Cyclone Exposure and Adaptation in Global Supply Chains

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Abstract

We investigate the impact of tropical cyclones on firm financial performance and supply chain dynamics, focusing on how firms adapt to increased environmental risks. Utilizing a comprehensive dataset that combines information on firm locations, financial performance, and detailed cyclone track data, the research analyzes the direct financial impacts and strategic adjustments within supply chains in response to cyclone exposures. We find that firms reduce their reliance on suppliers with heightened cyclone risk, indicating a proactive approach to risk management. We also find evidence of increased resilience among suppliers over time, suggesting that firms adapt by enhancing their preparedness and operational strategies post-exposure. Our results highlight the need for firms to integrate robust risk management strategies and adaptive measures in their operational and strategic planning.

Keywords: Global supply chains, tropical cyclones, climate econometrics

1 Introduction

In 2023, the Intergovernmental Panel on Climate Change published their Sixth Assessment Report (AR6) finding that human-caused climate change primarily through continued greenhouse gas emissions will continue to lead to increasing global warming, impacts to physical water availability and crop productivity, and increased flooding/storm damage in coastal areas (IPCC, 2023). Approximately 3.3 to 3.6 billion people live in contexts that are highly vulnerable to climate change. To protect people, livelihoods, and ecosystems, adaptation is a critical component of the long-term global response to climate change. Adaptation refers to changes in processes, practices and structures to moderate potential damages or to benefit from opportunities associated with climate change (UNFCCC, 2022). In IPCC (2023), the IPCC find that even though adaptation planning and implementation has progressed across all sectors and regions, gaps still exist. Most observed adaptation responses are fragmented, sector-specific, and unequally distributed across regions (IPCC, 2023). Some of the key barriers to adaptation are limited resources, lack of private sector and citizen engagement, low sense of urgency, and insufficient mobilization of finance.

While the exact consequences of climate change are uncertain, it is clear that its complex environmental impact will directly affect businesses, societies, and ecosystems. It is evident that to counter these impacts, governments worldwide will implement extensive regulatory measures. However, business efforts to address risks posed by climate change have in general lagged behind consideration of the financial risks associated with mitigation (IPCC, 2023). Businesses today face a variety of risks due to increased climate change and natural disasters. These risks can broadly be categorized into physical, transitional, and reputational risks. Firms constantly face scrutiny by investors, governmental regulators, and non-governmental organizations to limit their environmental impact on the planet. With the implementation of mandatory net zero planning, disclosure and reporting requirements, companies need to measure and manage all aspects of their environmental impact, including impacts across their operations and supply chains (CDP, 2023).

Recently, academic research on the effects of transitory weather shocks on firms' earnings, stock returns, and labor and capital productivity has emerged. Addoum et al. (2020) measure the effects of temperature shocks on firm productivity and establishment sales. The study finds that temperature exposures are generally unrelated with firm level sales and establishment-level productivity. Graff Zivin et al. (2018) investigate the potential impact of climate change on cognitive performance and human capital. They find that short-run changes in temperature led to significant decreases in math performance beyond 26°. Pankratz and Schiller (2022) examine how floods and heatwaves affect firm financial performance and risk management in global supply chains, finding that customers are 6-11% more likely to terminate existing supplier-relationships. However, research on how firms adapt to climate change over time is scarce, despite the fact that their endogenous responses are key to understanding the long-term influence of climate change on financial markets.

Additionally, there is a pattern of companies assessing their own direct operations and not looking at their wider impacts. Supply chain emissions (upstream) are, on average, 11.4

times greater than operational emissions (CDP, 2023). Currently, only 11% of respondents in the CDP Supply Chain Report 2022 include climate-related requirements in their supplier contracts and less than 3% require their suppliers to disclose climate-related data (CDP, 2023). Given the globalized state of supply-chains today, firms might be indirectly exposed to physical risks due to their suppliers. Overall, CDP (2023) finds that only three out of every 100 companies incentivize procurement-related teams for the management of climate-related issues.

In this paper, we study how firms adapt and restructure their supply-chain network in response to perceived changes in their suppliers' exposure to tropical cyclones (TCs). We begin by assessing whether large public firms suffer financial consequences due to unforeseen shocks from TCs to its physical assets. Then, we investigate whether public supplying firms see a reduction in revenue and relationship size in response to changes in supplier exposure. We also examine customer firms diversify their supply-chain network by reducing their dependence on a single supplier.

This study combines various datasets, including firm financial performance, firm locations, supply chain information and detailed data on cyclone tracks to create two novel datasets: firm-quarter-year dataset from 2013 to 2019 and a comprehensive supply-chain-year dataset from 2014 to 2019 for 9 customer public firms. Since there is no publicly available information on the exact cyclone exposure of firms, we use data from the International Best Track Archive for Climate Stewardship (IBTrACS) to reconstruct historical cyclone exposure for firm branches, focusing on maximum wind speeds and severe shocks during cyclone events. Methodologically, we first examine the immediate financial effects of cyclone exposures on firms using a fixed effects model to exploit within-firm variations over time. The supply chain analysis considers the dynamics of supplier-customer relationships and evaluate how adjustments in these relationships are influenced by increased observed cyclone risk. We use two functional forms: a time series with fixed effects model and a long differences model.

Our analysis on the direct exposure of *severe* cyclones through increased maximum wind speeds can lead to a decline in firm financial performance. After accounting for firm, industry and country-specific fixed effects, we find statistically insignificant estimates of reduction in revenue relative to assets and a slight increase in the debt to assets ratio. In terms of supply chain dynamics, we find that an increase in wind exposure significantly elevates the likelihood of reductions in the size of supplier-customer relationships. This response is particularly evident in relationships involving suppliers of direct inputs. Additionally, relationship size tends to decrease with the number and intensity of cyclones, leading to economically meaningful reductions in revenue for suppliers. Moreover, while immediate impacts of cyclone exposure are negative, we interestingly identify potential increases in supplier resilience over time through increases in supplier revenue two years after cyclone shocks. Our results suggest that firms need to assess and adapt to the risks posed by increased frequency and intensity of tropical cyclones. Tropical cyclones not only affect the immediate financial performance, but also the strategic configurations of global supply chains. This research contributes valuable insights into the economic resilience and adaptive strategies of firms in a changing climate. We highlight the importance of proactive risk management and adaptation planning in maintaining firm operational performance, profitability, and supply chain integrity.

The paper proceeds as follows. Section 2 describes the motivations, economics of natural disasters and academic research about global supply chains. Section 3 describes our data sources, data manipulations and computations, and the merging of reconstructed cyclone exposure measures with a firm-quarter-year dataset. We explain and evaluate our empirical strategy and intermediate product market structure in Section 4. In Section 5, we present our main results for direct cyclone exposure on firm financial performance and supply-chain adaptations to increased cyclone severity risk relative to historical expectations. We then consider the policy and strategic implications, and limitations of our findings in Section 6.

2 Context and Motivations

2.1 Economics of natural disasters

Research around the impacts of natural disasters have primarily surrounded the short-term effects of individualized or recurring disasters in specific regions of the world. In the long run, however, the notion that natural disasters can cause lasting damage is less obvious, since the global response to natural disasters is more localized to the areas that are affected.

While human-caused macroeconomic disasters tend to elicit a global response that lead to long-term change in regulations and business practices, the effects of natural disasters are more nuanced and varied. Literature on the adverse macroeconomic and developmental impacts of natural disasters is emerging, with better econometric and statistical modelling techniques (S. Hsiang, 2016). The bulk of studies identify negative effects of disasters, especially on shorter-term economic growth (Barro, 2006), however, some studies have found positive effects (Graff Zivin et al., 2018). These differences can be partly explained by the lack of a robust counterfactual in some studies, and this is even more problematic when attempting to estimate the long term effects of natural disasters.

Given the lack of clear empirical evidence on the impacts of natural disasters on economic growth, prior literature has converged on four competing hypotheses, with the null being no impact to the baseline trend (S. Hsiang & Jina, 2014). These hypotheses are based on point-in-time impacts of natural disaster in general and can be applied to most measures of economic growth and stability.

1. The **"no recovery"** hypothesis suggests that natural disasters slow growth to the point of no return or rebound. The destruction of productive capital or the loss of durable consumption goods leads to a decrease in productive financial investments. No recovery occurs because of the negative effects of losing capital to expensive recovery mechanisms. This hypothesis argues that post-disaster output may grow in the long run, but remains permanently lower than pre-disaster trajectory.

2. The **"recovery to trend"** hypothesis argues that growth will be impacted negatively for a finite period, but will return to the pre-disaster trajectory. This rebound should occur because of rising marginal product of capital as capital and labor decrease after a disaster due to destruction and mortality. Over time, due to appropriate disaster-response measures and inflow of capital, growth will eventually rebound.

3. The **"build back better"** hypothesis argues that growth may suffer initially due to loss of productive capital and labor, but due to efficient allocation of disaster-response funds and planning, there is a positive net effect on growth.

4. Finally, the **"blessing in disguise"** hypothesis argues that disasters stimulate firms and industries to grow faster because demand for their goods and services have increased. This is primarily observed in the construction industry where short-lived increases in output occur after catastrophes. This hypothesis can also be explained by endogenous growth models based on Schumpeterian creative destruction theory which describes the principle that old assumptions need to be broken so that new innovations can benefit from existing resources and energy (Youmatter, 2020).

While studies assessing the economic consequences attribtued to natural disasters focusing on macroeconomic indicators such as GDP or wealth and spending are plentiful, we know of no papers that have directly examined the effects of natural disasters on firms. Our motivation to study firms is rooted in the observation that firms play an important role in economic activity. Focusing on household impacts and country-specific economic losses not only provides an incomplete picture of the impact on the economy, but also doesn't explain the estimates of loss clearly.

2.2 Tropical cyclones

A tropical cyclones is a rotating, organized system of clouds and thunderstorms that originates over tropical waters and has a closed low-level circulation (WMO, 2022). The World Meteorological Organization (WMO) found that TCs are the second-most dangerous natural hazards, after earthquakes. 1,945 disasters have been attributed to tropical cyclones over the past 50 years and since 1970, approximately USD 1.4 trillion of economic losses has been caused by TCs (WMO, 2022). Interestingly, tropical cyclones represent 17% of natural disasters but were responsible for a third of both natural disaster-related deaths and economic losses over the last 50 years (WMO, 2022).

The economic impacts of TCs during a year depends on several factors: the location of economic activity, the number of storms, the intensity of storms, and the geographical features of the affected areas. However, measuring and predicting economic damage due to TCs is a complex and nuanced problem. Nordhaus (2006) lists three reasons for this:

1. The impact of maximum wind speeds on damage is not a linear relationship. Physical damage is low for low to medium wind speeds but increases sharply with maximum wind speeds.

2. Cyclone lifetime is highly dependent on maximum wind speed and therefore not all cyclones last the same time, making it difficult to build measures of duration.

3. Tropical cyclones above a certain threshold are rare events. The definition of this threshold has affects the measure of damage and therefore, damage is more likely to be observed at points of nonlinear failure.

In this study, we focus on tropical cyclones because they are common, recurring events that have enough variation in their timing, strength and location for me to use quasi-experimental techniques to identify treatment effects. Furthermore, unlike floods and wildfires, tropical cyclones form over warm oceans and quickly move over thousands of kilometers, all while increasing in intensity, making them stochastic and difficult to predict events. Since cyclone exposure at a specific location varies exogenously in its timing, intensity, and duration, apart from the seasonality and historical exposure at certain locations, tropical cyclone events can be considered random events (Deschênes & Greenstone, 2007). Such randomness is essential for us to identify causal effects of cyclones on firm productivity and supply chain adaptation. To address the concerns outlined by Nordhaus (2006), we construct a measure of *realized vs. expected climate risk* by comparing cyclone frequency and intensity before the fiscal year begins and after it ends (see Section 3.2.2).

3 Data

We combine data on tropical cyclone tracks, firm financial performance, firm locations, and supply chains from a variety of sources. In the following sections, we describe these sources, data quality, and processes to merge and link datasets. we end this section with descriptive statistics on two novel datasets: a global firm-year dataset and a supply-chain dataset linking nine customer companies with their supplying firms and their respective cyclone exposures.

3.1 Firm data

We obtain information on the largest firms in the world from 7 major global stock indices S&P 500, Nikkei 300, Bombay Stock Exchange 500, Shanghai Stock Exchange, Shenzhen Stock Exchange 100, S&P/ASX 200, and FTSE Straits Times Index from Refinitiv Eikon (Refinitiv, 2024). In total, we use the current companies part of these indices amounting to 3,438 companies.

The primary location of firms is their headquarters which is provided by Refinitiv Eikon, but any information about the location of their facilities is not provided. Hence, we collect information on additional firm plants, establishments, and branches from Orbis (van Dijk, 2024). In total, we obtain 276,000+ addresses of locations of the branches and establishments owned by the companies in my sample. We transform the city, state, and country into coordinates using the Bing Maps API. In the process of analyzing our dataset, we found it necessary to filter out companies that did not have any branch information provided. This decision was crucial to maintain the integrity of the comparison being drawn within the dataset. Including large firms without branch data could skew the results and lead to erroneous interpretations. The presence of branch-specific data is essential for accurately assessing the localized impact of cyclonic events on firm performance and enhancing the robustness of the results and avoiding the pitfalls of aggregation bias.

Next, we obtain quarterly financial performance data from 2013 to 2019 from Refinitiv Eikon. Our main variables of interest for measuring profitability and operating metrics are total current assets, total revenue, asset turnover and total debt to assets, scaled by one-year lagged total assets. To ensure that international financial records are comparable, we convert all variables into U.S. dollars and log-transform all variables.

After filtering out firms without branch data, our final sample of firms consists of 1,702 firms. Figure 2 presents a map of the firm locations. 49.77% of firms are located in Eastern Asia and 29% of firms are located in North America. Almost 50% of firms are manufacturing firms with the rest of the industries having less than 10% of coverage in the dataset.

3.2 Tropical cyclone data

To create direct measures of cyclone exposure on the physical assets of firms, we build a dataset that describes the physical exposure of all firms in my datasets. We expand the approach of S. M. Hsiang (2010) and S. Hsiang and Jina (2014) to measure each firm's branch's history of cyclone exposure. We utilize a comprehensive database comprised of ground, ship, aerial, and satellite-based observations with detailed estimates of wind distribution within each cyclone at sequential moments. This fusion allows us to reconstruct the precise conditions individuals on the ground would have experienced as each cyclone traversed their location.

3.2.1 Reconstructing tropical cyclone exposure history

We derive metrics for tropical cyclone occurrence by reconstituting the wind field of each cyclone listed in the International Best Track Archive for Climate Stewardship (IBTrACS) database (Knapp et al., 2010). Recognized as the most comprehensive global repository for tropical cyclone data, IBTrACS amalgamates information from a variety of sources including weather monitoring agencies and scientists globally. These contributors provide detailed data on the intensity and location of tropical cyclones, which are gathered through ground, ship, aerial, and satellite-based observations. IBTrACS provides limited information regarding the state of each storm, reporting the location of a cyclone's center, maximum sustained surface winds, and minimum central surface air pressure every three hours. This allows researchers to plot the trajectory of a storm's center and measure the core intensity of the storm. It also allows us to classify storms by intensity using the Saffir-Simpson Hurricane Wind scale which assigns storms a 1 to 5 rating based only on a hurricane's maximum sustained wind speed.

In Figure 4, we plot the track of Hurricane Harvey, the costliest tropical cyclone on record, over the United States along with the branches of the firms. The blue dots represent the latitude and longitude points of the cyclone's eye. These data are present in the IBTrACS but since the hurricane had a diameter of approximately 280 miles, the effects of Harvey were felt from Texas to Louisiana (NERC, 2018). Given that IBTrACS only tracks the location and intensity of winds around the eye of storms, we need to reconstruct the winds that employees, assets, and firms on the surface would have been exposed to.

Therefore, we follow the approach outlined by the Limited Information Cyclone Reconstruction and Integration for Climate and Economics (LICRICE) model applied in (S. M. Hsiang (2010), S. Hsiang and Jina (2014)). The authors apply LICRICE to estimate an instantaneous wind field within the storm at each moment from 1950-2008 across the entire surface of the planet to assess the effects of cyclones on gross domestic product and economic prosperity. In this study, we utilize Chapter 16.6 *A Tropical Cyclone Model* from Stull (2015) to build a similar model that estimates an instantaneous wind field around an observation of a storm and the exposure on the branches of firms in the wind field. The structure of the wind field within each storm is based on:

1. The **radius of the storm's inner core** (known as they "eye"). A statistical model is fitted to detailed observations from aircraft reconnaissance missions that fly through the eye. The IBTrACS dataset has these data points but is not "best tracked" or reanalyzed for accuracy. There are three primary meteorological agencies that run such missions: NOAA's Tropical Prediction Center (HURDAT, USA), Regional Specialized Meteorological Center La Reunion, and Australian Tropical Cyclone Warning Centre. Therefore, we fit the following model for each agency:

$$RMW_i = \alpha_0 + \alpha_1 WIND_i + \alpha_2 Latitude + \epsilon_i$$

   where α_1 represents the change in the radius of the eyewall for a 1 m/s increase in the maximum sustained wind speed. Then based on the location of the storm around the world, we calculate the radius of the storm's inner core when not provided.

2. A **structural model of surface winds within a cyclone vortex** built using the following model from textbook:

   - Define the <u>pressure distribution</u>. One measure of tropical cyclone strength is the pressure difference between the eye and the surrounding ambient environment: $\Delta P_{max} = P_\infty - P_{eye}$ where ambient pressure is $P_\infty = 101.3$ kPa and P_{eye} is the pressure around the eye.

- Calculate the radial distance from the storm's center. We employ the Haversine formula to compute the great circle distance between two points on the earth's surface, represented by their latitude and longitude coordinates in radians (Williams, n.d.):

$$d = 2R \arctan 2\left(\sqrt{a}, \sqrt{1-a}\right)$$

where R is the mean radius of the Earth, taken as $6,371$ km,

$$a = \sin^2\left(\frac{\Delta\text{lat}}{2}\right) + \cos(\text{lat}_1)\cdot\cos(\text{lat}_2)\cdot\sin^2\left(\frac{\Delta\text{lon}}{2}\right),$$

$$\Delta\text{lat} = \text{lat}_2 - \text{lat}_1, \quad \Delta\text{lon} = \text{lon}_2 - \text{lon}_1,$$

and $\text{lat}_1, \text{lon}_1$ and $\text{lat}_2, \text{lon}_2$ are the latitudes and longitudes of two points in radians.

- Calculate the tangential wind speed for a $0.1^\circ \times 0.1^\circ$ (~ 10 km) point in a $3^\circ \times 3^\circ$ grid around the point of observation of a cyclone. Tangential speed represents the speed of an object in circular motion. We are interested in the maximum tangential surface winds M_{max} around the eye wall which can be empirically approximated based on Bernoulli's equation: $M_{max} = a * (\Delta P_{max})^{1/2}$ where $a = 20(ms^{-1}) \cdot kPa^{-1/2}$. Then, since winds are assumed to be cyclostrophic (balanced between atmospheric pressure and centrifugal force), then the distribution of tangential velocity M_{tan} in the boundary layer is a function of maximum tangential surface winds and a given radius R (Brittanica, 2021):

$$M_{tan} = \begin{cases} M_{max} * (R/R_0)^2, & \text{for} R <= R_0 \\ M_{max} * (R/R_0)^{1/2}, & \text{for} R > R_0 \end{cases}$$

where R_0 is the critical radius (assumed to be twice the radius of the eye).

- Calculate the translational component of the cyclone vortex at each point. The translational component of the wind around the cyclone accounts for the overall movement of the cyclone itself across the Earth's surface. We compute this component by converting the storm's directional speed into its Cartesian coordinates, using the storm's travel direction and speed:

$$\text{velocity}_x = \text{speed} \cdot \cos(\text{direction radians})$$
$$\text{velocity}_y = \text{speed} \cdot \sin(\text{direction radians})$$

where velocity_x is the eastward component of velocity and velocity_y is the northward component of velocity.

- The overall wind vector at each grid point is the vector sum of the tangential and translational components. The magnitude of the overall wind vector is the total wind speed experienced on the surface at that grid point.

We reconstruct a wind exposure field for each observation of storms that passed over any firm branches at a $0.1° \times 0.1°$ spatial resolution. A model of a sample wind field of Hurricane Maria in 2017 is provided in Figure 5. We only consider storms that are between $48°N - 48°S$ latitude and storms that formed between 2013 and 2019. This results in 4,339 storms and approximately 45,385 storm-specific observations. After reconstructing wind fields and assigning each firm's location the maximum wind it was exposed to in each quarter, this dataset has 531,291 observations across 11,960 branches. Each observation are wind speeds at each location every three hours. A track of the wind fields for Hurricane Maria is showcased in Figure 6. In the following sections, we outline cleaning this dataset, aggregating this to the firm level and building my independent variables.

3.2.2 Matching firm historical cyclone exposure

During my period of observation from 2013 to 2019, simply matching firms with their cyclone exposure is not appropriate since firms are aware of operational risks from their past cyclone exposure. Therefore, we generate variables based on whether cyclone shocks between 2013 and 2019 were *greater in severity* than the past observations at those branch locations. For each firm location, we generate an "expectation" dataset that has reconstructed wind speeds from storm-specific observations from 1980 to 2012. Let's name the dataset of interest, the "*realized*" dataset. To assess the severity of shocks, we fit a lognormal distribution to each firm location's wind exposure history. The lognormal distribution is widely used in environmental and meteorological studies, particularly where the data are positively skewed, non-negative and vary over several orders of magnitude. Figure 8 presents the histograms of wind speeds for eight different cities and generally, we observe a right skew. Figure 9 showcases the distribution of winds in Hong Kong before and after a log transform. We see that the natural log of the distribution follows the standard normal distribution suggesting a lognormal distribution. After fitting a lognormal distribution, a shock threshold is chosen at a specific percentile of the distribution which represents the critical value above which the wind speeds are considered to be *severe shocks*. The definition of this threshold has a significant effect on the likelihood that firms are affected by the cyclone and upon conducting robustness checks, the optimal choice of threshold is 0.7.

To make the new dataset useful for estimating an entire firm's exposure to cyclones, we create the following variables by quarter-year for each firm in my dataset:

- Binary indicator of whether the company was exposed to a cyclone
- Mean maximum wind exposed to the firm across branches
- Average number of days with *severe shocks*

Table 1: Direct Exposure Descriptive Statistics

Variables	Obs.	Mean	Std. Dev.	Min	Max
Cyclone Exposure (1/0)	39,623	0.366	0.482	0	1
Average Maximum Wind (m/s)	14,492	27.184	12.577	1.134	100.206
Average Severe Cyclone Days	14,492	0.453	0.724	0	6
Total Current Assets (millions USD)	32,228	263,200	1,481,000	0.50	68,220,000
Total Revenue (millions USD)	39,623	88,680	33,600	-14,070	78,020
Asset Turnover	30,726	0.198	0.309	-0.4	44.847
Revenue (scaled by lagged assets)	30,757	0.964	0.037	0.434	1.242

In Table 1, descriptive statistics on the final dataset for measuring direct exposure of severe cyclone shocks on firms is provided and in Figure 10, a map of the cyclones that hit East Asia in 2018 Q3 is presented with the maximum wind exposure by branch with the intensity denoted by color. From the figure, we see that Japan, Taiwan and the Philippines experienced stronger storms than Mainland China. Additionally, coastal branches are more vulnerable to strong winds. We note that 36.6% of firms between 2013 to 2019 experienced a cyclone shock to at least one of their branches. The average maximum wind exposed to firms across their branches was 27.184 m/s. A key dependent variable here is revenue scaled by lagged assets (previous quarter). Assuming that a firm's assets are being utilized in the near future, assessing the impacts on the revenue of firms given the numerical value of their assets in the near past is more appropriate than just regressing exposure on revenue.

3.3 Supply chain data

Bloomberg has data on over 20,000 quantified supply chains, which comes from reputable public sources such as filings with the SEC, company reports and earnings conference call transcripts. Bloomberg applies its own propreitary algorithm to determine the costs that companies incur in doing business with each of their suppliers and also estimates the revenue that each supplier earns from the relationship. Finally, Bloomberg also calculates the total relationship size to determine the value of the relationship to both supplier and customer. Given the time required to scrape and transform the data, nine companies were handpicked given their size, geographic location, and industry: Microsoft Corporation, ExxonMobil Corporation, Nvidia Corporation, McKesson Corporation, Pfizer Inc., Procter & Gamble, and Honda Motor Co., Ltd. These companies are particularly suitable for analyzing the impacts of cyclones on supply chain relationships due to their diverse industry representation—spanning technology, energy, healthcare, consumer goods, and automotive—which allows for assessing sector-specific vulnerabilities and resilience strategies to extreme weather events. Additionally, these firms vary significantly in size and market capitalization, providing insights into how large multinational corporations versus smaller entities mitigate risks associated with supply chain disruptions caused by cyclones. Their geographic distribution across different regions also exposes them to varied cyclonic patterns, from tropical storms in Asia and hurricanes in North America, offering a comprehensive view of global supply chain challenges and adaptation mechanisms in the face of climatic disturbances. However, the data captures only a subsample of all supply-chain relationships. But finding and expressing all supply-chain relationships is a tedious task given the contractual terms associated with such ties and the variety in regulations across the world regarding disclosing supply chain relationships.

In total, from hand-collected data via Bloomberg, we create a sample of 830 unique supplier-customer relationships from 39 countries, comprising of 2,589 supplier-customer pair-year observations over the sample period of 2014 to 2019. Figure 3 presents the firm locations of the suppliers of our nine customer companies of interest. 48.2% of suppliers are located in the United States, 11.5% of suppliers are located in Japan, and 4% of suppliers are in China. Previous studies have found stronger effects of weather shocks on economic output in less developed economies (Burke 2015b). So, it is possible that the true effects of cyclones on supply chains is underestimated given that most of the suppliers in our sample are located in the United States. We apply the same steps outlined in Sections 3.2 to match cyclone exposure with firms, apart from Section 3.2.2. We explain the market structure of supply chain relationships in Section 4.2.1 and build our dependent variables of interest and identification strategy in Section 4.2.

Table 2: Supply Chain Descriptive Statistics

Variables	Obs.	Mean	Std. Dev.	Min	Max
Total Relationship Size (millions USD)	2,589	409.5957	1,018.598	0.01	12,485.53
Customer Cost	2,586	0.0098	0.0284	0	0.8511
Supplier Revenue	2,588	0.0686	0.1243	0	0.9982
Market Cap (millions USD)	2,485	1,911,875	19,600,000	1.25	308,000,000
Average Wind Exposure (m/s)	2,589	8.7622	9.1128	0	41.2896
Average Max Wind Sustained (m/s)	2,589	14.2651	16.1122	0	72.2758
Average Number of Cyclones	2,589	1.2358	1.5887	0	9
Average Cyclone Days	2,589	2.0463	2.7795	0	21

Descriptive statistics for the supply chain dataset are provided in Table 2. The average total relationship size of supply-chain relationships in our sample is USD 409 million. On average, a supply-chain relationship makes up 0.98% of a customer's total cost to produce, and approximately 6.9% of a supplier's total revenue. This suggests that suppliers are more reliant on customers for revenue and customers likely have diversified supply base where no single supplier has a large impact on the total cost structure. This also may mean reduced bargaining power of suppliers and a significant customer impact since losing a customer could have significant revenue implications.

4 Methodology

We establish three testable hypotheses:

1. An increase in the number of realized shocks beyond what is expected from historical shocks leads to a decrease in observed revenue of a company

2. An increase in the number of realized shocks beyond what is expected from a supplier leads to a reduction in relationship size (and a decrease in supplier revenue)

3. Persistent increases in the number of realized shocks is positively associated with an increased likelihood of reduction in the relationship size.

4.1 Direct exposure to tropical cyclones

Before we test the adaptation of supply chains to cyclone exposure, we test whether severe tropical cyclone shocks have economically important financial effects. Our primary variables for measuring firm operating performance are revenues scaled by assets and the debt to assets ratio. Since climate exposure and firm financial performance are potentially endogenous in the cross-section of all firms, our empirical strategy exploits short-term variation over time in cyclone shocks *within* firms, which are plausibly exogenous and randomly distributed, conditional on firm locations, industry, and seasons. Following Pankratz and Schiller (2022), we estimate models of the following form at the quarterly frequency:

$$y_{it} = \alpha + \sum_{t=-3}^{0} \beta_t * W_{it} + \pi_{it} + \mu_{iq(t)} + \gamma_{n(i)t} + \theta_{d(i)t} + \epsilon$$

where y_{it} is either *revenue/assets* or *debt to assets* of firm i in year-quarter t and W_{it} measures weather shocks i.e either a binary indicator of whether the company was exposed to a cyclone, mean maximum wind exposed to the firm, or the average number of days a firm was exposed to severe shocks. π_{it} represents firm fixed effects which absorb time-invariant firm-level characteristics, $\mu_{iq(t)}$ represent firm by quarter fixed effects which mitigates confounding seasonality patterns, $\gamma_{n(i)t}$ are industry-by-quarter-year fixed effects to absorb industry-specific trends, and $\theta_{d(i)t}$ are country of firm i linear trends to control for local climate, firm performance, and other geopolitical trends in the country of headquarters of firm i. Furthermore, we cluster robust standard errors at the firm level and include three lags of the cyclone exposure variables.

4.2 Supply chain exposure to tropical cyclones

If weather shocks prove to be economically significant and vary in occurrence over time, firms might find it necessary to modify and adapt their production networks. In this section, we formalize a conceptual framework on how firms enter into customer-supplier relationships. We will theoretically explore how variations in the occurrence of cyclone shocks might influence corporate decisions regarding the maintenance of existing supply-chains.

4.2.1 Theoretical framework

We assume that customers' production functions follow a Cobb-Douglas function of capital K and labor L to produce quantity Q. A fixed set of intermediate inputs M is required for production aside from labor and capital. The set of inputs is sourced from suppliers operating in a monopolistically competitive market for intermediate goods. Each supplier offers a good that can only be purchased as an intermediate good by another firm, and is differentiated from others by unique characteristics. Due to product differentiation, each supplier has a degree of market power to set prices above marginal cost. Barriers to entry and exit are relatively low, allowing for dynamic adjustment in the long run. Customers evaluate suppliers based on the trade-offs between the differentiated characteristics of the inputs and the associated costs. As seen in Table 2, customers can negotiate the terms of procurement including price, quantity and contract duration, to optimize their cost structures and maximize profits. In Figure 1, once customers perform adequate research on the operational risk posed from suppliers, customers make input decisions and commit to relationship-specific investments. Therefore, customers consider the *cyclone risk* associated with a supplier prior to commiting to a relationship. The formation of supply-chain relationships yields the prices p_{sc} and quantities of inputs q_{sc} between supplier $s \in S$ set of suppliers and $c \in C$ set of customers. The relationship size, determined by a function of p_{sc} and q_{sc}, is also subject to the exposure of the supplier to physical climate risks. So, a customer would not be willing to continue a relationship if exposure increases without an adjustment of input prices.

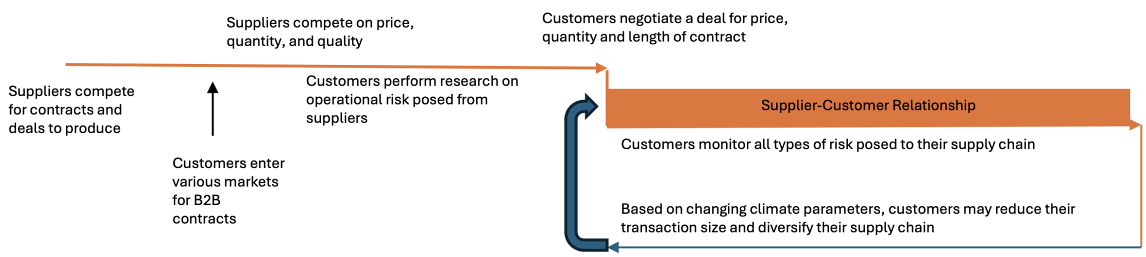

Figure 1: Market entry and supply-chain formation

We study the decision of customer firms that are in an existing supply-chain relationship to reduce their relationship size and reduce their dependency on a supplier with increased cyclone exposure. We are choosing to not study the formation and termination of relationships because of the lack of complete data about the full supplier network of the firms in our sample. We only know the top suppliers that have been disclosed by the customer firms so our analysis is constrained to observable interactions with primary suppliers. We leave the study of termination of supply chain relationships due to cyclone exposure to future research.

We assume customers estimate parameters of a cyclone exposure measure distribution W before entering a new supply-chain relationship and during the fiscal year of a relationship. The mean of this distribution w_t is a measure of the average number of realized cyclone risk per year. Increases in w_t from w_{t-1} may indicate an increase in cyclone risk, and therefore, an increase in the operational risk of the customer's supply-chain network. When realized shocks w_t are below or equal to the ex-ante expectation w_{t-1}, customers have no incentive to deviate from the relationship. The decision can be written as:

$$P_t = \begin{cases} 0, & \text{if} w_t <= w_{t-1} \\ 1, & \text{if} w_t > w_{t-1} \end{cases}$$

4.2.2 Empirical strategy

Firms may use various types of information to assess whether cyclone risk has increased and therefore, adjust their supply-chain network. Literature in finance and economics suggest Bayesian updating to model how players in a strategic game infer information about changing environments in general, but in climate econometrics, this is difficult to implement given the structure of the underlying climate distribution which is complex and noisy. Firms could also use projections of weather events from reputable sources such as the IPCC who build models to estimate temperature increases in the long-term. But, these models are not interpretable in the short-term and neither are they granular enough to be interpreted by supply-chain managers. So, we implement empirical tests that focus directly on firm's responses to direct increases in cyclone risk.

Therefore, we are interested in identifying the effect of tropical cyclones on supply-chain relationships, holding all other factors fixed. We can express the average treatment effect β for a change in cyclone intensity measures Δw_{sct} as:

$$\beta = E[Y_{sct}|w_{sct} + \Delta w_{sct}, x_{sct}] - E[Y_{sct}|w_{sct}, x_{sct}]$$

β cannot be observed directly, since a supplier s in a relationship sc can never be exposed to both counterfactuals w and $w + \Delta w$ for the exact same time period t (Holland, 1986). S. Hsiang (2016) introduces two approaches to approximating β: time series and long differences.

Identification in time series. In a linear framework, we can examine a relationship sc across separate periods (indexed by t) when different cyclone exposure conditions are realized at t. Since a firm is only comparable to itself across moments in time, this satisfies the unit homogeneity assumption. Using our panel data, we can estimate the equation of form:

$$y_{sct} = \alpha_{sc} + w_{st}\beta_{TS} + x_{sct}\gamma + \theta(t) + \epsilon_{sc}$$

where β_{TS} estimates the effect of an increase in cyclone intensity such as maximum wind or average severe shock days. x_{sct} represents a vector of supply-chain relationship characteristics such as the cost category, market cap and industry of the supplier. $\theta(t)$ represents year fixed effects. By comparing a relationship to itself in the future, we account for unobservable differences between supplier-customer relationships. However, this approach is still vulnerable to omitted variable bias if supply-chain relationship size can be influenced by time-varying factors that are correlated with w_{sct} or x_{sct} after conditioning on trends $\theta(t)$.

Long differences. A hybrid approach utilizing cross-sectional and time series analysis is the long differences strategy. We assume that changes for both the outcome and the climate within locations are correlated across locations. We implement the following functional form to compare changes over two periods of observation $(\tau_1, \tau_0) \rightarrow (t, t-1)$:

$$1[y_{sc\tau_1} - y_{sc\tau_0}] = \alpha + 1[c_{s\tau_1} - c_{s\tau_0}]\beta_{LD} + x_{sc\tau_1}\delta + \gamma_{n(s)\tau_1} + \rho_{d(s)d(c)} + \epsilon_{sc\tau_1}$$

where β_{LD} represents the extent to which trends in cyclone exposure are correlated with trends in supply-chain relationship size, $x_{sc\tau_1}$ is a vector of relationship characteristics, and $\rho_{d(s)d(c)}$ is a country-relationship fixed effect to account for macroeconomic conditions, trade sanctions, or any geopolitical constraints specific to the supply-chain relationship. Standard errors are clustered at the relationship level.

5 Results

5.1 Direct exposure impact on financial performance

Table 3 presents OLS regressions estimates on the impact of average maximum sustained wind across the locations of firms on revenue over lagged assets and the debt to assets ratio. Under no controls, the effects of increased maximum wind exposure in the quarter prior results in, on average, a 1.3% and 0.272 percentage point decrease in debt to assets. These values are statistically significant.

However, with the aforementioned fixed effects, the coefficients become statistically insignificant and close to zero. Intriguingly, the sign of the coefficient for the impact of a 1 m/s rise in average maximum wind speed on debt to assets changes from positive in specification 3 to negative in specification 4. There are several potential concerns with our empirical design that may influence our estimates. Across all specifications, we note that

Table 3: Cyclone Exposure on Revenue

	(1) Rev/ Assets	(2) Rev/ Assets	(3) D/A	(4) D/A
Maximum Wind (t)	0.00132	0.000581	0.0646*	-0.0194
	(0.00133)	(0.00149)	(0.0384)	(0.0377)
Maximum Wind (t-1)	-0.0137***	0.000187	-0.272***	-0.00260
	(0.00129)	(0.00163)	(0.0374)	(0.0398)
Maximum Wind (t-2)	0.00374*	-0.00293	0.0829	0.0794
	(0.00210)	(0.00230)	(0.0601)	(0.0561)
Firm FE	No	Yes	No	Yes
Firm x Qtr FE	No	Yes	No	Yes
Industry x Qtr-Year FE	No	Yes	No	Yes
Regional Time Trend FE	No	Yes	No	Yes
Observations	2089	1785	2322	2001

Robust standard errors clustered at the firm level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

the number of observations is far lesser than the true size of the dataset, which may be a result of missing values for at least three lags of the maximum wind. Furthermore, using public firms that are among the largest in global markets based on market capitalization may bias our estimates towards zero as these firms are able to efficiently divert operations and production to other non-affected branches.

5.2 Supply chain impacts

Table 4 presents the results of a logit model fitted to the long differences model shown in Section 4.2. The coefficients are estimated using maximum likelihood estimation (MLE). We find that if the average wind exposed to suppliers' branches increased from the year before, the odds of a decrease in the total relationship size increases by a factor of $e^{0.822}$. And, across all specifications, an increase in the realized average wind exposed to suppliers from the year before, results in an increase in the likelihood of seeing adaptations in the customer's supply-chain network. We include the coefficients for suppliers that provide intermediate goods used in the cost of goods sold (COGS), research and development suppliers (RND), and selling and general administrative expenses (SGA).

Table 4: Logit: Expected vs. Realized Average Wind Shocks

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variables:	Total Relationship		% Cust. Cost		% Sup. Rev.	
$1[AvgWind_{\tau_1} > AvgWind_{\tau_0}]$	0.769***	0.822***	0.710***	0.698***	0.832***	0.827***
	(0.0982)	(0.113)	(0.0976)	(0.117)	(0.0961)	(0.113)
COGS	-0.179	-0.235	0.151	0.0561	-0.0388	-0.258*
	(0.111)	(0.151)	(0.125)	(0.176)	(0.110)	(0.153)
RND	-0.834*	-0.452	-0.850*	-0.786	-0.402	-0.203
	(0.461)	(0.563)	(0.493)	(0.548)	(0.433)	(0.640)
SGA	-0.355**	-0.368	-0.435**	-0.618*	-0.00114	-0.0586
	(0.173)	(0.256)	(0.198)	(0.320)	(0.155)	(0.261)
Market cap	1.99e-09*	4.03e-09	1.57e-09	2.52e-09	-2.49e-09	-4.53e-10
	(1.20e-09)	(2.47e-09)	(1.19e-09)	(1.96e-09)	(1.82e-09)	(2.60e-09)
Industry FE	No	Yes	No	Yes	No	Yes
Year FE	No	Yes	No	Yes	No	Yes
Country Relationship FE	No	Yes	No	Yes	No	Yes
Observations	2483	2027	2483	2017	2483	2031

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The total relationship variable is log transformed and all dependent variables are binary indicators: $1[y_{\tau_1} < y_{\tau_0}]$. And, $(\tau_0, \tau_1) \rightarrow (t-1, t)$.

Across all specifications, RND suppliers have a lower likelihood of seeing decreases in the relationship measures, however these estimates are not statistically significant. In specification (6), the coefficient for average wind exposed to suppliers' branches increased from the year before, the odds of a decrease in the percent of supplier's revenue from that particular customer increases, and supplying firms that contribute direct inputs into the productivity of the customer firm (COGS) have a slightly lower likelihood of seeing decreases in their revenue. Specifications (3) and (4) regress average wind on the % of customer's costs. We find the same increase in the likelihood of the customer decreasing the supplier's weight (by percent spent) in their supply-chain network. Intriguingly, cost of goods sold firms have an increased likelihood of being substituted with other firms in the customer's supply-chain network, however, these estimates are not statistically significant.

In Table 5, we present OLS regression of the total relationship size on mean wind speed, mean number of cyclones, and mean cyclone days. In specifications 3, 6, and 9, the estimates for the effect of cyclone exposure on total relationship size is negative. On average, for an additional cyclone exposed to all supplier locations, the supplier-customer relationship size decreases by approximately 7.4% and for an additional day of being exposed to a cyclone, relationship size decreases by approximately 4.1%. These are a slightly statistically significant estimates and are very economically meaningful. From 1, mean relationship size is 409 million USD so, a 7.4% decrease translates to over 30 million USD.

Table 5: OLS: Cyclone Exposure on Total Relationship Size (USD)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Dependent Variable: Total Relationship Size (log USD)								
Mean Wind Speed (m/s)	0.0111	0.00429	-0.0108						
	(0.00733)	(0.00765)	(0.00763)						
Mean Number of Cyclones				0.0558	0.0118	-0.0741*			
				(0.0428)	(0.0438)	(0.0424)			
Mean Cyclone Days							0.0142	-0.0111	-0.0412*
							(0.0241)	(0.0246)	(0.0241)
COGS		0.632***	0.153		0.640***	0.154		0.661***	0.225
		(0.189)	(0.216)		(0.190)	(0.216)		(0.189)	(0.209)
RND		0.234	-0.619		0.244	-0.619		0.244	-0.489
		(0.413)	(0.497)		(0.407)	(0.500)		(0.404)	(0.488)
SGA		-0.0397	-0.122		-0.0434	-0.106		-0.0481	0.030
		(0.206)	(0.270)		(0.206)	(0.269)		(0.206)	(0.257)
Market Cap		7.19e-09**	1.16e-08***		7.20e-09**	1.17e-08***		7.38e-09***	7.97e-09***
		(2.81e-09)	(4.25e-09)		(2.82e-09)	(4.26e-09)		(2.80e-09)	(2.77e-09)
Industry FE	No	No	Yes	No	No	Yes	No	No	Yes
Year FE	No	No	Yes	No	No	Yes	No	No	Yes
Country Relationship FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	2589	2483	2483	2589	2483	2483	2589	2483	2483
R-squared	0.00293	0.0326	0.352	0.00225	0.0323	0.352	0.000448	0.0324	0.352

Robust standard errors clustered at the relationship level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Therefore, an increase in the cyclone exposure of a supplying firm can result in a substantial loss of revenue, potential layoffs, and increased costs of adaptation or insurance for businesses. Furthermore, assessing the potential cost of cyclone exposure is extremely important. In regions where cyclone frequency and intensity has increased over the past 50 years, supplying firms may choose to not expand production in those regions.

To test for whether persistent shocks in wind exposure cause changes in the supply chain of firms, in Table 6, we run OLS regressions using the time series identification strategy on all supply chain variables with three measures of cyclone severity. None of the coefficients in specifications 1-3 are statistically significant, but the coefficients in specification 2 and 3 become more negative for the first and second lag. This may suggest that the effect of average number of cyclones impacting a supplying firm on its relationship size with a customer may materialize with a lag of one or two years. Interestingly, specifications 5 and 6 suggest that the immediate effect of an increase in the number of cyclones impacting a supplying firm on the weight of the supplier in the customer's supply chain network decreases by approximately 0.001 percentage points. This estimate is slightly statistically significant. While the coefficients are close to zero, the direction of the coefficients are consistent with the notion that customers decrease their dependence on a supplier with increased cyclone risk.

Table 6: OLS: Persistent Shocks to Supply Chain Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Total Rel. Size			Cust. Cost %			Sup. Rev %	
Wind exposure (t-0)	-0.0121			-0.000117			0.000359		
	(0.00984)			(0.000155)			(0.000812)		
Wind exposure (t-1)	0.00307			-0.0000388			0.000990		
	(0.00861)			(0.000138)			(0.000687)		
Wind exposure (t-2)	0.0106			-0.0000559			0.00153*		
	(0.00848)			(0.000125)			(0.000801)		
Number of cyclones (t-0)		0.0323			-0.00161*			-0.00228	
		(0.0521)			(0.000875)			(0.00547)	
Number of cyclones (t-1)		0.0220			0.000374			0.00322	
		(0.0542)			(0.00105)			(0.00397)	
Number of cyclones (t-2)		-0.0972			0.000544			0.0178**	
		(0.0686)			(0.00109)			(0.00723)	
Number of cyclone days (t-0)			0.0416			-0.00107*			0.00220
			(0.0303)			(0.000603)			(0.00277)
Number of cyclone days (t-1)			-0.00326			0.000441			0.00113
			(0.0309)			(0.000903)			(0.00271)
Number of cyclone days (t-2)			-0.0511			0.000590			0.00714**
			(0.0368)			(0.000626)			(0.00316)
Observations	989	989	989	989	989	989	989	989	989
R-squared	0.438	0.438	0.438	0.224	0.224	0.226	0.417	0.419	0.417

Robust standard errors clustered at the relationship level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Total relationship size is a log transformed variable. All specifications include controls for the type of supplier, market cap, supplier industry, and country relationship.

Next, we examine persistent shocks of cyclone severity on supplier revenue. In specifications 7-9, we observe statistically significant positive effects of increased wind exposure, number of cyclones and number of cyclone days, on supplier revenue two years after shocks to the respective variables. This is a counter-intuitive result that may suggest suppliers become more resilient after experiencing cyclone shocks. Such resilience could result in longer-term contracts and stronger business relationships, leading to increased revenue in the future.

6 Discussion and Conclusion

This study contributes to a growing body of research on the economic impacts of climate change on firms, particularly focusing on the implications of tropical cyclones for firm financial performance and supply chain dynamics. The findings reveal that while direct financial impacts of cyclone exposure on firms are not statistically significant after accounting for fixed effects, increases in cyclone exposure significantly raise the likelihood of reductions in the size of supplier-customer relationships. This behavior reflects a proactive risk management strategy where firms adjust their reliance on suppliers in high-risk areas, potentially to mitigate vulnerability to future shocks.

The observed adjustments in supply chain relationships are consistent with broader trends identified in the literature. For instance, Pankratz and Schiller (2022) found that firms are more likely to terminate relationships following acute weather events like floods and heatwaves. This study extends that understanding to the realm of tropical cyclones, underscoring that firms are not only reactive but also adaptively recalibrating their dependencies and exposures in anticipation of or in response to weather shocks. The resilience of suppliers, as evidenced by the increase in their revenues following initial exposures to cyclones, suggests a possible 'hardening' effect where firms that survive initial shocks improve their operations and become more integral to their customers over time. This could be due to several factors including enhanced operational strategies, increased investments in resilience, or customers' desire to support strategic partners who have weathered shocks effectively. Interestingly, our findings also suggest a potential increase in supplier resilience over time, possibly due to 'learning effects' or increased investments in disaster preparedness, which align with the "build back better" hypothesis from disaster economics literature. This implies that while immediate impacts are deleterious, the long-term adaptation could lead to more robust supply chain structures, potentially enhancing overall economic resilience.

The findings also align with broader research indicating that firms often overlook the wider implications of their direct operations. According to the CDP Supply Chain Report 2022, most firms do not incorporate climate-related requirements in their supplier contracts, nor do they incentivize the management of climate-related issues in procurement strategies. This study's results highlight a critical gap in current business practices regarding supply chain management under climate change pressures. Firms may need to adopt more comprehensive strategies that include evaluating and enhancing the resilience of their suppliers to ensure sustainability and reliability of their operations amidst increasing climate volatility.

Our findings are not complete without their limitations. First, the focus on large, publicly traded firms may limit the generalizability of the findings. These firms often have more resources to cope with and adapt to climate shocks compared to smaller firms, which might experience more significant impacts. Additionally, the measure of cyclone exposure and its impacts could be understated due to the limitations in capturing the full extent of indirect and long-term damages from such events. Furthermore, the Orbis database that was used for finding firm locations is the most up to date source, therefore, the locations may not be indicative of the physical assets of firms between 2013 and 2019.

Another limitation is the potential bias introduced by missing data, particularly the missing values for lagged variables of maximum wind, which reduced the number of observations significantly. This might have affected the robustness of the findings, particularly in assessing the direct financial impacts of cyclone exposure.

In conclusion, we shed light on the significant, though nuanced, impacts of tropical cyclones on firm performance and supply chain dynamics. We highlighted the importance of incorporating climate risk into corporate strategy and supply chain management, emphasizing the need for firms to enhance resilience and adaptability in the face of climate change. Further research in this area could help refine strategies for managing climate risks, ultimately contributing to more sustainable and resilient business practices.

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Appendix

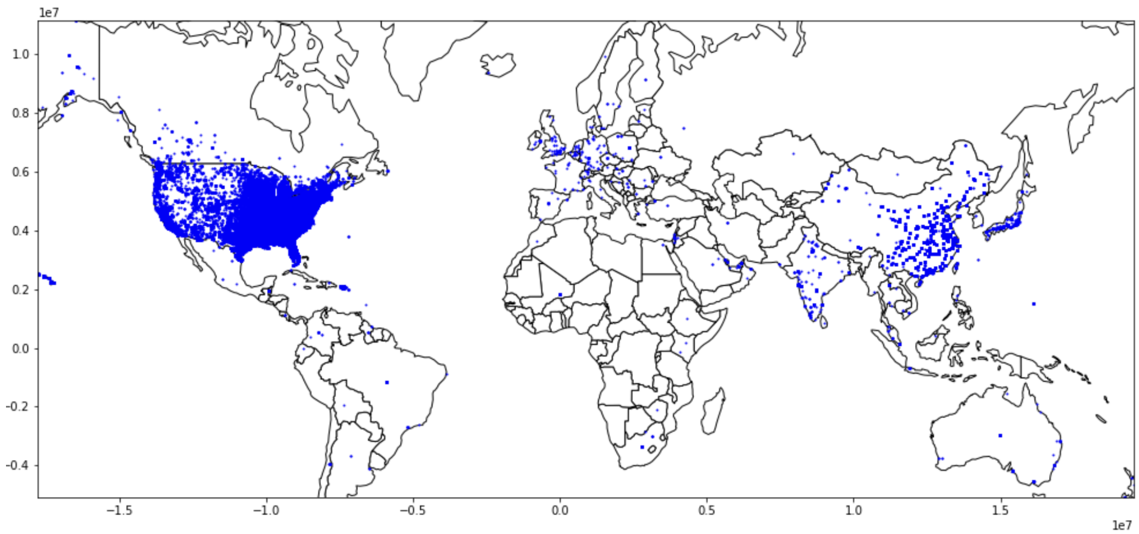

Figure 2: Firm locations in the Direct Exposure dataset with 1,702 firms

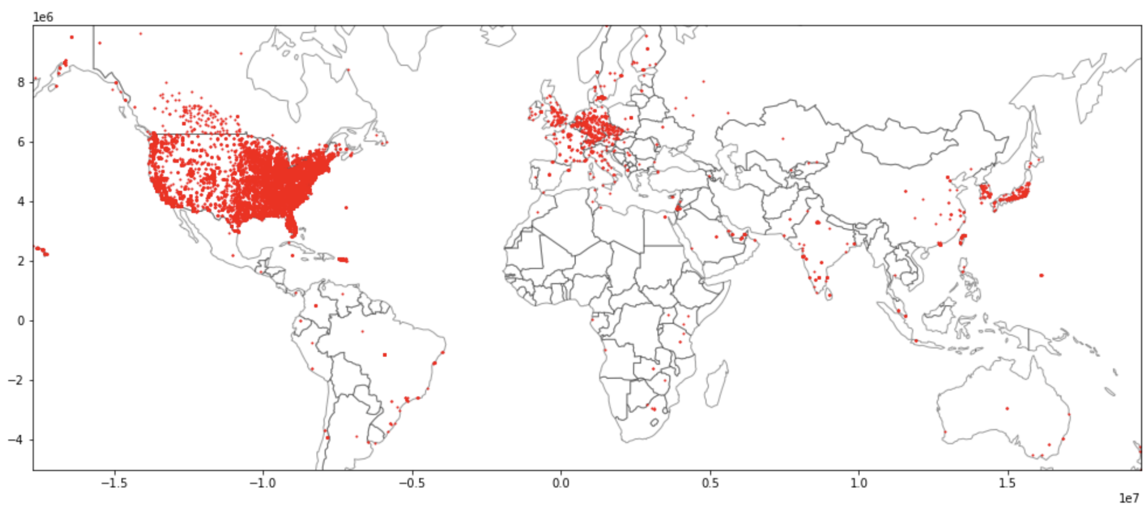

Figure 3: Firm locations in the Supply Chain dataset with 1,148 firms

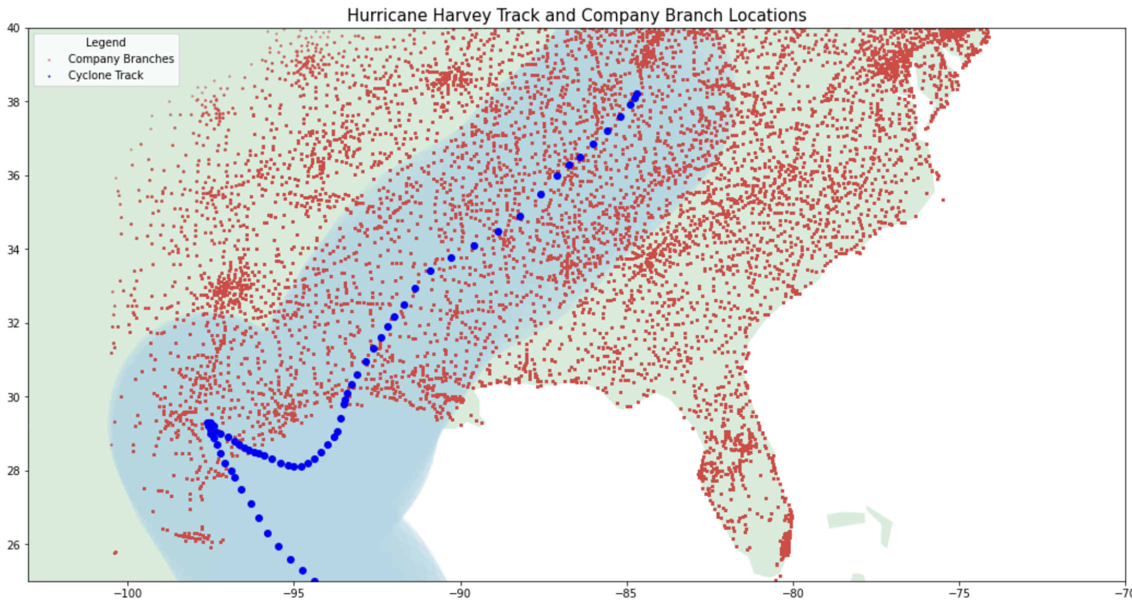

Figure 4: Hurricane Harvey Exposure to Firms

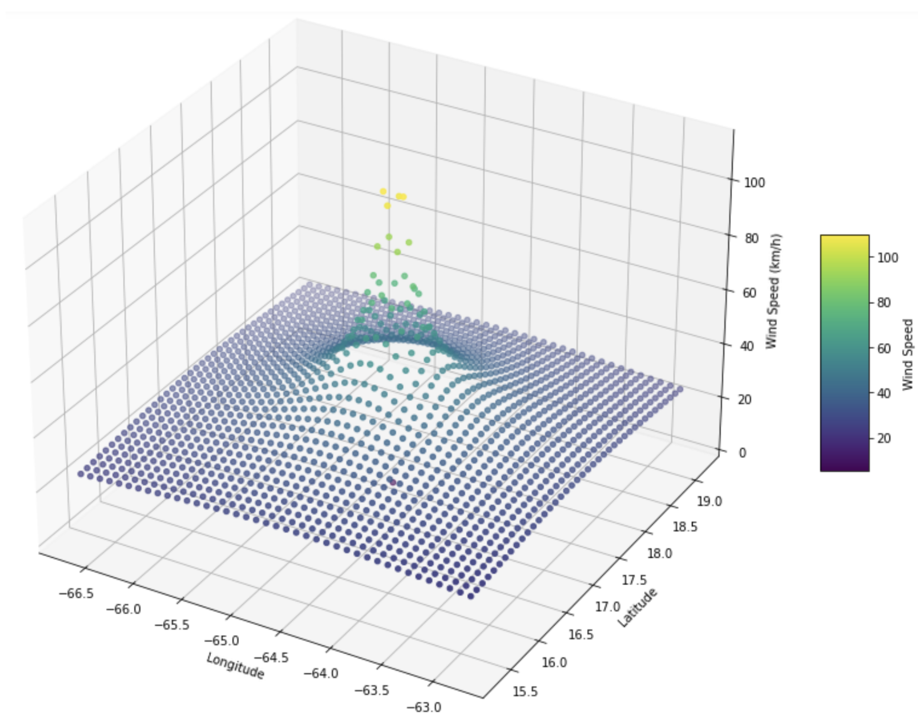

Figure 5: Reconstructed wind field of Hurricane Maria (2017) at (17.3, -64.7)

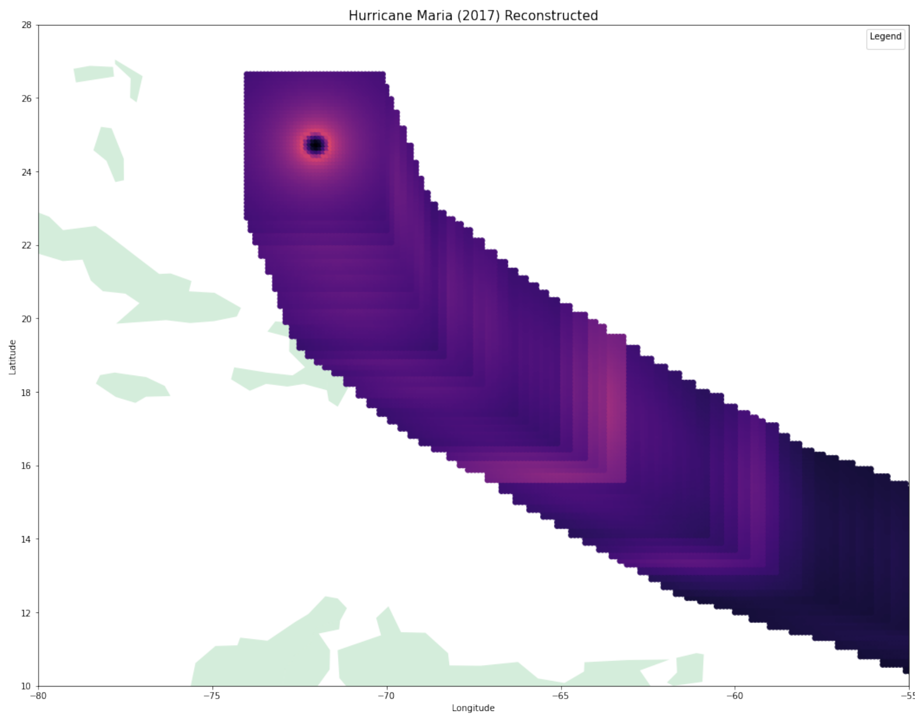

Figure 6: Reconstructed track of Hurricane Maria

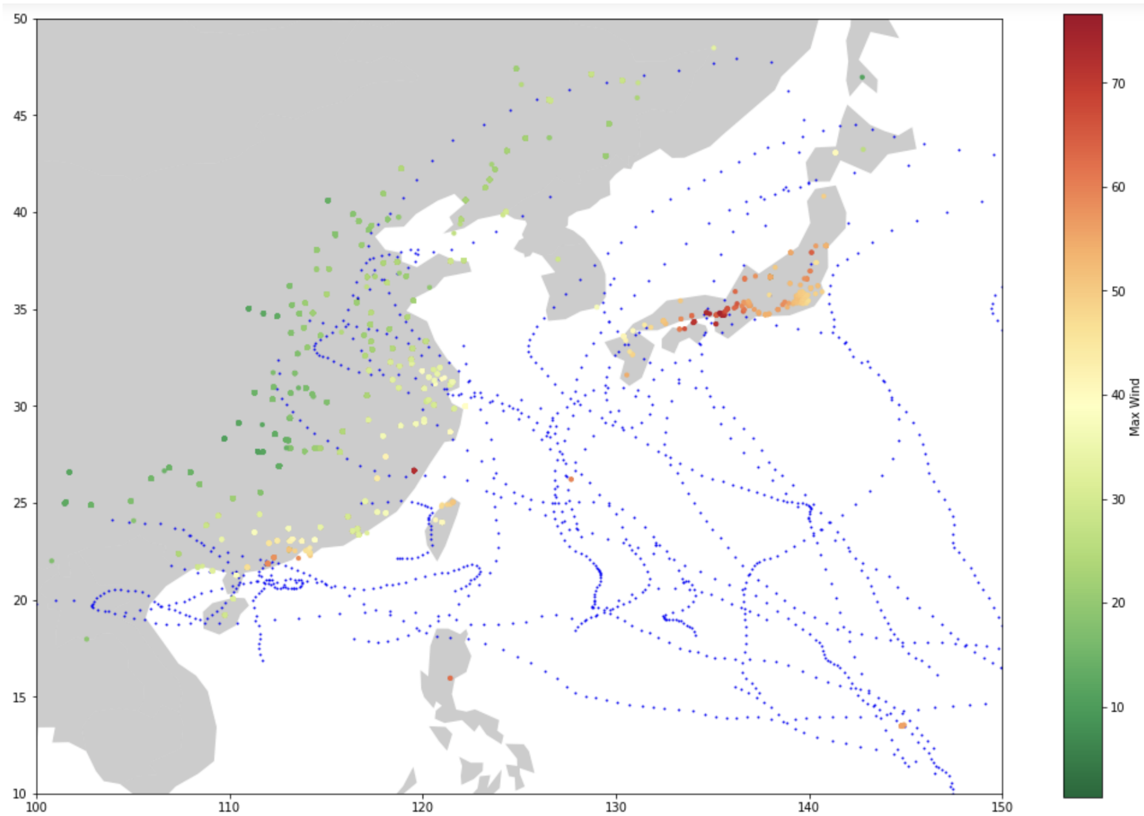

Figure 7: Cyclone tracks and maximum wind exposure on branches in East Asia (2018Q3)

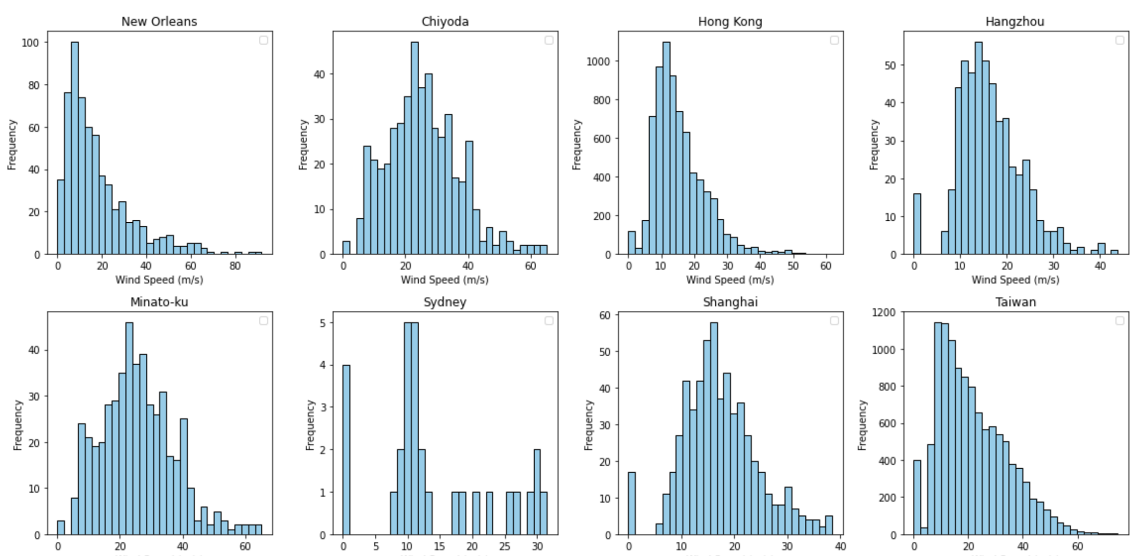

Figure 8: Histograms of wind speeds for various cities in the dataset

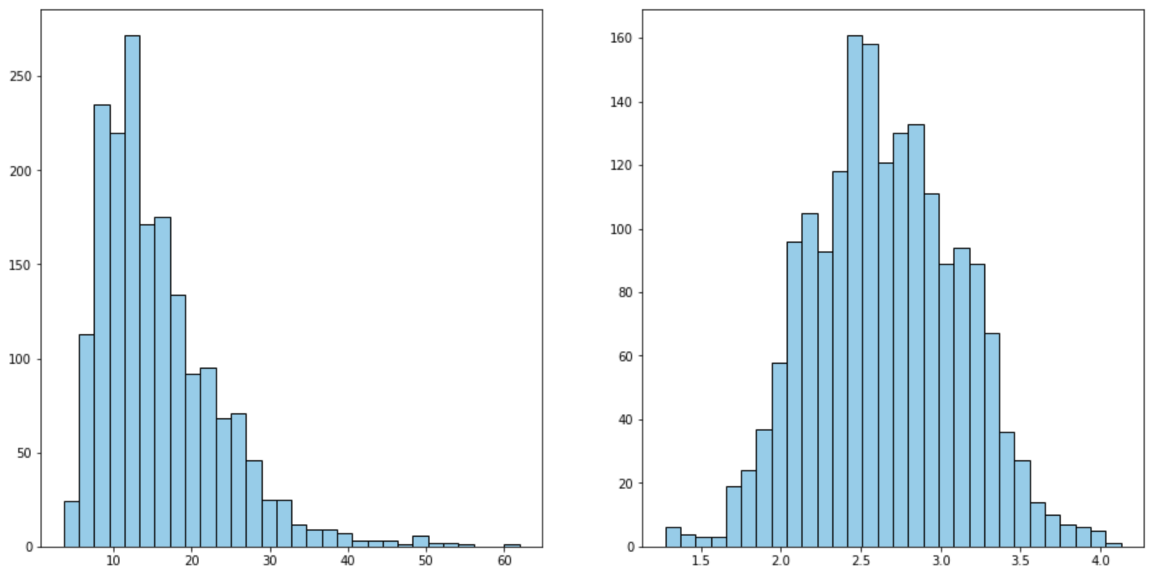

Figure 9: Distribution and Log Transformed Distribution of Wind Speeds in Hong Kong

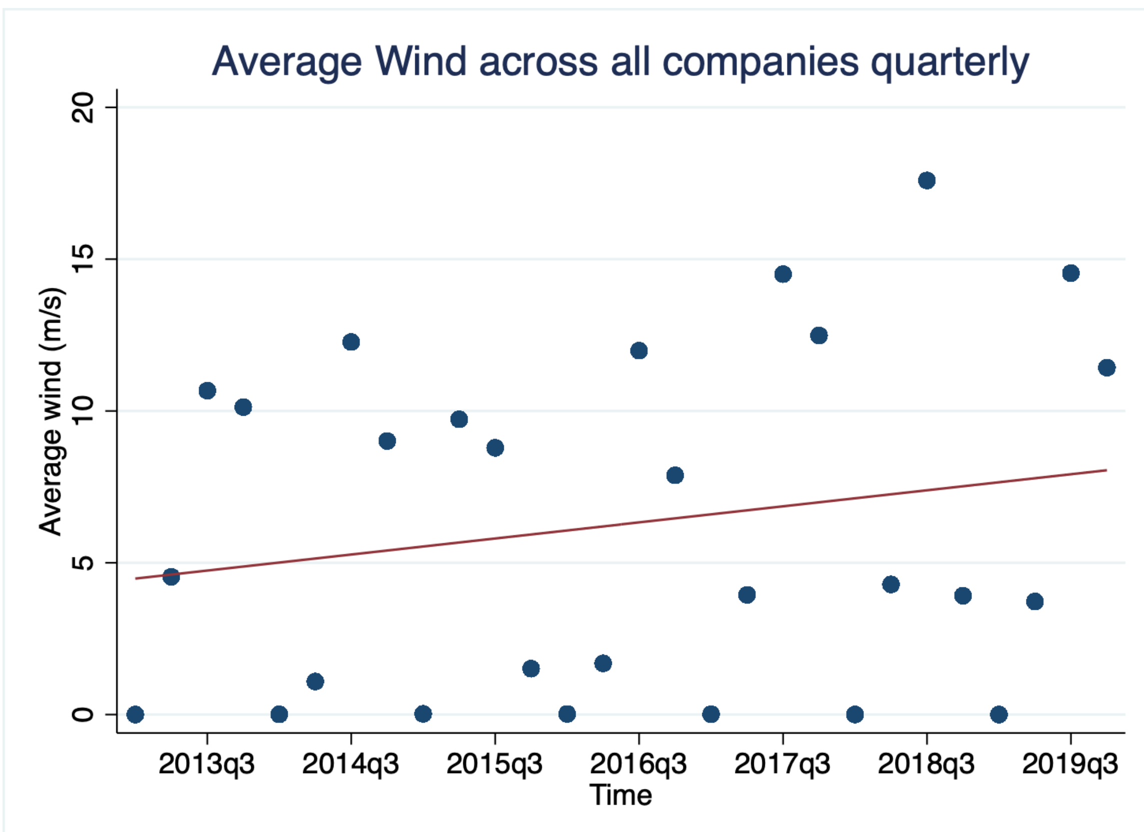

Figure 10: Average wind over time