flood Observatory (DFO) data (Kocornik-Mina et al., 2020; Zhou and Botzen, 2021). However, flash floods are likely not captured by this data. The DFO relies on satellite imagery on cloud-free days to quantify the extent of flooded areas. Since floods often occur in combination with heavy rainfalls and thus cloud coverage, and flash floods usually do not remain for long as shallow, standing floods, the DFO will not capture them in most instances.

based measure of incidence from satellite rainfall data. This classification employs a conditional copula model and exhaustive information on all confirmed flash flood events in Jamaica from 2001 to 2018. Jamaica shares a similar topography, soil composition, and climate with the whole region, such that the method is well-calibrated. Second, using Worldbank Enterprise Survey data, I analyze the establishment impact of flash floods consistently across a large group of countries in Central America and the Caribbean. After data cleaning, surveys from ten different countries[5] are used to estimate how establishments are affected in terms of sales, employment, investments and productivity of labor and capital.

There are two strands of the literature to which this study directly relates. One body of work investigates the firm and establishment-level impact of natural disasters. Leiter et al. (2009) have been pivotal in estimating the effects of floods on European firms' capital, labor, and factor productivity. They examine the impact on firms in a region hit by a major flood and document higher growth rates of assets and employment but a decline in productivity. Similarly, Zhou and Botzen (2021) study the impacts of storms and floods on firm growth in Vietnam and find that flooding increases labor and capital growth but reduces sales. In contrast to this paper, both studies use data from large-scale flood events and aggregate these onto the province level, likely aggregating out some of the impacts. Elliott et al. (2019) estimate typhoons' direct and indirect effects on manufacturing plant performance in China. Plant sales decrease significantly, but the effects are relatively short-lived. Some studies analyze the firm-level impact of a single event: Okubo and Strobl (2021) investigate the 1959 Ise Bay Typhoon and find that firms in retail and wholesale are less likely to exit the market, whereas those in manufacturing and construction are more likely to upgrade their capital. Several studies analyze a specific earthquake to investigate the role of creative destruction: Tanaka (2015) and Cole et al. (2019) study the 1995 Great Kobe Earthquake while Okazaki et al. (2019) study the 1923 Great Kanto Earthquake. Evidence of creative destruction due to an earthquake is mixed with Tanaka (2015) finding adverse effects while Cole et al. (2019) and Okazaki et al. (2019) are more positive.

This study also relates to the literature on the economic impacts of weather anomalies (Dell et al., 2012; Felbermayr et al., 2022; Kotz et al., 2022). Positive temperature anomalies are generally associated with negative economic impacts, whereas results have been mixed for rainfall (Dell et al., 2012). An exception to this is Barrios et al. (2010), who find that the declining rainfall rates in sub-Saharan Africa are a significant determinant of the regions' lower economic growth rates. These earlier studies focus on the long-run climatic variation on the country level with panels of country-by-year rainfall data. Arguably, this cannot be informative concerning rainfall-induced flash floods. Spatial and temporal aggregation average out short extreme events, so excess rainfall has an ambiguous interpretation.[6] The spatial resolution improved with the advent of satellite

[5] These countries are: Columbia, Venezuela, Panama, Nicaragua, El Salvador, Guatemala, Costa Rica, Mexico, Dominican Republic, and Haiti.

[6] Excess rainfall in a country in a given year could be evenly distributed throughout the year or short,

data in recent years. Kotz et al. (2022) estimate the effect of rainfall on sub-national region's economic growth. They find that growth is reduced by the number of wet days and in extreme daily rainfall, while the annual total rainfall is positively associated with growth. Felbermayr et al. (2022) connect monthly weather anomalies with night light data on a 0.5×0.5 grid (approx. 55 km $\times$ 55 km at the equator). They find that rainfall anomalies reduce night light growth contemporaneously with a rebound in the following periods and contemporaneous positive spatial spillover into neighboring areas. The work in this study has been influenced by the development of increasing resolution to capture the economic impacts of weather anomalies. It ties together the weather anomaly with the disaster on firm impact literature in the case of extreme rainfall and flash flood events.

To summarize the results, I show that flash floods impact establishment performance, resulting in less output, fewer workers employed, a change in investments, and increased capital productivity. Financial market access plays a central role. Establishments for which financial market access is an obstacle drive the documented reduction in output. They further have a decreased labor productivity, whereas firms with financial market access experience the increased capital productivity found in the overall analysis. I further explore heterogeneity by industry. There is comparatively little variation in the effect of flash floods across sectors, except for the construction sector. The construction sector is not negatively impacted as it does not see a reduction in output or workers employed but still reacts strongly in its investments. This might indicate that flash floods affect establishments through more than one mechanism.[7]

The remainder of the paper is organized as follows: Section 2 provides background and discusses theoretical considerations. Section 3 presents the flash flood classification and describes the data. In Section 4, the empirical strategy is detailed, and results are shown in Section 5. Section 6 then discusses the main implications and concludes.

2 Background

Flash floods are a subtype of pluvial floods caused by extreme rainfall. These can be categorized into flash and surface water floods. Surface water floods are shallow, standing floods that occur when rain falls over a prolonged period, and the water cannot run off. On the contrary, flash floods are characterized by their quick onset and ravageous, debris-sweeping flow. Meteorological conditions that cause flash floods are mostly convective and orographic, which are naturally localized. Since most precipitation in the tropics is convective, the potential for frequent flash floods is given

extreme rainfall in a specific region for one day - with likely different economic effects.

[7] There is a literature that documents how natural disasters have an impact along supply chains (Rose and Liao, 2005; Altay and Ramirez, 2010; Henriet et al., 2012). For instance, Altay and Ramirez (2010) show that the impact of a flood depends on the flood's position in the supply chain: upstream firms are positively, and downstream firms are negatively affected.

almost anywhere in the study region.

While flash floods are local events, they are a global phenomenon with potentially disastrous impacts. Besides the 2021 London Floods, there are many other recent instances where heavy rainfall led to catastrophic flash floods: 2021 in Zhengzhou, China, 2017 in Megara, Greece, and 2013 in La Plata, Argentina, to name a few of the most disastrous incidents. However, not every flash flood causes such destruction, as local characteristics shape the impact. The risk or impact of natural hazards can be decomposed into vulnerability, exposure, and hazard (Field and Barros, 2014). The exposure is given by the subject at risk in a certain location, such as population and economic assets. Vulnerability is a scalar function that maps how a specific hazard affects the locally exposed people and assets. Therefore, depending on local exposure and vulnerability, a given natural hazard becomes a natural disaster. In the case of flash flood hazard, changes in the socio-economic dimension can strongly affect the vulnerability (Terti et al., 2015). It follows that evaluating the impact of flash floods has significant economic and social implications, which requires knowledge across disciplines of social and physical sciences (Ruin et al., 2014).

So far, the vulnerability to flash floods has mainly been investigated in non-economic terms. This includes Špitalar et al. (2014), who evaluate fatalities from flash floods in the United States from 2006 to 2012. While most fatalities accrue in rural areas, impacts on humans are said to be higher in urban areas. Vulnerability to flash floods can also be in terms of the built environment where structural parameters are assessed relative to the hazard intensity (Milanesi et al., 2018). From a socio-economic perspective, there have been efforts to evaluate flash flood vulnerability by creating an index for the United States (Khajehei et al., 2020) and Spain (Aroca-Jiménez et al., 2018). This study is, however, the first to consider economic consequences on firms on the establishment level.

2.1 Hypotheses

With the hazard impact on firms in mind, certain hypotheses can be derived from theoretical considerations. These hypotheses are then subject to the empirical analysis. The theoretical literature on the economic impact of natural disasters mainly focuses on the macroeconomic perspective. However, some recent papers specifically model firm behavior in response to natural hazards with the macroeconomic impact as objective or do so implicitly with a general equilibrium model (Hallegatte et al., 2007; Hallegatte and Dumas, 2009; Henriet et al., 2012; Barrot and Sauvagnat, 2016; Hallegatte and Vogt-Schilb, 2019; Strulik and Trimborn, 2019; Cantelmo et al., 2023). I subsequently summarize the main insights into hypotheses for the empirical analysis.

Hallegatte and Vogt-Schilb (2019) model impacts of natural hazards with different layers of capital and assume that part of a firm's capital is destroyed and thus output and labor decrease. Because a natural hazard does not discriminate between capital types in its destruction, total losses relate to the average and not the marginal productivity of capital. In most instances, capital productivity increases, whereas labor productivity decreases.[8] Further echoing the insight from Hallegatte et al. (2007), the reconstruction phase is crucial for economic dynamics. For instance, if investments in reconstruction are limited due to financial and technical constraints, the economy or firm recovers more slowly. A particular role in reconstruction plays financial access, e.g., the ability to get a loan (Hallegatte et al., 2016). The demand for such loans increases significantly after a natural disaster, whereas the supply remains stable, creating a credit crunch (Czura and Klonner, 2023). Strulik and Trimborn (2019) model the impact of natural disasters, distinguishing between a firm's productive capital and durable goods. They find that if a natural disaster destroys predominantly either productive capital or durable goods, the initial decline in output can become a net increase over time. This is due to the mechanism of investment choice between the two types of capital, which is also impacted by natural disasters. Barrot and Sauvagnat (2016) analyze whether natural disaster impact propagates in production networks when embedding the single firm in industries and value chains via input-output linkages. They derive hypotheses based on the static network model analysis of Acemoglu et al. (2012), assuming that when a firm is hit by a natural hazard, some share of output is destroyed. The model predicts positive horizontal and downstream pass-through rates that are confirmed empirically, which implies that heterogeneity in impact across sectors and layers of the value chain is limited.

Taking these theoretical considerations concerning the mechanism of how natural disasters impact firms' production into account, five main results emerge as hypotheses. After a flash flood,

1. Output Y and labor L decrease.
2. The productivity of capital increases, and the productivity of labor decreases.
3. Establishments adjust their new investments.
4. Establishments with constrained financial access are more impacted.
5. Heterogeneity in impacts across industries is limited.

These hypotheses on how flash floods might impact establishments will guide the empirical analysis and frame the discussion. Note that not all implications are voiced in unison in the literature. While output and capital generally decrease by assumption, the effect on labor depends on model specification. The choice of dynamic versus static and general versus partial equilibrium models can alter some of the predictions.

[8] Taking a dynamic perspective, the impact of a one-off destruction of the capital stock due to a natural disaster depends on the specific mechanism. For instance, Cantelmo et al. (2023) model it as a permanent one-off depreciation of the capital stock and a temporary decline in productivity growth, resulting in equal capital and productivity growth but a permanently lower level.

3 Data

To study the stated hypotheses empirically, information regarding flash flood occurrence and establishment-level data is necessary. I derive information on flash flood occurrence with a physical hazard indicator. Specifically, I use satellite rainfall data and employ a classification scheme based on hydrological modeling of extreme rainfall events. Establishment-level data is taken from the Worldbank Enterprise Surveys, which provide a wide array of data on establishment performance. Subsequent sections present the study region and detail the data preparation.

3.1 Study Region

The study region of Central America and the Caribbean is particularly exposed to climate shocks in the form of natural disasters. By 2050, the gross domestic product of countries in the region that are highly exposed could be between 9% and 12% lower than under a business-as-usual growth scenario (ECLAC, 2023a). At least in part, this exposure derives from the tropical location and the high proximity to the sea, where no location is further than 200 km away from the nearest shore (Encyclopedia Britannica, 2022). Albeit the region lies in the Atlantic hurricane belt and is one of the most rainfall-heavy regions in the world, the tropical climate is often tempered by local topography. Rainfall occurs in a dry and wet season pattern and is heaviest between May and November. Topography is diverse: most countries have humid lowlands along the coast, while there are pronounced forest-clothed hills and mountain ranges. However, much of Central America and the Caribbean's lowland timber has been cleared for crop cultivation.

Countries in the study region are mainly medium to high development, as measured by the United Nations' Human Development Index (HDI). There are, however, significant differences, with countries such as Panama and Costa Rica having a very high HDI while Haiti has one of the lowest in the world. The sectoral share of the economy is equally varied. While agriculture and tourism are key (export) sectors in most countries, some countries have specialized in specific industries (ECLAC, 2023b). For instance, Panama has a considerable banking, commerce, and insurance sector, whereas the Dominican Republic is highly invested in mining and tourism. Furthermore, economies in Latin America and the Caribbean are characterized by a high share of 48% informal workers, making precise sectoral assessments difficult (ECLAC, 2023a).

3.2 Flash Flood

In this study, flash floods are measured via a binary classification that indicates whether an episode of heavy rainfall likely triggered some flash flood at a location. The classification is based on Collalti et al. (2023), who employ a hydro-statistical methodology and exhaustive data on confirmed flash flood events in Jamaica to estimate a decision rule for the optimal classification of flash flood incidence. The method uses extreme rainfall and the confirmed flash flood events to generate intensity-duration-frequency (IDF) curves from copula functions. Such a curve relates points in the intensity-duration space to a given frequency or return period. In that sense, one can interpret it as a two-dimensional severity measure. With comprehensive data on flash floods in Jamaica, Collalti et al. (2023) define the IDF curve for classification as the threshold above which the ratio of hazardous events against non-hazardous extreme events is maximized.

The procedure is tailored to the Global Precipitation Measurement (GPM) Integrated Multi-satellitE Retrievals (IMERG) data, which has been globally available since June 2000 (Huffman et al., 2015).[9] The data contains half-hourly rainfall measurements on a $0.1° \times 0.1°$ grid (approx. 11 km $\times$11 km at the equator). From the half-hourly data, meteorologically distinct events are defined with a 12-hour inter-event time. For each of these events, its duration and average intensity relate it with respect to the IDF curves from Collalti et al. (2023). This can be used to classify rainfall episodes that cause flash floods. As a decision rule, I require that a rainfall event must have an intensity of at least 2 mm/h above the IDF curve for classification to reduce the number of false positives.[10] Every time the GPM/IMERG cell within which an establishment is located experiences a rainfall event above that threshold, I treat it as affected by a flash flood. Note that this does not imply that there has been direct damage to the establishment, as it could be that the extreme rainfall event did not cause flooding precisely where the establishment is located. However, it is still likely that it has been affected by the extreme rainfall in that case, as the inundation of roads and sweeping torrents of water affect their vicinity.

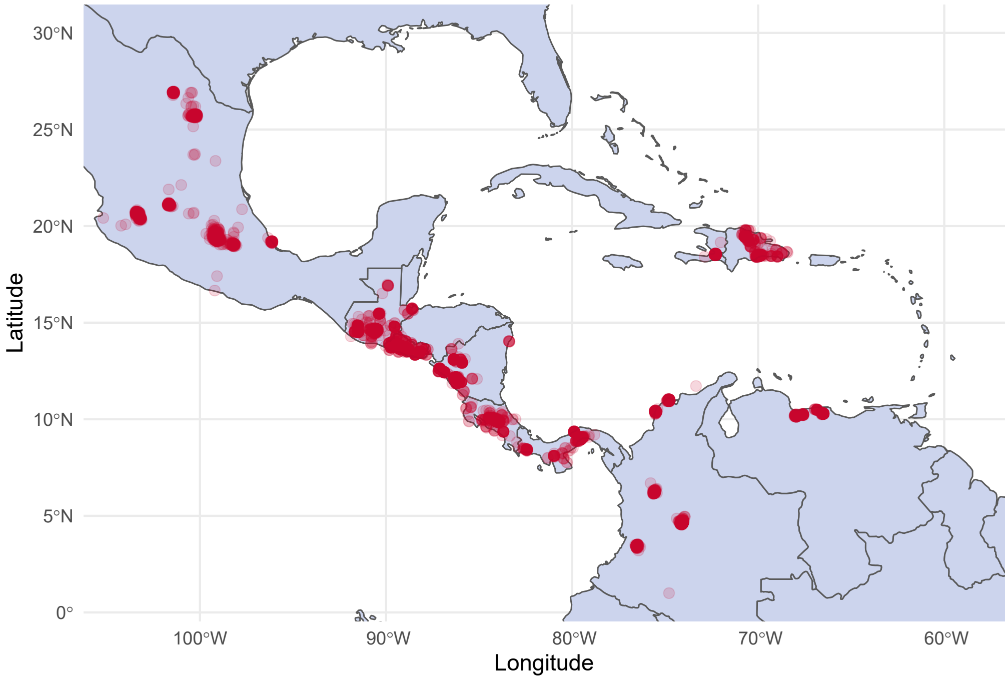
3.3 Enterprise Surveys

Data on firms are drawn from the World Bank Enterprise Surveys. These are firm-level surveys of a representative sample of the economy's private sector and cover various topics, from corruption and crime to competition, infrastructure, and various other measures. They also include general information on the establishment in terms of sales, number of employees, investments, and labor and electricity costs, which are of particular interest for this study. Since 2005, the methodology has been globally standardized, and a total of 177'000 surveys in 153 countries have been carried out in various rounds. Table 1 displays the countries of the study region for which surveys were conducted. It further shows how many rounds and in which year those surveys were conducted for a total of 37 rounds with 16'414 establishments. The Worldbank Development Economics Enterprise Analysis Unit (DECEA) generously provided information about each establishment's location. Due to confidentiality reasons, the locations come in the form of masked coordinates randomly displaced by 500 meters to 2'000 meters in each axis. This results in a random displacement of approximately

[9] The satellite precipitation algorithm combines various microwave and infrared precipitation measurements to produce precipitation estimates, adjusted with surface gauge data.

[10] In robustness Section 5.3 I employ a more restrictive threshold of 3 mm/h. This approximately halves the number of events, but results do not change meaningfully.

Figure 1: Map of Establishments



Map of all 7'755 geographically located establishments with a random displacement in each axis of 500 meters to 2'000 meters by the Worldbank Enterprise Surveys.

700 meters to 2400 meters. Unfortunately, establishment locations were not captured as part of all surveys. In earlier rounds in 2005 and 2006, the surveyors were not yet equipped with tablets to record GPS coordinates as they were later. A total of 7'755 establishments remain for which detailed surveys and their approximate locations are combined. Figure 1 depicts their geographical distribution in the study region.

3.4 Sample Restriction

Not all of these 7'755 surveys can be used for the analysis. For one, many respondents report questions regarding the whole firm and not the single establishment. When a firm has several establishments, connecting a single establishment to a flash flood incident would not be informative when surveys are answered for the whole firm and only part of the firm's operation is at this location. Therefore, The sample is reduced to those 6'423 surveys where the firm is a single establishment or the financial statements are separately prepared for each establishment corresponding to a physical location. Further, not all surveys contain all relevant information for the analysis. Only 1,925 establishments reported sales, the number of full-time employees, investments, labor,

Table 1: Summary of Surveys

Country/Year	2005	2006	2010	2016	2017	2019	Geo-Coded
Antigua & Barbuda			✓				
Bahamas			✓				
Barbados			✓				
Belize			✓				
Colombia		✓	✓		✓		2010, 2017
Costa Rica	✓		✓				2010
Dominica			✓				
Dominican Republic	✓		✓	✓			2016
El Salvador		✓	✓	✓			2010, 2016
Grenada			✓				
Guatemala		✓	✓		✓		2010, 2017
Guyana						✓	
Haiti			✓			✓	2019
Jamaica	✓		✓				
Mexico		✓	✓				2010
Nicaragua		✓	✓	✓			2010, 2016
Panama		✓	✓				2010
St. Kitts & Nevis			✓				
St. Lucia			✓				
St. Vincent & Grenadines			✓				
Trinidad & Tobago			✓				
Venezuela		✓	✓				2010

Notes: List of all countries in the region for which there are any Worldbank Enterprise Surveys. Columns of the years indicate whether a round of surveys was conducted in a specific year. A majority of surveys were conducted in 2010. Geo-Coded indicates the countries and surveys for which the establishment's location was surveyed.

and electricity costs as a proxy for capital costs.[11] Even then, some surveys are implausible. There is, for instance, the establishment from Colombia that produces corn syrup and allegedly reports revenue of 327 B USD in 2010. I remove all observations that report sales, investments, or the number of employees five times larger than the 0.99 quantile, which reduces the sample by 25 observations. While I cannot verify that these 25 surveys were indeed faulty in the reporting or transcription, the manual inspection of these surveys reveals that at least some are implausible.[12] In the robustness Section 5.3, I estimate the main model without removing these 25 surveys, and

[11] In the Appendix Section B, I estimate the main model without removing surveys unless the variable of interest is missing. There are, for instance, 6'230 establishments that report the number of full-time employees and 5'323 that report sales. Results do not change compared to the main analysis.

[12] There is also an establishment that deals with raw material products with eight full-time employees that invested 150 B USD in machines and equipment and 15 B USD in land and buildings while only selling goods for 0.26 M USD in that year. Examples like this illustrate that these outliers are likely driven by mistakes reporting or converting decimals.

the results do not change.

3.5 Two Indices of Flash Floods

Flash floods can occur continuously in time, whereas the establishment surveys constitute a cross-section. To relate one with the other, we need to consider that questions in the surveys are always in relation to the last fiscal year. Therefore, for every establishment, I construct an index of the number of flash floods in the 12 months of the last fiscal year,

$$Flood_j^t = \sum_{t=0}^{12} Flash\,Flood_{jt} \tag{1}$$

where j is the establishment identifier, and t denotes the time-shift in months relative to the establishment j's end of the last fiscal year. The variable $Flash\,Flood_{jt}$ gives the number of flash floods in the rainfall cell where j is located for the month t. If the end of the fiscal year was not collected in the survey, I assume that the fiscal year ends on the 31^{st} of December. Similarly, I create an index of previous ("historic") flash flood events to control for location-specific flash flood risk in the analysis,

$$Flood_j^h = \sum_{t=13}^{96} Flash\,Flood_{jt}. \tag{2}$$

The variable $Flood_j^h$ thus gives the number of flash floods in the rainfall cell where j is located for the seven years before the start of the last fiscal year. The choice of seven years is due to rainfall data availability - ideally, one would provide a longer history of events.

Table 2: Summary Statistics

Statistic	Mean	St. Dev.	Min	Max
Floods Fiscal Year	2.65	2.46	0	10
Prior Floods	18.03	11.02	0	50
Access to Finance	0.54	0.50	0	1
Sales Last Year (M USD)	23.79	105.90	0.003	1'872.31
Full-Time Employees	145.95	325.53	3	6'513
Inv. Land & Buildings (M USD)	0.13	0.75	0.0000	16.03
Inv. Machines & Equipment (M USD)	0.95	10.08	0.0000	374.70
Firm Age	25.31	17.69	1	127
Power Outages	0.60	0.49	0	1
Generator Owned	0.23	0.42	0	1
% of Direct Exports	8.83	21.01	0	100
Female Ownership	0.39	0.49	0	1

Notes: Summary statistics after data cleaning for the 1'900 remaining observations.

3.6 Summary Statistics

Table 1 displays summary statistics. There are 1'900 establishments in the data that experienced an average of 2.65 potential flash flood events in their last fiscal year and 18.03 in the seven years before that. For 54% of establishments, access to finance is no major obstacle. In the previous fiscal year, average sales were 23.8 M USD with 146 full-time employees, though there can be as little as 3 and as many as 6'513 people employed at the single establishment. Note that all monetary values have first been transformed to USD with exchange rates at the end of the respective fiscal year and then inflated to December 2021. Investments also exhibit large variation, with an average of 1.08 M USD in total investments. Of that, the majority (88%) is in the category of machines, equipment, and vehicles. The oldest establishment in the sample is 127 years old, five times more than the average of 25.31 years. Many establishments report issues about electricity, where 60% report at least one power outage in the last fiscal year and 23% own a generator, likely an adaption strategy. Some establishments engage in direct exports with an average value of 8.8% of total sales. Lastly, in about 40% of firms, at least one of the owners is female.

4 Empirical Strategy

The survey data are cross-sectional, so the potential of endogeneity has to be addressed. To estimate a causal effect with a simple regression model, treatment assignment should be independent of potential outcomes after conditioning on observed covariates. In the case of flash floods, treatment can arguably be viewed as quasi-random with respect to a certain location. For instance, the specific timing of an extreme rainfall event in one location cannot be forecasted in any way. Therefore, the only way the occurrence of a flash flood in the fiscal year before the survey is correlated with establishment outcomes is through the underlying probability of treatment in that area. In other words, if one conditions for the location-specific differences in the likelihood of flood occurrence, then an estimate of the effect of flash floods on establishment outcomes should not suffer from endogeneity bias. In that setting, all relevant unit-specific time invariants can be captured with the flash flood history as the innate local risk. I account for that risk with the sum of flood events in the seven years before the last fiscal year. A regression that further controls for country, industry (two-digits), and year-fixed effects can be written as

$$log\,(Y_j) = \beta_1 Flood_j^t + \beta_2 Flood_j^h + \beta_3 Access_j^f + \delta X_j + C_j + V_j + T_j + \varepsilon_j \tag{3}$$

where Y_j is a variable of performance for establishment j, $Flood_j^t$ the flood index from Equation 1 and β_1 the corresponding coefficient. $Flood_j^h$ is the number of floods in the period 1 to 8 years after the end of the last fiscal year in the cell of establishment j from Equation 2, and $Access_j^f$ is an indicator of financial market access. X_j is a vector of establishment-specific control variables,[13]

[13]These controls are: access to finance, the age of the establishment, the size of the locality/city, the share of direct exports of all revenues, the share of the establishment owned by the government or state, and

C_j are country, V_j industry and T_j year fixed effects. The error term ε_j is assumed to be two-way clustered at the country and industry level.

4.1 Hypotheses Testing

With a regression in 3 and the appropriate dependent variable Y_j, I can study Hypotheses 1, 2 and 3. That is, whether a flash flood causes an establishment's output and labor to decrease, whether the productivity of capital increases and that of labor decreases, and whether investment is affected. I use sales in the last fiscal year in M USD as the dependent variable Y_j for output. Labor is proxied by the number of workers in full-time equivalence. In contrast, investments are reported separately for *Land & Buildings* and *Machines, Equipment & Vehicles* in M USD. Productivity can be estimated in monetary terms as the ratio between output and factor input. For the average productivity of labor, I use sales per labor cost.[14] I approximate capital cost with electricity cost to calculate the average productivity of capital as sales per electricity cost.[15]

To explore Hypothesis 4, that establishments with constrained financial access are more impacted, I modify the model in Equation 3 with an interaction between $Flood_j^t$ and financial market access,

$$\begin{aligned} log\left(Y_j\right) =& \beta_1 Flood_j^t + \gamma\left(Flood_j^t \times Access_j^f\right) + \beta_2 Flood_j^h + \beta_3 Access_j^f + \\ & \delta X_j + C_j + V_j + T_j + \varepsilon_j \end{aligned} \tag{4}$$

where $Access_j^f$ denotes a binary indicator of whether access to financial services is considered no or a minor obstacle to operations (0) or a medium, severe, or very severe obstacle to operations (1). Conveniently, 54% fall into the first category such that the indicator can be interpreted as approximately relative to the average financial access.

To review Hypothesis 5, that there is only limited heterogeneity across industries, the model should allow for heterogeneity across industries. There are 29 industry codes in the data, with sometimes only one entry. I group industries into larger sectors: Chemical & Plastic (n=309), Construction (n=41),[16] Food (n=329), Metals & Minerals (n=225), Textile & Garments (n=241), Other Manufacturing (n=272) and Other (n=483).[17] I modify the model in Equation 3 with an

an indicator of whether the establishment is small, medium or large by a number of workers classification.

[14] Labor cost is surveyed as *"total annual cost of labor including wages, salaries, bonuses, and social payments"*.

[15] This strategy has been used before, e.g. Cole et al. (2018).

[16] The choice of a separate construction sector as an indicator is driven by theoretical considerations, albeit the small number of establishments in that industry. Specifically, the reconstruction after a natural hazard is often associated with a boom in the construction sector. It is thus of interest to see whether there is a distinct effect heterogeneity.

[17] Other includes diverse sub-sectors such as IT or transportation that could not be grouped otherwise.

interaction between $Flood_j^t$ and industry,

$$log\left(Y_j\right) = \theta\left(Flood_j^t \times Industry_j\right) + \beta_2 Flood_j^h + \beta_3 Access_j^f + \delta X_j + C_j + V_j + T_j + \varepsilon_j \tag{5}$$

where $Industry_j$ is an indicator of the different industry groups. With this specification, I estimate the effect a flash flood has on each industry and compare for heterogeneity.

5 Results

Regression results of the model in Equation 3, estimated with ordinary least squares (OLS), are displayed in Table 3. Each flash flood in the last fiscal year reduces sales by 3.3% and the number of full-time employees by 2.9%, consistent with Hypothesis 1 (*Output Y and labor L decrease*). The productivity of capital as measured by sales per electricity cost E_{cost} increases by 6% while labor productivity measured with sales per labor cost L_{cost} is unaffected.[18] This is consistent with Hypothesis 2 (*The productivity of capital increases, and the productivity of labor decreases*). Investments in land and buildings $Inv_{L\&}$ decrease by 8.3% while investments in machines, equipment, and vehicles $Inv_{M\&E}$ increase by 12.5% (statistically not significant). This is some indication for Hypothesis 3 (*Establishments adjust their new investments.*). Floods before the last fiscal year $Floods_j^h$ are associated with 0.7% higher sales but no effect otherwise. Obstacles to finance are important, with negative effects across the board that are statistically significant in the three variables measuring productivity: -13.9% in sales per worker, -12.4% in labor productivity and -8.3% in capital productivity. Together, this suggests a story where firms that have difficulties accessing the financial market are less productive, probably due to outdated capital.

To put the impacts of flash floods into perspective, comparing them to other natural hazards is informative. Zhou and Botzen (2021) analyze large floods on the province level in Vietnam and find immediate effects of -1.5% and -2.9% on sales growth with a measure based on casualties and damages, respectively.[19] While methodologically different from this paper, it is striking how comparable these estimates are. However, they find evidence of delayed positive impacts on capital and labor growth for up to three years, while I cannot directly study the dynamics in the following years. However, from the coefficient of flood history, we can infer that the negative impacts in the first year are also reverted after some time. Elliott et al. (2019) study the effect of typhoons on Chinese manufacturing plants. Their estimates suggest that the average damaging storm reduces a plant's turnover by 1% in the year of the strike for an average reduction of 3.7% due to typhoon activity, comparable to the estimate of flash floods. They do not find evidence of an effect beyond

[18] All effects are calculated from the coefficients with $(exp(\beta_1) - 1) \times 100$.

[19] The measure determines which provinces are affected, given a certain threshold. If they use their physical-based measure with DFO inundation maps, they find an effect of -2.3% on growth in the next year.

Table 3: Regressions: Establishment Impacts

All in log(·)	Sales/Worker (1)	Worker (2)	Sales (3)	$\text{Inv}_{L\&B}$ (4)	$\text{Inv}_{M\&E}$ (5)	Sales/L_{cost} (6)	Sales/E_{cost} (7)
$Floods_j^t$	-0.006	-0.029**	-0.034**	-0.087**	0.118	-0.015	0.058***
	(0.012)	(0.011)	(0.011)	(0.037)	(0.076)	(0.011)	(0.014)
$Floods_j^h$	0.004*	0.003	0.007**	0.010	-0.021	0.001	-0.006
	(0.002)	(0.002)	(0.002)	(0.007)	(0.025)	(0.002)	(0.003)
$Access_j^f$	-0.150*	-0.021	-0.170	-0.143	0.032	-0.132**	-0.087***
	(0.070)	(0.045)	(0.095)	(0.133)	(0.304)	(0.053)	(0.004)
Observations	1,883	1,883	1,883	1,883	1,883	1,880	1,877
R^2	0.41	0.82	0.71	0.29	0.08	0.92	0.83
Controls	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓

Notes: Table of regression results of the model in Equation 3 without coefficients of the control variables X_j for brevity. The full table with all the coefficient estimates is Table 7 in the Appendix. Standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01

the year of impact. Tanaka (2015) investigates the effect of the Great Kobe Earthquake and finds 11.1% lower value added of manufacturing plants in the most devastated area of Kobe. Naturally, the effect of a severe earthquake is expected to be magnitudes larger than that of one flash flood. Because the Worldbank Enterprise Surveys are a representative sample of an economy's private sector, we can perform some back-of-the-envelope calculations about the economic cost caused by flash floods. Taking the average of 2.65 potential flash floods per fiscal year multiplied by the estimated coefficient of -3.3% for $Floods_j^t$ on sales in the baseline specification in Equation 3, the yearly average reduction in sales is $2.65 \times -3.3\% = -8.745\%$. That is under the assumption that the establishment surveys are also representative concerning flash flood risk and vulnerability such that external validity is given. Suppose we further assume that the establishment's reduction in output is proportional to direct flood damages, which, according to the 6^{th} IPCC Report, are approximately doubling with a 2°C compared to a 1.5°C global warming. In that case, flash floods in Central America and the Caribbean will likely cause substantial overall economic loss in the future unless resilience improves dramatically through adaptation.

5.1 Financial Access

OLS regression results of the model with the financial access interaction in Equation 4 are displayed in Table 4. Coefficients of $Flood_j^t$ are smaller than those of the model without interaction in Table 3 and are no longer statistically significant. They correspond to the effect for establishments where financial access is no obstacle. Notably, only capital productivity is statistically significantly affected by a flash flood, increasing by 7.4%. Coefficients of the interaction term $Floods_j^t \times Access_j^f$ can then be interpreted as the effect of a flash flood for those establishments for which financial access is an obstacle. Sales significantly decrease by 4.8% while the number of workers is unaffected, resulting in a 3.4% lower Sales/Worker ratio. The productivity of labor decreases by 3.9% as well. In summary, establishments that are facing obstacles concerning their financing are more negatively impacted by flash floods, consistent with Hypothesis 4 (*Establishments with constrained financial access are more impacted*).

Financial market access has been suggested to facilitate and accelerate recovery after a natural disaster (Benson and Clay, 2004). For Mexico, De Janvry et al. (2016) find that access to disaster funding boosts local economic activity between 2% and 4% in the year following a disaster, as measured by night light activity. Here, I can confirm this mechanism for flash floods and establishment impacts. Namely, adequate financing opportunities makes establishments resilient to flash floods and can be part of the efforts to decrease natural hazard vulnerability for economic development in Central America and the Caribbean.

Table 4: Regressions: Financial Access

All in log(·)	Sales/Worker (1)	Worker (2)	Sales (3)	Inv$_{L\&B}$ (4)	Inv$_{M\&E}$ (5)	Sales/L$_{cost}$ (6)	Sales/E$_{cost}$ (7)
$Floods_j^t$	0.013	-0.020	-0.007	-0.077	0.143	0.008	0.071***
	(0.015)	(0.012)	(0.014)	(0.046)	(0.082)	(0.015)	(0.010)
$Floods_j^t \times Access_j^f$	-0.034*	-0.015	-0.049***	-0.017	-0.044	-0.040***	-0.022
	(0.018)	(0.016)	(0.013)	(0.029)	(0.072)	(0.008)	(0.014)
$Floods_j^h$	0.004**	0.003	0.007*	0.010	-0.021	0.0009	-0.006*
	(0.002)	(0.002)	(0.003)	(0.007)	(0.025)	(0.004)	(0.003)
$Access_j^f$	-0.060	0.019	-0.041	-0.097	0.148	-0.024	-0.028
	(0.085)	(0.063)	(0.088)	(0.144)	(0.361)	(0.047)	(0.046)
Observations	1,883	1,883	1,883	1,883	1,883	1,880	1,877
R^2	0.41	0.82	0.71	0.29	0.08	0.92	0.83
Controls	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓

Notes: Table of regression results of the model in Equation 4 with the interaction for financial access, without coefficients of the control variables X_j for brevity. The full table with all the coefficient estimates is Table 8 in the Appendix. Standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01

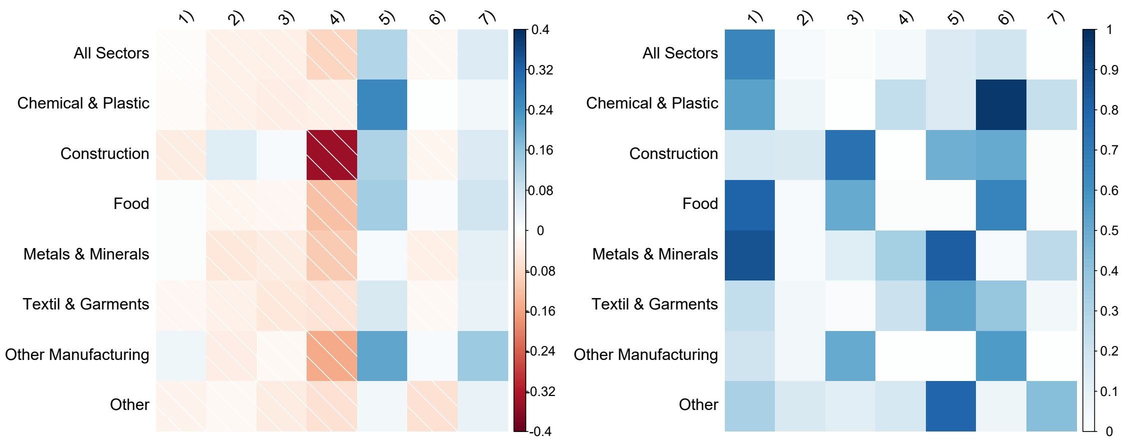
5.2 Sector Heterogeneity

I study heterogeneity across different industries with the model in Equation 5. Figure 2 displays the results of regressions with OLS.[20] The first row shows the results from regressions without

[20]The full results are in Table 9 in the Appendix.

Figure 2: Industry-Specific Effects

(a) Coefficients (b) P-Values



Notes: Matrix-plot of coefficients from regressions with industry indicator and matrix-plot of corresponding p-values. The columns relate to the various dependent variables Y_j: column 1) is the regression with $Sales/Worker$, column 2) with $Worker$, column 3) with $Sales$, column 4) with $Inv_{L\&B}$, column 5) with $Inv_{M\&E}$, column 6) with $Sales/L_{cost}$ and column 7) with $Sales/E_{cost}$. The first row shows the result from the regressions without interaction as in Equation 3 whereas the other rows are results from Equation 5.

any interaction, as in Equation 3, for comparison. Studying the heterogeneity with respect to the industry by comparing coefficients of a single column, it is apparent that there is little variation. That is, most industries are affected similarly by a flash flood. For instance, all industries but construction see a reduction in workers by 2% to 5% and a reduction in sales by 1% to 5%. The construction sector is indeed out of line: instead of a decrease in workers and sales as for all other industries, coefficients are positive, albeit not statistically significant.[21] Investments also show more variation across industries: investment into land & buildings decreases by 4% to 29% while investment into machines, equipment, and vehicles increases by 2% to 30%. The productivity of capital and labor is similarly affected by flash floods across industries. For labor productivity, the effect is slightly negative between 0% and −6% and not statistically significant in most cases. The effect on capital productivity is positive throughout between 2% to 16%.

From a qualitative point of view, the differences across industries are not substantial for any measure of firm performance, except for the construction sector. The construction sector is less negatively affected in terms of workers and sales but stands out for reducing land & building investments significantly. Note that a smaller group size mechanically drives the lower statistical confidence in industry-specific effects in a model with interactions. Also, there might be heterogeneity within the relatively large industry categories. In summary, there is evidence for Hypothesis

[21] Note, however, that there are only 41 establishments in the construction sector in the data.

5 (*Heterogeneity in impacts across industries is limited*).

5.3 Robustness

While the lack of heterogeneity in the estimates of an establishment's industry is already an indicator of the effects' robustness, I perform several further checks. I start by relaxing the sample restriction and estimate the model in Equation 4 without removing either missing values for any of the other Y_j or implausible observations. Table 10 in Appendix B reports the estimates of the variables of interest. The main implications remain the same if we compare it to Table 4. Establishments that have no obstacles with regard to financial access are not affected in terms of workers or sales but see an increase in capital productivity by around 7%, whereas establishments with obstacles to financial market access are negatively affected in terms of workers and sales and also see a decrease of labor productivity by 4%.

Table 5: Regressions: Alternative Event Definition

All in log(·)	Sales/Worker (1)	Worker (2)	Sales (3)	Inv$_{L\&B}$ (4)	Inv$_{M\&E}$ (5)	Sales/L$_{cost}$ (6)	Sales/E$_{cost}$ (7)
				2 mm/h Definition			
$Floods_j^t$	0.013	-0.020	-0.007	-0.077	0.143	0.008	0.071***
	(0.015)	(0.012)	(0.014)	(0.046)	(0.082)	(0.015)	(0.010)
$Floods_j^t \times Access_j^f$	-0.034*	-0.015	-0.049***	-0.017	-0.044	-0.040***	-0.022
	(0.018)	(0.016)	(0.013)	(0.029)	(0.072)	(0.008)	(0.014)
				3 mm/h Definition			
$Floods_j^t$	0.030	-0.011	0.018	-0.101	0.155	0.018	0.043*
	(0.021)	(0.018)	(0.024)	(0.056)	(0.094)	(0.019)	(0.021)
$Floods_j^t \times Access_j^f$	-0.057**	-0.029	-0.087***	-0.055	-0.076	-0.058***	-0.013
	(0.025)	(0.025)	(0.009)	(0.033)	(0.130)	(0.009)	(0.016)

Notes: Table of regression results of the model in Equation 4 for event definition with 2 mm/h and 3 mm/h minimum excess intensity. Standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01

Next, I check whether the results are driven by the flood definition of 2 mm/h in intensity above the respective IDF curve. More precisely, one might be cautious that the average of 2.65 events overall establishments in the last fiscal year is producing some false positives. Thus, I use a much more restrictive 3 mm/h above the threshold, such that there is only an average of 1.38 events in the last fiscal year. I estimate the model in Equation 4 and report the coefficient estimates for $Flood_j^t$ and $Flood_j^t \times Access_j^f$ in Table 5. Results remain similar, though the coefficients of $Flood_j^t \times Access_j^f$ are more strongly negative. This can be expected since the 3 mm/h minimum excess selects more extreme and potentially hazardous events, compared to the 2 mm/h definition. I next run a series of permutation tests for each dependent variable Y_j. That is, I randomly permute the order of the Y_j relative to the rest of the data. Then, I estimate Equation 3 and

Table 6: Regressions: P-Values from Permutation

All in log(·)	Sales/Worker	Worker	Sales	Inv$_{L\&B}$	Inv$_{M\&E}$	Sales/L$_{cost}$	Sales/E$_{cost}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Floods_j^t$	-0.006	-0.029	-0.034	-0.087	0.118	-0.015	0.058
p-value Regression	0.657	0.037	0.015	0.042	0.156	0.195	0.003
p-value Permutation	0.390	0.127	0.171	0.033	0.073	0.378	0.140

Notes: Table of regression results of the model in Equation 3 with p-values from regression estimation and permutation.

obtain the coefficient β_1 of $Flood_j^t$.[22] I repeat this process 10'000 times and calculate the quantile of the coefficient estimate with un-permuted data relative to the 10'000 permutations' estimates as p-value. I repeat that process for all dependent variables Y_j. Table 6 shows coefficients and p-values from the regression as in Table 3 together with the p-values from permutation. The p-values from the permutation are, in most cases, larger than their counterpart. This is due to the more conservative nature of permutation tests, which make no assumptions about the distributional properties of the data. This is especially the case for the variables Worker, Sales, and Sales/E$_{cost}$, which have a p-value around 0.1 larger when calculated by permutation than with the OLS regression. Thus, these estimates that do not differentiate between an establishment's financial access should be understood with some caution. In the case of investments, however, the p-values by permutation are smaller. Histograms of the 10'000 permutation coefficient estimates are shown in Figure 3 in Appendix B.

6 Conclusion

I study the effect of extreme rainfall events that lead to flash floods on local economic activity as measured by establishment performance in Central America and the Caribbean. One such flash flood in a fiscal year decreases sales and the number of employees by around 3%, the investments into land and buildings by 8.3%, and increases capital productivity by 6%. This indicates that a flash flood is a negative shock to an establishment, while the increase in capital productivity indicates a mechanism such as build-back-better or creative destruction.

My results further suggest that financial access is a major determinant of impact. Establishments that report no obstacles to financial access do not see a reduction in sales or workers, but experience increased capital productivity. In contrast, establishments that report obstacles to financial access see a decrease in sales of 4.8% and even a decrease in labor productivity. Back-of-the-envelope calculations indicate that the yearly flash flood impact on establishments equals a reduction in

[22] I choose the model in Equation 3 over the one in Equation 4 because the evaluation of the interaction in a permutation setting to calculate p-values is not straightforward and requires treatment of joint-significance.

output of 8.745% due to their high frequency. I find no evidence of heterogeneous effects across industries, except for the construction sector. Estimates on sales and employees are consistently negative for all other sectors, whereas the construction sector sees a zero effect on these two measures.

The paper is the first to study the establishment-level economic impacts of flash floods. It does so with a physically derived hazard index for a region especially at risk (Pinos and Quesada-Román, 2021). There is both the contribution to the literature regarding the hazard methodology and the implication to climate change adaptation. In that sense, the focus on countries in Central America and the Caribbean is a double-edged sword. Since countries in that region would be affected gravely by an increase in flash floods (Seneviratne et al., 2021), knowledge of adaptation is crucial. However, consistent data across several countries that provide geo-located information on establishment performance is scarce. Identifying the effect of flash floods with cross-sectional data from establishment surveys is difficult. Since the effects are likely dynamic, these dynamics cannot be adequately modeled with the data, which is the main weakness of this analysis. However, by exploiting the timing of flash floods before the last fiscal year, concerns for endogeneity can be relaxed. Since the occurrence of a flood in a given year against the underlying risk of floods in that area is quasi-random, the identified effects serve as a credible baseline for policy recommendations. Nonetheless, future studies should aim to obtain panel data on establishment performance to identify the dynamic effects.

My findings have two main implications for policy. First, flash floods negatively impact establishment performance within the fiscal year of the flood. Evidence in the literature for other hazards is somewhat mixed (Leiter et al., 2009; Tanaka, 2015; Elliott et al., 2019; Cole et al., 2019; Okazaki et al., 2019; Zhou and Botzen, 2021). Spatial and temporal aggregation of the research design and the severity of the hazard and institutional context play an important role in the outcome. A warming and more humid climate will likely further increase the frequency and severity of flash floods in countries with an already high risk. Second, financial access is an effective modulator of impact in the case of flash floods. Adequate financing opportunities appear to make establishments resilient to flash floods and can be part of the efforts to decrease natural hazard vulnerability for economic development in Central America and the Caribbean. This finding echoes Hallegatte et al. (2016) who advocate for better financial inclusion to increase resilience and reduce the impacts of natural hazards in the light of climate change. Hence, the possibility of quickly refunding destroyed productive capacity is a way to manage what cannot be avoided.

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Availability of data

The primary data used or analyzed in this study are available at the indicated source. Data that result from applying the methodology in this work are available from the corresponding author upon reasonable request.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author used Grammarly in order to assist in the writing of the manuscript. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

References

Acemoglu, Daron, Philippe Aghion, Leonardo Bursztyn, and David Hemous, "The environment and directed technical change," *American economic review*, 2012, *102* (1), 131–166.

Albala-Bertrand, Jose-Miguel, "Natural disaster situations and growth: A macroeconomic model for sudden disaster impacts," *World Development*, 1993, *21* (9), 1417–1434.

Altay, Nezih and Andres Ramirez, "Impact of disasters on firms in different sectors: implications for supply chains," *Journal of Supply Chain Management*, 2010, *46* (4), 59–80.

Aroca-Jiménez, Estefanía, José M Bodoque, Juan A García, and Andrés Díez-Herrero, "A quantitative methodology for the assessment of the regional economic vulnerability to flash floods," *Journal of hydrology*, 2018, *565*, 386–399.

Barrios, Salvador, Luisito Bertinelli, and Eric Strobl, "Trends in rainfall and economic growth in Africa: A neglected cause of the African growth tragedy," *The Review of Economics and Statistics*, 2010, *92* (2), 350–366.

Barrot, Jean-Noël and Julien Sauvagnat, "Input specificity and the propagation of idiosyncratic shocks in production networks," *The Quarterly Journal of Economics*, 2016, *131* (3), 1543–1592.

Benson, Charlotte and Edward J Clay, *Understanding the economic and financial impacts of natural disasters* number 4, World Bank Publications, 2004.

Berlemann, Michael and Daniela Wenzel, "Hurricanes, economic growth and transmission channels: Empirical evidence for countries on differing levels of development," *World Development*, 2018, *105*, 231–247.

Botzen, Wouter, Olivier Deschenes, and Mark Sanders, "The economic impacts of natural disasters: A review of models and empirical studies," *Review of Environmental Economics and Policy*, 2019.

Cantelmo, Alessandro, Giovanni Melina, and Chris Papageorgiou, "Macroeconomic outcomes in disaster-prone countries," *Journal of Development Economics*, 2023, *161*, 103037.

Cavallo, Eduardo, Ilan Noy et al., "Natural disasters and the economy—a survey," *International Review of Environmental and Resource Economics*, 2011, *5* (1), 63–102.

_ , Sebastian Galiani, Ilan Noy, and Juan Pantano, "Catastrophic natural disasters and economic growth," *Review of Economics and Statistics*, 2013, *95* (5), 1549–1561.

Charvériat, Céline, "Natural disasters in Latin America and the Caribbean: An overview of risk," 2000.

Cole, Matthew, Robert Elliott, Giovanni Occhiali, and Eric Strobl, "Power outages and firm performance in Sub-Saharan Africa," *Journal of Development Economics*, 2018, *134*, 150–159.

_ , _ , Toshihiro Okubo, and Eric Strobl, "Natural disasters and spatial heterogeneity in damages: the birth, life and death of manufacturing plants," *Journal of Economic Geography*, 2019, *19* (2), 373–408.

Collalti, Dino, Nekeisha Spencer, and Eric Strobl, "Flash Flood Detection via Copula-based IDF Curves: Evidence from Jamaica," *Natural Hazards and Earth System Sciences*, 2023. preprint in review.

Czura, Kristina and Stefan Klonner, "Financial market responses to a natural disaster: Evidence from credit networks and the Indian Ocean tsunami," *Journal of Development Economics*, 2023, *160*, 102996.

Dell, Melissa, Benjamin Jones, and Benjamin Olken, "Temperature shocks and economic growth: Evidence from the last half century," *American Economic Journal: Macroeconomics*, 2012, *4* (3), 66–95.

ECLAC, "Economic Survey of Latin America and the Caribbean," *Economic Commission for Latin America and the Caribbean*, 2023.

_ , "International Trade Outlook for Latin America and the Caribbean," *Economic Commission for Latin America and the Caribbean*, 2023.

Elliott, Robert, Yi Liu, Eric Strobl, and Meng Tong, "Estimating the direct and indirect impact of typhoons on plant performance: Evidence from Chinese manufacturers," *Journal of Environmental Economics and Management*, 2019, *98*, 102252.

Encyclopedia Britannica, "Central America," Website 2022. https://www.britannica.com/place/Central-America.

Felbermayr, Gabriel, Jasmin Gröschl, Mark Sanders, Vincent Schippers, and Thomas Steinwachs, "The economic impact of weather anomalies," *World Development*, 2022, *151*, 105745.

Field, Christopher and Vicente Barros, *Climate change 2014–Impacts, adaptation and vulnerability: Regional aspects*, Cambridge University Press, 2014.

Friedt, Felix L and Aidan Toner-Rodgers, "Natural disasters, intra-national FDI spillovers, and economic divergence: Evidence from India," *Journal of Development Economics*, 2022, *157*, 102872.

Hallegatte, Stephane, Adrien Vogt-Schilb, Mook Bangalore, and Julie Rozenberg, *Unbreakable: building the resilience of the poor in the face of natural disasters*, World Bank Publications, 2016.

_ and _ , *Are losses from natural disasters more than just asset losses? the role of capital aggregation, sector interactions, and investment behaviors*, Springer, 2019.

Hallegatte, Stéphane and Patrice Dumas, "Can natural disasters have positive consequences? Investigating the role of embodied technical change," *Ecological Economics*, 2009, *68* (3), 777–786.

_ , Jean-Charles Hourcade, and Patrice Dumas, "Why economic dynamics matter in assessing climate change damages: illustration on extreme events," *Ecological economics*, 2007, *62* (2), 330–340.

Henriet, Fanny, Stéphane Hallegatte, and Lionel Tabourier, "Firm-network characteristics and economic robustness to natural disasters," *Journal of Economic Dynamics and Control*, 2012, *36* (1), 150–167.

Hsiang, Solomon M and Amir S Jina, "The causal effect of environmental catastrophe on long-run economic growth: Evidence from 6,700 cyclones," Technical Report, National Bureau of Economic Research 2014.

Huffman, George J, David T Bolvin, Eric J Nelkin et al., "Integrated Multi-satellitE Retrievals for GPM (IMERG) technical documentation," *NASA/GSFC Code*, 2015, *612* (47), 2019.

IPCC, "Climate Change 2023: Synthesis Report. Summary for Policymakers. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, Core Writing Team, H. Lee and J. Romero (eds.)," 2023, pp. 1–34.

Janvry, Alain De, Alejandro Del Valle, and Elisabeth Sadoulet, "Insuring growth: the impact of disaster funds on economic reconstruction in Mexico," *World Bank Policy Research Working Paper*, 2016, (7714).

Khajehei, Sepideh, Ali Ahmadalipour, Wanyun Shao, and Hamid Moradkhani, "A place-based assessment of flash flood hazard and vulnerability in the contiguous United States," *Scientific Reports*, 2020, *10* (1), 448.

Kocornik-Mina, Adriana, Thomas KJ McDermott, Guy Michaels, and Ferdinand Rauch, "Flooded cities," *American Economic Journal: Applied Economics*, 2020, *12* (2), 35–66.

Kotz, Maximilian, Anders Levermann, and Leonie Wenz, "The effect of rainfall changes on economic production," *Nature*, 2022, *601* (7892), 223–227.

Kousky, Carolyn, "Impacts of natural disasters on children," *The Future of children*, 2016, pp. 73–92.

Leiter, Andrea M, Harald Oberhofer, and Paul A Raschky, "Creative disasters? Flooding effects on capital, labour and productivity within European firms," *Environmental and Resource Economics*, 2009, *43*, 333–350.

Loayza, Norman V, Eduardo Olaberria, Jamele Rigolini, and Luc Christiaensen, "Natural disasters and growth: Going beyond the averages," *World Development*, 2012, *40* (7), 1317–1336.

Marto, Ricardo, Chris Papageorgiou, and Vladimir Klyuev, "Building resilience to natural disasters: An application to small developing states," *Journal of Development Economics*, 2018, *135*, 574–586.

Mendelsohn, Robert, "The economics of adaptation to climate change in developing countries," *Climate Change Economics*, 2012, *3* (02), 1250006.

Miao, Qing and David Popp, "Necessity as the mother of invention: Innovative responses to natural disasters," *Journal of Environmental Economics and Management*, 2014, *68* (2), 280–295.

Milanesi, Luca, Marco Pilotti, Andrea Belleri, Alessandra Marini, and Sven Fuchs, "Vulnerability to flash floods: a simplified structural model for masonry buildings," *Water Resources Research*, 2018, *54* (10), 7177–7197.

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

Okazaki, Tetsuji, Toshihiro Okubo, and Eric Strobl, "Creative destruction of industries: Yokohama city in the Great Kanto Earthquake, 1923," *The journal of economic history*, 2019, *79* (1), 1–31.

Okubo, Toshihiro and Eric Strobl, "Natural disasters, firm survival, and growth: Evidence from the Ise Bay Typhoon, Japan," *Journal of regional science*, 2021, *61* (5), 944–970.

Pinos, Juan and Adolfo Quesada-Román, "Flood risk-related research trends in Latin America and the Caribbean," *Water*, 2021, *14* (1), 10.

Rose, Adam and Shu-Yi Liao, "Modeling regional economic resilience to disasters: A computable general equilibrium analysis of water service disruptions," *Journal of regional science*, 2005, *45* (1), 75–112.

Ruin, Isabelle, Céline Lutoff, Brice Boudevillain, Jean-Dominique Creutin, Sandrine Anquetin, M Bertran Rojo, Laurent Boissier, Laurent Bonnifait, Marco Borga, L Colbeau-Justin et al., "Social and hydrological responses to extreme precipitations: An interdisciplinary strategy for postflood investigation," *Weather, climate, and society*, 2014, *6* (1), 135–153.

Seneviratne, Sonia I, Xuebin Zhang, Muhammad Adnan, Wafae Badi, Claudine Dereczynski, Alejandro Di Luca, Sergio M Vicente-Serrano, Michael Wehner, and Botao Zhou, "11 Chapter 11: Weather and climate extreme events in a changing climate," 2021.

Špitalar, Maruša, Jonathan J Gourley, Celine Lutoff, Pierre-Emmanuel Kirstetter, Mitja Brilly, and Nicholas Carr, "Analysis of flash flood parameters and human impacts in the US from 2006 to 2012," *Journal of Hydrology*, 2014, *519*, 863–870.

Strobl, Eric, "The economic growth impact of natural disasters in developing countries: Evidence from hurricane strikes in the Central American and Caribbean regions," *Journal of Development economics*, 2012, *97* (1), 130–141.

Strulik, Holger and Timo Trimborn, "Natural disasters and macroeconomic performance," *Environmental and resource economics*, 2019, *72*, 1069–1098.

Tanaka, Ayumu, "The impacts of natural disasters on plants' growth: Evidence from the Great Hanshin-Awaji (Kobe) earthquake," *Regional Science and Urban Economics*, 2015, *50*, 31–41.

Terti, Galateia, Isabelle Ruin, Sandrine Anquetin, and Jonathan J Gourley, "Dynamic vulnerability factors for impact-based flash flood prediction," *Natural Hazards*, 2015, *79*, 1481–1497.

Thames Water, "Internal Review into the 12 and 25 July 2021 storms in London - Actions taken, lessons learnt and further actions to be taken," Technical Report 2021.

Yin, Jie, Yao Gao, Ruishan Chen, Dapeng Yu, Robert Wilby, Nigel Wright, Yong Ge, Jeremy Bricker, Huili Gong, and Mingfu Guan, "Flash floods: why are more of them devastating the world's driest regions?," *Nature*, 2023, *615* (7951), 212–215.

Zhou, Fujin and Wouter Botzen, "Firm level evidence of disaster impacts on growth in Vietnam," *Environmental and Resource Economics*, 2021, *79* (2), 277–322.

A Appendix

Table 7: Regressions: Establishment Impacts

All in log(·)	Sales/Worker (1)	Worker (2)	Sales (3)	$\text{Inv}_{L\&B}$ (4)	$\text{Inv}_{M\&E}$ (5)	Sales/L_{cost} (6)	Sales/E_{cost} (7)
$Floods_j^t$	-0.006	-0.029**	-0.034**	-0.087**	0.118	-0.015	0.058***
	(0.012)	(0.011)	(0.011)	(0.037)	(0.076)	(0.011)	(0.014)
$Floods_j^h$	0.004*	0.003	0.007**	0.010	-0.021	0.001	-0.006
	(0.002)	(0.002)	(0.002)	(0.007)	(0.025)	(0.002)	(0.003)
$Access_j^f$	-0.150*	-0.021	-0.170	-0.143	0.032	-0.132**	-0.087***
	(0.070)	(0.045)	(0.095)	(0.133)	(0.304)	(0.053)	(0.004)
Firm: Small	0.429	0.641***	1.07*	-0.093	1.16***	-0.043	0.709
	(0.436)	(0.131)	(0.532)	(0.148)	(0.175)	(0.294)	(0.425)
Firm: Medium	0.651	1.90***	2.55***	0.987***	1.39***	0.121	0.769
	(0.430)	(0.208)	(0.567)	(0.281)	(0.189)	(0.286)	(0.432)
Firm: Large	1.08**	3.45***	4.53***	2.32***	2.91***	0.272	0.834*
	(0.442)	(0.324)	(0.656)	(0.427)	(0.638)	(0.275)	(0.419)
Firm: V. Large	1.29**	4.49***	5.78***	3.35***	3.04***	0.396	0.845
	(0.442)	(0.259)	(0.622)	(0.443)	(0.375)	(0.287)	(0.475)
% Public	0.003	0.007	0.010	0.023	0.034	-0.0002	-0.019***
	(0.004)	(0.004)	(0.007)	(0.019)	(0.043)	(0.007)	(0.004)
Firm Age	0.005**	0.008***	0.013***	0.009	-0.006	0.0008	-0.0009
	(0.002)	(0.001)	(0.003)	(0.007)	(0.010)	(0.0006)	(0.003)
% Direct Exports	0.005**	0.005***	0.010***	0.008	0.006	0.003**	0.0008
	(0.002)	(0.001)	(0.002)	(0.006)	(0.008)	(0.001)	(0.002)
Size of City	0.057*	0.013	0.070**	0.063	-0.078	-0.003	-0.0005
	(0.026)	(0.012)	(0.025)	(0.073)	(0.104)	(0.025)	(0.016)
Observations	1,725	1,725	1,725	1,725	1,725	1,722	1,719
R^2	0.40	0.83	0.71	0.28	0.08	0.93	0.83
Controls	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓

Notes: Table of regression results of the model in Equation 3. Standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table 8: Regressions: Financial Access

All in log(·)	Sales/Worker (1)	Worker (2)	Sales (3)	$\text{Inv}_{L\&B}$ (4)	$\text{Inv}_{M\&E}$ (5)	Sales/L_{cost} (6)	Sales/E_{cost} (7)
$Floods_j^t$	0.013	-0.020	-0.007	-0.077	0.143	0.008	0.071***
	(0.015)	(0.012)	(0.014)	(0.046)	(0.082)	(0.015)	(0.010)
$Floods_j^t$ ×	-0.034*	-0.015	-0.049***	-0.017	-0.044	-0.040***	-0.022
$Access_j^f$	(0.018)	(0.016)	(0.013)	(0.029)	(0.072)	(0.008)	(0.014)
$Access_j^f$	-0.060	0.019	-0.041	-0.097	0.148	-0.024	-0.028
	(0.085)	(0.063)	(0.088)	(0.144)	(0.361)	(0.047)	(0.046)
$Floods_j^h$	0.004**	0.003	0.007*	0.010	-0.021	0.0009	-0.006*
	(0.002)	(0.002)	(0.003)	(0.007)	(0.025)	(0.004)	(0.003)
Firm: Small	0.428	0.641***	1.07*	-0.094	1.16***	-0.045	0.707
	(0.450)	(0.133)	(0.551)	(0.152)	(0.177)	(0.308)	(0.435)
Firm: Medium	0.647	1.89***	2.54***	0.985***	1.39***	0.116	0.766
	(0.446)	(0.210)	(0.589)	(0.286)	(0.174)	(0.303)	(0.444)
Firm: Large	1.07**	3.45***	4.52***	2.32***	2.90***	0.263	0.830*
	(0.456)	(0.325)	(0.674)	(0.428)	(0.631)	(0.292)	(0.430)
Firm: V. Large	1.28**	4.49***	5.77***	3.34***	3.03***	0.390	0.842
	(0.458)	(0.260)	(0.641)	(0.447)	(0.356)	(0.305)	(0.485)
% Public	0.002	0.007	0.009	0.023	0.033	-0.0008	-0.019***
	(0.004)	(0.004)	(0.007)	(0.023)	(0.043)	(0.009)	(0.005)
Firm Age	0.005**	0.008***	0.013***	0.009	-0.006	0.0008	-0.0009
	(0.002)	(0.002)	(0.003)	(0.006)	(0.010)	(0.003)	(0.003)
% Direct Exports	0.005**	0.005**	0.010***	0.008	0.006	0.003	0.0008
	(0.002)	(0.001)	(0.002)	(0.007)	(0.011)	(0.003)	(0.002)
Size of City	0.058*	0.013	0.072**	0.063	-0.077	-0.002	0.0002
	(0.026)	(0.012)	(0.025)	(0.077)	(0.106)	(0.028)	(0.018)
Observations	1,883	1,883	1,883	1,883	1,883	1,880	1,877
R^2	0.41	0.82	0.71	0.29	0.08	0.92	0.83
Within R^2	0.13	0.80	0.66	0.20	0.03	0.04	0.009
Controls	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓

Notes: Table of regression results of the model in Equation 4 with the interaction for financial access. Standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table 9: Regressions: Industry Heterogeneity

All in log(·)	Sales/Worker (1)	Worker (2)	Sales (3)	$\text{Inv}_{L\&B}$ (4)	$\text{Inv}_{M\&E}$ (5)	Sales/L_{cost} (6)	Sales/E_{cost} (7)
$Floods_j^t$ ×	-0.010	-0.029*	-0.040***	-0.035	0.259	0.0007	0.021
Chemicals/Plastic	(0.016)	(0.014)	(0.009)	(0.028)	(0.165)	(0.017)	(0.017)
$Floods_j^t$ ×	-0.042	0.056	0.014	-0.341***	0.121	-0.022	0.062**
Construction	(0.028)	(0.037)	(0.041)	(0.062)	(0.168)	(0.032)	(0.019)
$Floods_j^t$ ×Food	0.005	-0.024**	-0.018	-0.119**	0.139**	0.011	0.077**
	(0.022)	(0.010)	(0.026)	(0.039)	(0.043)	(0.024)	(0.026)
$Floods_j^t$ × Metals	0.004	-0.048**	-0.044	-0.102	0.014	-0.033**	0.046
& Minerals	(0.026)	(0.020)	(0.027)	(0.099)	(0.063)	(0.013)	(0.039)
$Floods_j^t$ × Textile	-0.018	-0.032*	-0.050**	-0.058	0.067	-0.015	0.039*
& Garments	(0.014)	(0.014)	(0.019)	(0.044)	(0.104)	(0.016)	(0.018)
$Floods_j^t$ × Other	0.024	-0.036*	-0.012	-0.149***	0.209***	0.015	0.146***
Manufacturing	(0.018)	(0.016)	(0.017)	(0.044)	(0.058)	(0.026)	(0.022)
$Floods_j^t$ × Other	-0.027	-0.016	-0.043	-0.061	0.024	-0.063*	0.038
	(0.026)	(0.010)	(0.025)	(0.042)	(0.090)	(0.031)	(0.045)
$Floods_j^h$	0.005**	0.003	0.007***	0.010	-0.019	0.002	-0.006
	(0.002)	(0.002)	(0.002)	(0.010)	(0.021)	(0.003)	(0.005)
$Access_j^f$	-0.150*	-0.019	-0.170	-0.148	0.031	-0.132**	-0.087**
	(0.072)	(0.042)	(0.098)	(0.137)	(0.300)	(0.055)	(0.035)
Firm: Small	0.428	0.643***	1.07*	-0.082	1.18***	-0.030	0.694
	(0.427)	(0.131)	(0.525)	(0.156)	(0.170)	(0.271)	(0.417)
Firm: Medium	0.645	1.90***	2.55***	0.994***	1.42***	0.132	0.744
	(0.420)	(0.207)	(0.561)	(0.276)	(0.200)	(0.256)	(0.420)
Firm: Large	1.08**	3.45***	4.53***	2.34***	2.93***	0.283	0.813*
	(0.434)	(0.324)	(0.652)	(0.420)	(0.590)	(0.247)	(0.411)
Firm: V. Large	1.29**	4.49***	5.78***	3.34***	3.09***	0.416	0.841
	(0.435)	(0.258)	(0.620)	(0.431)	(0.360)	(0.259)	(0.467)
% Public	0.003	0.007	0.010	0.022	0.030	-0.0005	-0.018
	(0.004)	(0.005)	(0.006)	(0.022)	(0.040)	(0.010)	(0.010)
Firm Age	0.005**	0.008***	0.013***	0.009	-0.006	0.0007	-0.0010
	(0.002)	(0.002)	(0.003)	(0.008)	(0.012)	(0.003)	(0.005)
% Direct Exports	0.005*	0.005***	0.010***	0.009	0.006	0.003	0.0007
	(0.002)	(0.001)	(0.002)	(0.006)	(0.010)	(0.003)	(0.004)
Size of City	0.058**	0.014	0.071**	0.059	-0.079	-0.004	0.003
	(0.025)	(0.012)	(0.026)	(0.078)	(0.116)	(0.028)	(0.024)
Observations	1,883	1,883	1,883	1,883	1,883	1,880	1,877
R^2	0.41	0.82	0.71	0.30	0.08	0.92	0.83
Controls	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓

Notes: Table of regression results of the model in Equation 5 with the interactions for industry. Standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01

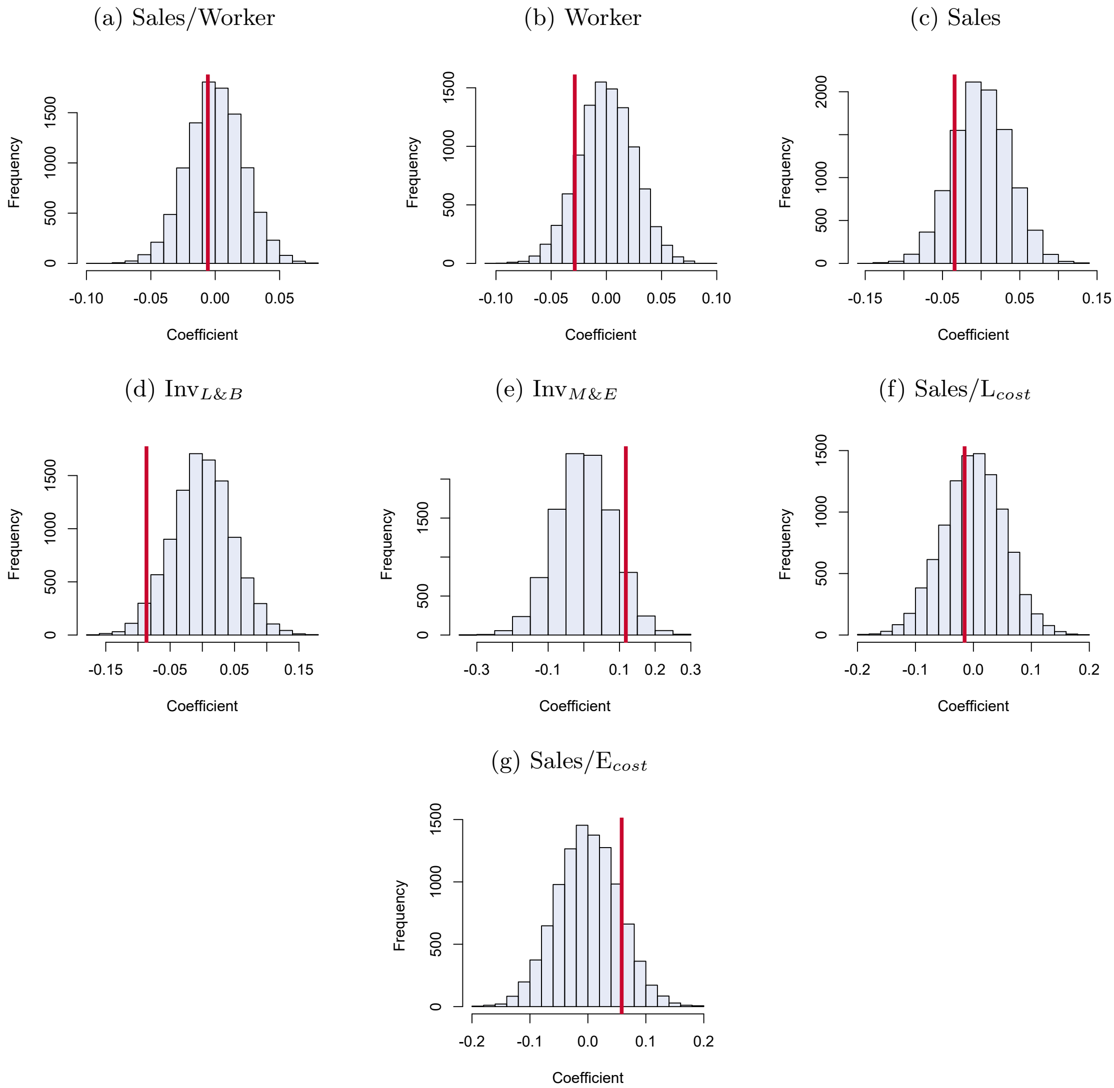
B Robustness

Table 10: Regressions: All Observations

All in log(·)	Sales/Worker (1)	Worker (2)	Sales (3)	$\text{Inv}_{L\&B}$ (4)	$\text{Inv}_{M\&E}$ (5)	Sales/L_{cost} (6)	Sales/E_{cost} (7)
$Floods_j^t$	0.030	-0.004	0.028	-0.098**	0.205	0.011	0.073***
	(0.022)	(0.010)	(0.029)	(0.034)	(0.133)	(0.012)	(0.016)
$Floods_j^t \times Access_j^f$	-0.018	-0.017*	-0.034*	0.027	-0.060	-0.040***	-0.021
	(0.019)	(0.007)	(0.017)	(0.027)	(0.060)	(0.008)	(0.014)
$Floods_j^h$	5.21×10^{-5}	-0.0001	-0.0001	0.004	-0.023	0.003*	-0.005
	(0.002)	(0.001)	(0.002)	(0.007)	(0.023)	(0.002)	(0.008)
$Access_j^f$	-0.034	0.014	-0.012	-0.281*	-0.025	-0.009	-0.013
	(0.055)	(0.033)	(0.036)	(0.146)	(0.310)	(0.049)	(0.027)
Observations	5,313	6,230	5,323	2,654	2,725	4,904	4,291
R^2	0.40	0.82	0.66	0.28	0.15	0.90	0.79
Controls	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓

Notes: Table of regression results of the model in Equation 4 with all observations. The table is without coefficients of the control variables X_j for brevity. Standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01

Figure 3: Histograms of Coefficients from Permutation



Notes: Histograms of the coefficient estimates with random permutation in Y_j. The red line indicates the estimate with unpermuted data. The regression model estimated is the one in Equation 3.