Climate Change and Adaptation in Global Supply-Chain Networks

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Abstract

This paper examines how physical climate risks affect firms' financial performance and operational risk management in global supply-chains. We document that weather shocks at supplier locations reduce the operating performance of suppliers and their customers. Further, customers respond to perceived changes in suppliers' climate-risk exposure: When realized shocks exceed ex-ante expectations, customers are 6-11% more likely to terminate existing supplier-relationships. Consistent with models of experience-based learning, this effect increases with signal strength and repetition, is insensitive to long-term climate projections, and increases with industry competitiveness and decreases with supply-chain integration. Customers subsequently choose replacement suppliers with lower expected climate-risk exposure.

Keywords: Climate Change, Adaptation, Firm Performance, Production Networks.
JEL Codes: G15, Q54, G30, F64

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1 Introduction

Businesses face increasing pressure to address their operational exposure to physical climate risks. While managers and investors are looking for ways to alleviate climate change risks by adapting their operations (Lin, Schmid, and Weisbach, 2020) and investments (Krueger, Sautner, and Starks, 2020; Ilhan, Krueger, Sautner, and Starks, 2020), academic research has primarily studied how transitory weather shocks affect firms' earnings (Addoum, Ng, and Ortiz-Bobea, 2020), stock returns (Kumar, Xin, and Zhang, 2019), and labor and capital productivity (Graff-Zivin, Hsiang, and Neidell, 2018; Zhang et al., 2018), among others. Much less is known about how firms adapt to climate change, despite the fact that firms' endogenous responses to physical climate risks are crucial to understanding the long-run effects of climate change on financial market outcomes.

Operational risk management in response to climate change is particularly important for firms engaged in extensive international production networks. In a globalized economy, supply-chains often move through parts of the world that are most vulnerable to the impact of climate change. As a result, firms might be indirectly exposed to physical risks due to their suppliers. Reflecting these concerns, over 50% of CEOs mentioned risks posed to their global supply chains by climate change as one of their primary concerns in a recent survey (PWC, 2015).

However, adapting to climate change is a complex task for economic agents in general and firms in supply-chain organizations in particular. Climate change is characterized by unknowable uncertainty – particularly in the short- and medium-run – as weather realizations provide a noisy signal of potential changes in the underlying distribution (Deryugina, 2013; Kala, 2019). Further, indirect exposure to physical climate risks due to suppliers and customers can be challenging to identify. In this environment, it is unclear how weather shocks affect firms' expectations of climate risks and, as a consequence, the adjustment of their supply-chain networks.

In this paper, we study whether firms adjust their supply-chain networks in response to perceived changes in their suppliers' exposure to physical climate risks. First, we establish that the financial consequences of weather shocks propagate from suppliers to their corporate customers around the world. Next, we investigate if and how firms adapt their supply-chain organizations in response to changes in supplier exposure. In particular, we examine how discrepancies between realized and expected weather shocks affect the continuation of existing and the initiation of new supply-chain

relationships. Our main contribution is to show that customers are more likely to terminate suppliers when climate-related shocks increase beyond historical expectations, and switch to replacements in less exposed climate zones. Our study provides novel evidence on how changes in perceived climate risk affect firms' operational risk management and the formation of global supply-chains.

We combine detailed firm-level supply-chain data from FactSet Revere with financial performance data from Worldscope, geographic location and establishment-level data from FactSet Fundamentals and Orbis, data on local temperatures from the European Center for Medium-term Weather Forecasts, floods from the Darthmouth Flood Observatory, and temperature projections computed in the framework of the fifth phase of the Coupled Model Intercomparison Project (CMIP5). Our supply-chain dataset includes 5,628 (8,200) unique supplier (customer) firms, comprising over 500,000 quarterly supplier-customer observations across 92 (74) countries around the world, over the period from 2003 to 2016.

We focus on two types of weather shocks – heat and floods – for the following reasons. First, the literature in physiology and economics has documented several channels through which temperatures affect firm productivity. For example, heat reduces worker performance (Graff-Zivin et al., 2018), labor supply (Graff-Zivin and Neidell, 2014), and firm-level output (Zhang et al., 2018), with sharp declines at temperatures over 30°C. These risks are expected to increase, as the number of heat days (i.e. days that exceed 100° F) is projected to rise from currently 1% of days to more than 15% of days by 2099 without substantial efforts to reduce emissions (Graff-Zivin and Neidell, 2014). Second, flooding incidents can cause enormous economic damage. According to FEMA, the U.S. suffered more than $260 billion in flood-related damages between 1980 and 2013. Both inland and coastal floods are expected to become more frequent and severe due to climate change (CSSR, 2017). Third, extreme heat and floods differ in their duration and impact on physical and human capital, allowing us to study differences in firms' adaption across different types of physical climate risks.

We begin by examining if firms face financial incentives to adapt their supply-chain organizations due to the heat and flood exposure of their suppliers. Whereas Barrot and Sauvagnat (2016) and Carvalho, Nirei, Saito, and Tahbaz-Salehi (2021) show that the effect of large-scale natural disasters can propagate through production networks, it is unclear if other weather shocks – which are projected to change heterogeneously around the world but are too small to be classified as disasters

– cause similar distortions.[1] Heat and floods might reduce supplier productivity or impose additional costs for suppliers, for example by increasing air conditioning or clean-up costs. This can affect customer profits, especially if frictions such as relationship-specific investments prevent customer firms from making operational adjustments in the short-run. However, customers' operational risk management strategies could insulate them against disruptions, and suppliers may not be able to pass on increased costs downstream.

Following the literature (e.g. Dell, Jones, and Olken, 2014; Burke, Hsiang, and Miguel, 2015a; Carleton and Hsiang, 2016; Auffhammer, 2018), we construct location-specific measures of heat and flood exposure for our sample of suppliers based on daily temperatures and inundation records over a given quarter in the location of firms' production facilities. Consistent with Somanathan et al. (2015), Zhang et al. (2018), and Pankratz et al. (2019), we find a significant negative effect of high temperatures and floods on supplier operating performance.[2] This effect is stronger for geographically concentrated suppliers, and firms in industries which have been shown to be vulnerable to climate risks such as agriculture, mining, and construction (Addoum et al., 2019).

Next, we document that weather shocks to suppliers negatively affect the performance of their customers. Following the occurrence of prolonged periods of heat in a given firm-quarter at supplier locations, customer revenues (operating income) over assets decrease by 0.3% (0.9%) relative to the sample mean. When suppliers are affected by a local flooding incident, customer revenue and operating income are reduced by 1.6% and 6%, respectively, with a lag of up to four quarters.[3] Further, we find that a customer's ability to source inputs from alternative sources mitigates the propagation of supplier disruptions.

Our main analysis focuses on the question of whether and how firms learn about climate change and adapt their supply-chains when global climate risk exposure changes. Given that short- and medium-term weather realizations provide noisy signals for the underlying distribution, detecting changes in climate risk is challenging. Prior research in finance and economics has proposed experience-based Bayesian updating to model learning in general (Alevy, Haigh, and List, 2007;

[1] Previous research has found mixed results on the effects of extreme temperatures on firm productivity. While Addoum et al. (2020) find no statistically significant link between temperatures and establishment-level sales, other studies document heterogeneous but largely adverse effects of heat on firm productivity and financial performance (Somanathan, Somanathan, Sudarshan, and Tewari, 2015; Zhang et al., 2018; Pankratz, Bauer, and Derwall, 2019; Addoum, Ng, and Ortiz-Bobea, 2019; Custodio, Ferreira, Garcia-Appendini, and Lam, 2020).

[2] We conduct a series of robustness tests using various absolute and relative measures of heat exposure.

[3] We do not find evidence that such decreases are compensated in later financial quarters.

Chiang, Hirshleifer, Qian, and Sherman, 2011), and about climate change in particular (Kelly, Kolstad, and Mitchell, 2005; Deryugina, 2013; Moore, 2017; Kala, 2019; Choi, Gao, and Jiang, 2020). We follow this literature and conjecture that when entering a supplier relationship, customers trade off perceived costs and benefits such as climate risks, product quality, and input prices of prospective suppliers based on observable characteristics. Under basic assumptions about production and input markets, prices and quantities of inputs and the matches of customers to suppliers are determined in equilibrium, and reflect the underlying probabilities of heat and flooding events. In this setting, adverse weather shocks in line with the expected distribution would not affect the longevity of supply chain relations. However, if firms perceive that the underlying distribution of weather shocks may have changed, the original supplier choice may no longer be optimal. Hence, existing supplier-relations may be terminated more frequently when climate-related shocks observed over the course of a supply-chain relationship exceed ex-ante anticipated risks.

To test this idea, we construct a measure of *realized vs. expected climate risk* by comparing heat and flood days before and during any given supply-chain relationship. We document a large, positive effect of climate risk exceedance on supplier termination. Our results show that a supply-chain link is 6.1-7.8 (7.9-11.1) percent more likely to be terminated in a given year, if the realized exposure to heat (floods) exceeds proxies of customers' ex-ante expectations. This result is robust to alternative benchmark periods, and holds controlling for industry and country-by-time fixed effects for suppliers and customers. Further, the effect is stronger for suppliers in competitive industries and weaker for closely integrated supply-chains. We find similar results implementing our tests as linear probability models, logistic regressions, and as Cox proportional hazard models.

In line with with models of experience-based learning (Deryugina, 2013), our results show that the likelihood of supplier termination is increasing in signal strength and repetition, i.e. the magnitude and number of times realized weather shocks exceeded prior expectations. Moreover, consistent with customer learning and inconsistent with explanations related to supply-side terminations, we find an economically small effect of transitory shocks on supply-chain terminations. In addition, our results are unaffected by excluding delisted suppliers.

While our main tests reflect the idea that firms form priors and update their beliefs based on observable shocks, we also consider the role of long-term climate projections. Using model output from the CMIP5 project, we obtain projections for the average number of heat days between 2040

and 2059.[4] We then estimate our main tests for subsamples of suppliers for which long-term climate models project minimal changes under various emission trajectories. We find that customers strongly respond to short-run increases in weather shocks beyond ex-ante expectations even when long-run projections indicate little to no change, which may emphasize the challenges of learning about climate change based on perceived changes in the distribution of weather shocks.

Last, we examine if firms consider suppliers' potential exposure when switching to new suppliers. For this purpose, we identify 'replacement' suppliers as firms with identical 4-digit SIC codes as the terminated suppliers which entered a new supplier-relationship with the same customer within one year. We estimate linear probability models to test if replacement suppliers have a lower exposure to heat and floods than terminated suppliers conditional on realized vs. expected weather shocks during the terminated supplier relationship. For heat, we find a positive effect of climate-risk exceedance on the likelihood that customers choose a replacement supplier with lower ex-post exposure observed both *during* as well as *after* the initial relationship. An unexpectedly high number of shocks during the initial relationship increases the probability that the customer chooses a less exposed replacement supplier by 6 to 10 percentage points, controlling for industry- and country-specific time fixed effects of both suppliers and customers. We find a smaller, less precisely estimated effect for floods and when considering climate risk based on long-term projections.

Our paper contributes to the literature on climate change, finance, and economics along several dimensions. First, our paper provides novel evidence on the implications of climate change for firms and investors. Previous research in finance has studied the direct effects of weather shocks on firm profitability (Zhang et al., 2018; Addoum et al., 2020; Pankratz et al., 2019), housing prices (Baldauf, Garlappi, and Yannelis, 2020), stock returns (Kumar et al., 2019), financial markets (Hong, Li, and Xu, 2019; Schlenker and Taylor, 2019), and capital structure (Ginglinger and Moreau, 2019). We add to this literature by showing that firms can be indirectly exposed to physical climate risks due to their global supplier network. This aspect of our findings is most closely related to Barrot and Sauvagnat (2016), Boehm, Flaaen, and Pandalai-Nayar (2019), and Carvalho et al. (2021), who document the propagation of natural disasters along firm linkages. In contrast to these studies, we focus on weather events that are less severe than natural disasters but closely tied to long-term

[4] We access projections through the ECMWF. They are part of the CMIP5 project, which is the primary source of climate data for the Intergovernmental Panel on Climate Change (IPCC) Assessment Reports.

climate change, allowing us to explicitly examine long-run projections and changes in the underlying distribution of events.

Second, our paper is among the first in the finance and environmental economics literature to study how firms learn about and adapt to climate change. In recent work, Lin et al. (2020) show that electricity providers increase investments in flexible power plants in response to long-term changes in local climate, Li, Lin, Jin, and Zhang (2020) document a negative effect of changes in long-term climate conditions on local employment, and Li, Shan, Tang, and Yao (2020) find that firms with high climate uncertainty increase their capital investments. Our paper is part of this emerging literature by studying firms' endogenous responses to indirect climate risk exposure in a unique empirical setting, using a framework of experience-based learning about climate change.

Third, we contribute to the literature on learning about climate change. Choi et al. (2020) find that market participants revise their beliefs about climate change when experiencing unusual weather using Google search data. Deryugina (2013) uses survey data on beliefs about global warming to show that local temperature fluctuations affect these beliefs in a Bayesian framework. Moore (2017) and Kala (2019) develop and test theoretical models on experience-based learning about climate change. Our work builds on these theoretical frameworks but explores learning and adaptation outside of the agricultural sector, combining both observed signals and climate projections.

Our main finding on the adaptation of supply chains to physical risks has potentially important implications, as the areas of the world which are disproportionately affected by the impact of climate change are already less developed today (Burke et al., 2015b; Carleton and Hsiang, 2016). Hence, our findings also speak to the growing literature on endogenous production networks and macroeconomic growth and productivity (e.g. Antràs, Fort, and Tintelnot, 2017; Lim, 2018; Oberfield, 2018; Acemoglu and Azar, 2020).

2 Data Sources and Descriptive Statistics

We combine data on global supply-chains, firm financial performance, and local climate exposure from four main sources. In the following sections we describe these sources, explain how we link the individual datasets, and provide summary statistics for our main sample. Throughout the paper, we provide relevant summary statistics and details in the context of the respective empirical tests.

2.1 Global Supply Chains

We obtain data on customer-supplier relationships from FactSet Revere. Previous related research (e.g. Hertzel, Li, Officer, and Rodgers, 2008; Cohen and Frazzini, 2008; Banerjee, Dasgupta, and Kim, 2008; Barrot and Sauvagnat, 2016) has primarily relied on SEC regulation S-K, which requires U.S. firms to disclose customers which account for at least 10% of their total sales. In contrast, the Revere data includes both U.S. and foreign firms and does not require sales volumes to exceed 10%. This is important, because many of the regions most vulnerable to climate change are located outside of the United States. Further, the research relying on SEC regulation has been unable to study the termination of supplier-customer relationships, since the appearance and disappearance of links due to actual starts and ends of relationships cannot be distinguished from changes in the relative sales volumes around the reporting threshold. The Revere supply-chain data is hand-collected, verified, and updated by FactSet analysts relying on a range of primary sources of information, including companies' annual reports and SEC filings, investor presentations, company websites and press releases, supply contracts, and purchase obligations.

Nonetheless, the data captures only a subsample of global supply-chain relationships. First, we require financial and accounting data for our sample firms, limiting the sample to listed firms. Smaller, private firms may be more strongly affected by weather shocks if such firms are geographically more concentrated and more financially constrained. Therefore, we might observe a lower bound of the effect of heat and flooding on firms in our analysis. Second, the heterogeneity in the availability of financial data around the world is likely to bias the sample towards firms in developed markets. In total, we obtain a sample of 8,200 (5,769) unique customer (supplier) firms from 74 (92) countries, comprising almost 595,000 supplier-customer pair-year-quarter observations over the sample period from 2003 to 2017. As Figures 1a and 1b show, most suppliers are located in Asia (40.3%), North Americas (38.8%), and Europe (17.4%). Previous studies have shown stronger effects of weather shocks on economic output in less developed economies (Burke et al., 2015b). Hence, our findings may underestimate the effects of disruptions in less developed markets. Table 1 documents the industry composition of our sample. Most of the suppliers and customers in our sample operate in manufacturing (SIC 1st digits 2 and 3) or transport and utilities (SIC 1st digit 4). Tables 2a and 2b report summary statistics at the supplier and customer level. Table 2c presents relationship-level

summary statistics for the firm-pairs in our sample. In line with prior research (e.g. Banerjee et al., 2008), we document an asymmetric mutual importance between customers and their suppliers in our sample. First, sample customer firms are much larger than their suppliers. The median customer holds 19 times the assets of the median supplier firm (book value of assets). Second, for firm-pairs where detailed sales data from the supplier to the customer is available (less than 10% of the sample), the customers on average represent 18.6% of the suppliers' total sales, but sales from the suppliers only account for 2.06% of the customers' cost of goods sold.

2.2 Accounting Performance and Firm Characteristics

Next, we obtain quarterly financial performance data from 2000 to 2016 from Worldscope. Our main variables of interest for measuring operating firm performance in Section 3.1 are quarterly revenues and operating income, scaled by one-year lagged total assets. In addition, we obtain information on firms' financial reporting schedules to ensure that we correctly match climate and performance records when financial quarters deviate from calendar quarters.

We additionally collect data on asset tangibility, defined as the ratio of property, plants, and equipment (PPE) to total assets, operating margin, inventory, accounts receivables, and cost of goods sold (COGS), and delisting dates from Worldscope and Datastream. Further, we construct measures of industry competitiveness as the number of firms in a given SIC 2-digit code industry in the universe of Compustat Global firms. From the U.S. Bureau of Economic Analysis (BEA) we obtain input-output matrices for 2012 and use this data to construct "industry-level input concentration" as the Herfindahl-Hirschman Index of dollar values across all input industries for each customer industry. To ensure that international financial records are comparable, we convert all variables into U.S. dollars. To remove outliers, we winsorize all variables above (below) the 99th (1st) percentile. We further drop firms with incomplete records of financial information and exclude firms in the financial industry (SIC code between 6000 and 6999).

2.3 Firm Locations

We obtain information on the location of firms' operations from two different sources, FactSet Fundamentals and Orbis. First, we use the addresses of firm headquarters from FactSet as our primary measure for firm location. Of course, firms' plants and establishments might be located

remote from headquarters. Hence, we collect information on additional firm locations from Orbis. In total, we obtain 1.1 million addresses of locations of incorporated subsidiaries, branches, and establishments.[5] We transform city, zip code, and street names into coordinates using the Bing Maps API. To obtain a measure of geographic concentration, we calculate the share of firm establishments located within a 30km radius of the firm's headquarters.

Next, we apply two location-based data filters to our main sample: First, we remove dispersed firms with fewer than 10% of assets within 30km of the firms' headquarters. We choose this cutoff following Barrot and Sauvagnat (2016), who limit their sample to firms with at least 10% of employees at the headquarter locations.[6] Second, we drop all supplier-customer-pairs with headquarter locations within 500km of each other to limit the potential for firms to be affected by the same shocks.[7]

2.4 Temperatures, Floods, and Climate Projections

We study two of the most pervasive types of shocks related to climate change – extreme heat and floods – which are both projected to become more frequent and severe in the near future (CSSR, 2017). [8] While both extreme heat and floods can cause significant economic damage (see e.g. Graff-Zivin et al., 2018; Zhang et al., 2018), the two types of weather shocks possibly affect firms' operating performance and resulting propagation effects through different channels. This allows us to compare how different weather shocks affect supply-chain formation, and use the heterogeneity in the magnitudes and channels to assess the plausibility of our results. To capture both the occurrence and intensity of these shocks, we use the number of days on which firms were affected by high heat or floods per financial quarter as our main measures.

[5] In principle, these addresses could encompass the headquarters of incorporated subsidiaries with additional facilities. Apart from other data limitations, the data may therefore not represent the universe of firms' locations.

[6] We choose to restrict the sample of firms instead of aggregating shocks across locations, as the lack of consistent data on the scope of economic activity across facilities makes it difficult to aggregate shocks across locations for each firm in a meaningful way. In principle, we could attempt to aggregate shocks across locations using equal weighting. However, we observe a large number of small locations, i.e. sales locations and dealerships in the case of car manufacturers. Hence, equal weighting is conceptually inaccurate, and the value of pursuing this approach is unclear as we could not distinguish actual null results from null results caused by incomplete observations of locations and inaccurate weighting. The drawback of our approach is that measures of heat and flood exposure based on headquarters are observed with noise, even after filtering out dispersed firms. However, the direction of this potential measurement error is likely to bias our estimates in Sections 3.1 and 4 against finding significant effects.

[7] As we discuss below, this filter is crucial for upholding the exclusion restriction. In robustness tests, we test the sensitivity of our results to the threshold, and find very similar results when we impose a distance of 1000km instead.

[8] In contrast, other types of natural disasters such as earthquakes and broad groupings of different hazard types, which have been frequently studied in the literature, cannot be unambiguously linked to climate change.

2.4.1 Temperatures

We construct measures of firms' exposure to high temperatures at the firm-quarter-level from location-specific information on daily maximum temperatures. For this purpose, we rely on the ERA5 re-analysis database from the European Center for Medium-term Weather Forecasts (ECMWF).[9] The dataset provides global, daily coverage of a $0.25 \times 0.25°$ latitude-longitude grid, and is available starting in 1979 (Hersbach 2016).

We match daily maximum temperatures to customer and supplier firms using the closest ERA5 grid node and convert temperatures from Kelvin to Celsius. Our main measure of high heat exposure is based on the literature on physiology, temperatures, and labor productivity (Graff-Zivin and Neidell, 2014; Burke et al., 2015b; Carleton and Hsiang, 2016; Sepannen, Fisk, and Lei, 2006), which documents a sharp decline in worker performance for temperatures above 30° C. Similarly, the National Weather Service defines a heatwave based on a sequence of days with temperatures exceeding a threshold of 90° F (32° C). Hence, we use a daily maximum temperature of 30° Celsius as our main temperature threshold to define a day as hot. In extensive robustness tests, we also combine this absolute threshold with relative definitions of high temperatures based on season- and location-specific historical temperature distributions. Accounting for firms' reporting schedules, we sum the number of days on which firms are affected by high temperatures per financial quarter as our main measure of heat exposure. In addition, we construct a measure of local heatwaves by identifying spells of seven or more consecutive days with daily maximum temperatures over 30° Celsius. Table 2d shows the related summary statistics.

2.4.2 Floods

Second, we obtain data on exceptional global surface water levels to determine whether firms are affected by flooding incidents in a given quarter. While surface temperatures are the most commonly cited consequence of global climate change, the scientific literature also indicates that flooding incidents will increase in frequency and severity, i.e. due to heavy rainfall, rapid melting of snow and ice, and parched soil (CSSR, 2017).

We gather information on floods from the Dartmouth Flood Observatory (DFO), which uses

[9] Re-analyses are generated by interpolating local temperatures based on data from existing weather stations and a number of other atmospheric data sources based on scientifically established climate models.

satellite images and remote sensing sources to identify inundated areas. In addition, the DFO collects information on floods from news and governmental sources, and spatially maps materially affected areas.[10] The dataset includes start and end dates for each flood, detailed geographical information on the inundated areas from 1984 until today, and information on the associated damages, size of the affected area, and deaths. Based on the provided flood polygons, we spatially match the coordinates of our sample firms to the flooded areas. Compared to the country-level flooding data used in previous research, this approach allows us to determine more precisely if firm locations were inundated. Similar to Section 2.4.1, we compute the number of days on which a firm was exposed to flooding during each financial quarter, and additionally aggregate the incidence, count, and severity indicators of floods on a quarterly basis as alternative measures. Table 2d shows flood-related summary statistics at the firm-quarter level. On average, suppliers are exposed to floods in 6.4% of all firm-quarters.[11] Conditional on occurrence, floods in our sample last 10.74 days on average.

2.4.3 Temperature Projections

Third, we use data on temperature projections from the fifth phase of the Coupled Model Intercomparison Project (CMIP5). The CMIP5 data are used extensively in the Intergovernmental Panel on Climate Change (IPCC) Assessment Reports, and daily projections are made accessible by the ECMWF.[12] To make our measures of realized temperatures comparable with the projections, we calculate the projected change at supplier locations as the average number of days over 30° Celsius modelled from 2006 to 2019 and mid-century between 2040 to 2059. Moreover, we obtain climate projections following the Representative Concentration Pathway (RCP) 2.6, 4.5, and 8.5, which provide different pathways of the future climate. The RCP 8.5 comes closest to a 'business as usual scenario', which assumes very limited policy interventions directed at emissions reduction. To capture cross-sectional variation in the projected change of temperatures, we obtain data for the

[10] The DFO data includes both granular inundations and hand-mapped flood polygons which cover entire continents. To remove extremely large polygons which are unlikely to reflect firms' actual physical exposures, we limit the sample to floods which exceed 333km in width. As this exclusion is discretionary, we test the sensitivity of the results to the filter. We find very similar results for a more restrictive limitation of floods which do not exceed 100km in width.

[11] The frequency of flood events in DFO appears plausible compared to the matched sample of firm-quarters with EM-DAT disaster data (44% of firm-quarters instead of 6%). Of course, country-level information may overstate the extent to which firms are affected if flood events only affect parts of the country. At the same time, only a subset of the DFO flood events is registered in EM-DAT, as only incidents which caused ten or more casualties, affected more than 100 people, lead to a state of emergency, or resulted in a call for international assistance are recorded.

[12] An overview of various aspects of CMIP5 is provided by Hurrell, Visbeck, and Pirani (2011), and the primary reference for experiment design is Taylor, Stouffer, and Meehl (2012).

periods from 2006 to 2019 and 2040 to 2059 from the MPI-ESM-LR model and average estimated exposure across all available ensemble members.

2.4.4 Natural Disasters

For comparison and robustness tests in Section 3.1, we also include data from the international disaster database EM-DAT, provided by the Centre for Research on the Epidemiology of Disasters (CRED, 2011). EM-DAT is one of the most commonly used global databases in the literature on the economic cost of natural disasters.[13] We distinguish if the temperature-related EM-DAT events are heatwaves or cold spells, and aggregate flood and heat events at the firm quarter-level.

3 Physical Climate Risk and Firm Performance

3.1 Direct Exposure to Weather Shocks

Our main tests on the adaptation of supply chains rely on the assumption that heat and flood events have economically important direct and indirect effects. To validate this assumption, we first examine how these shocks affect supplier performance. Our two main variables for measuring firm operating performance are revenues and operating income scaled by assets. In all tests, we lag assets by one year to ensure that our results are not confounded by potential direct effects on assets.[14]

Of course, climate exposure and firm financial performance are likely endogenous in the cross-section. For example, if firms organize production to maximize profits and weather shocks affect financial performance, managers may choose production locations based on existing climatic conditions. In contrast, both floods and heat days can only be predicted with precision over very short horizons (i.e. days in advance), which are unlikely to allow for substantial adjustment in production planning. Therefore, our empirical strategy aims to exploit short-term variation over time in weather shocks *within* firms, which are plausibly exogenous and randomly distributed conditional on firm locations and seasons.

To isolate this variation, we estimate OLS regressions with firm-by-fiscal-quarter fixed effects.

[13] See for example Strömberg (2007); Noy (2009); Lesk, Rowhani, and Ramankutty (2016).

[14] We focus on these two measures – as opposed to for example earnings – since revenues and operating income are less subject to firms' strategic accounting choices. This consideration is important, as the incentive to smooth earnings might be particularly high following adverse financial shocks.

This empirical design is widely applied in environmental economics (Auffhammer, 2018; Dell et al., 2014; Kolstad and Moore, 2020) and serves two important goals: First, firm fixed effects absorb time-invariant and potentially endogenous firm-level characteristics. Second, by interacting firm-with quarter fixed effects, we mitigate concerns about potentially confounding firm-specific patterns of seasonality. For example, certain types of firms earn higher revenues during the summer, which could mechanically be correlated with the incidence of weather shocks.[15] Further, we follow the literature and include industry-by-year-by-quarter fixed effects to absorb any industry-specific time trends and patterns. Since non-trivial changes to the climate might have occurred over our 15-year sample period, we also include country-specific linear trends to control for confounding simultaneous trends in local climate and firm performance.

To address the possibility that heat and floods randomly coincide with changes in firm characteristics over time, we also introduce size-, age-, and profitability-specific time fixed effects. For this purpose, we sort all firms into size, age, and profitability terciles, which we interact with with year-by-quarter fixed effects, following Barrot and Sauvagnat (2016) (i.e. BS2016). We estimate models of the following form at the quarterly frequency:

$$y_{it} = \sum_{t=-3}^{0} \beta_t \times W_{it} + \mu_{iq(t)} + \gamma_{n(i)t} + \theta_{d(i)t} + \delta_{BS2016,t} + \epsilon_{it} \tag{1}$$

where y_{it} is either *Revenue/Assets* or *Operating Income/Assets* of firm i in period (i.e. year-quarter) t, W_{it} measures weather shocks, i.e. the number of days on which firm i was exposed to heat and floods in t, respectively. $\mu_{iq(t)}$ are firm by fiscal-quarter fixed effects, $\gamma_{n(i)t}$ are industry (of firm i) by year-quarter fixed effects based on 2-digit SIC codes, $\theta_{d(i)t}$ are country (of firm i) linear trends at the quarterly frequency, and $\delta_{BS2016,t}$ are firm size, age, and profitability terciles interacted with year-quarter fixed effects. Following Barrot and Sauvagnat (2016), we cluster robust standard errors at the firm level. As it is ex-ante unclear if the financial impact of weather shocks manifests immediately or with some delay throughout the financial year, we include three lags of heat and flood days.

[Insert Table 3 here.]

[15] Since firms likely differ in these seasonal patterns, quarterly fixed effects alone are not sufficient to address this issue.

The results, reported in Table 3, indicate that both heat and floods adversely affect supplier performance in our sample. In line with the findings of Barrot and Sauvagnat (2016), the full effect materializes over the course of the financial year but dissipates after three quarters. Focusing on floods, one day of flooding at the firms' headquarters is associated with an average decrease in *Revenue/Assets* of 0.074 percentage points. In comparison, the daily damage caused by high temperatures is smaller and translates to 0.042 percentage points.[16] Compared to the average revenues over assets per day – i.e. the quarterly value divided by the number of workdays per fiscal quarter – one additional flood day (heat day) represents a decrease in *daily* scaled revenue of 18% (12%). This magnitude is in line with effects of heat on worker performance documented in the literature. For example, according to Sepannen et al. (2006), an increase in temperatures from 25 to 30° C decreases task performance in an office environment by 10%.

Further, we find that one additional day of flooding (heat) decreases quarterly *Operating Income/Assets* by 0.019 (0.010) percentage points. These coefficients are economically meaningful: The standard deviation in the number of affected days conditional on the occurrence of a flood or heat event is 11.5 and 16.2 days, respectively. Thereby, the effect translates to a 17.2% (12.69%) decrease for a one standard deviation increase in flood days (heat days).[17]

Given the larger effects on operating income compared to revenues, supplier profitability is likely affected both through cost and revenue channels. Focusing on heat, the literature has documented several economic channels driving aggregate economic losses. For instance, electricity prices increase with heat exposure (Pechan and Eisenack, 2014), water supply tightens (Mishra and Singh, 2010), and both cognitive and physical labor productivity are compromised (Sepannen et al., 2006; Xiang, Bi, Pisaniello, and Hansen, 2014). Compared to heat, floods have a more direct and lasting negative effect on physical capital, potentially damaging equipment, local infrastructure, and disrupting production.[18] This is consistent with the larger negative operating performance effects of floods compared to heat documented in Table 3.

In Appendix Table A2, we further examine the heterogeneity of heat and flood effects by industry. For heat, we observe particularly pronounced effects in agriculture, transportation, manufacturing,

[16] These estimates are obtained by summing over the coefficient estimates for lags $t = -4, ..., 0$.

[17] In robustness tests we replace heat and flood days with counting variables indicating the number of weather shocks per financial quarter. Results are reported in Appendix Table A1 and corroborate the main result.

[18] As the focus of our analysis lies on the indirect exposure to physical climate risk and adaptation of supply-chains, we do not aim to uncover the precise mechanics driving the directly observable effects in this paper.

mining and construction, and services. These effects are in line with evidence on the negative effect of heat on crop yields, outdoors industries, and labor and capital productivity.[19] For floods, we observe the strongest effects in industries with high asset tangibility, including mining and construction, manufacturing, and agriculture, consistent with the idea that floods primarily affect capital productivity.

A potential concern with our empirical design is that weather shocks are measured with error for firms with geographically dispersed production sites. We validate our choice of matching heat and floods with firms based on headquarter addresses by estimating the regression in Equation (1) for different subsamples of firms depending on their geographic concentration. For this purpose, we collect information on 1.1 million locations of incorporated subsidiaries, branches, and establishments, and limit our sample to firms with at least 10% of assets within 30km of the firm's headquarters.[20] Figure 4 plots the results. For both floods and heat, the effect is consistently negative and increases in magnitude with firm-level geographic concentration, providing supportive evidence for our location matching strategy.[21]

3.2 Indirect Exposure to Weather Shocks

Next, we examine if heat and floods propagate along the supply-chain affecting the operations of downstream firms. Previous research (e.g. Barrot and Sauvagnat, 2016; Carvalho et al., 2021) has documented performance spillovers along the supply chain following large-scale natural disasters. In contrast to these shocks, heat and floods are closely linked to climate change. This is important since the frequency of heat and flood occurrences is expected to change heterogeneously across the world, and may lead firms to update their beliefs about the probability of their occurrence.

The downstream effects of weather shocks in production networks are theoretically ambiguous. On the one hand, customers might already use risk management strategies such as multi-sourcing to mitigate the propagation of shocks to suppliers. Similarly, if suppliers' bargaining power is small, their ability to pass on higher costs due to heat or flood exposure downstream may be limited. In both cases, heat- and flood-related distortions would not propagate along the supply-chain, and we

[19] See e.g. Zhang et al., 2018; Sepannen et al., 2006; Somanathan et al., 2015; Burke and Emerick, 2016.

[20] The choice of this threshold is by nature arbitrary. We follow Barrot and Sauvagnat (2016), who exclude firms with fewer than 10% of employees at the headquarter.

[21] However, the differences have to be interpreted with some caution given that firms in different concentration quartiles might differ along other dimensions, which might in turn affect firms' sensitivity to heat and floods.

should be unable to find a significant impact of climate shocks to suppliers on customer financial performance. On the other hand, even small shocks resulting from heat or floods could increase supplier costs, decrease production output, or cause supply-chain glitches, particularly given modern just-in-time production systems. These disruptions are particularly likely to occur if the inputs have a high level of specificity (Barrot and Sauvagnat, 2016) or when customers' ability to procure inputs from alternative sources is limited for other reasons.

We empirically test these competing hypotheses by examining whether customers' operating performance is affected by weather shocks to their suppliers. As in Section 3.1, we use revenue and operating income (scaled by lagged assets) as our two main dependent variables. Since weather shocks to suppliers might distort and strain supply-chain operations in ways not reflected in financial performance, our tests likely understate the extent to which supplier-customer relationships are challenged by floods and high temperatures. Further, heat and floods do not only affect firms' production facilities directly but also indirectly through transportation links and other local infrastructure (Boehm et al., 2019; Carvalho et al., 2021). Since the main focus of our analysis is on supply-chain adaptation, we do not aim to distinguish between immediate and indirect disruptions of our sample suppliers in this analysis, as customers would have a strong incentive to mitigate spillovers due to either type of disruption.

Our primary identifying assumption is that weather shocks are drawn randomly from the underlying distribution over short horizons. We rely on this variation for causal interpretation of the observed effects by estimating OLS regressions with firm-by-quarter fixed effects to account for any firm-specific seasonal patterns. Hence, our results are identified from within-firm variation in local climate realizations of remote suppliers.[22] We further saturate our model with industry-by-year-quarter fixed effects and country-specific time trends to account for time-series patterns at the industry level and long-term trends in local climate, as in Equation (1). Therefore, even if suppliers differ in their propensity of experiencing climate-relate shocks, unobserved characteristics are unlikely to be driving our results given the random timing of our shocks. Any alternative explanation for our results related to endogenous selection would have to systematically explain

[22] In contrast, it would be problematic to study the effect of supplier exposure to physical risks on customers in the cross-section, as the exposure of customers to weather shocks through suppliers may be endogenous. For example, if certain industries systematically depend on specific inputs from suppliers clustered in risky areas, shocks and customer firm performance could be endogenously determined.

both changes in supplier climate-shock occurrence and customer firm performance over time, in a way that is not captured by firm-specific seasonality, industry patters, and country-level trends.

A potential concern with our empirical design is the possibility that both supplier and customer could be simultaneously affected by a given shock, either directly, through local infrastructure, or simultaneous demand-side effects. To address this potential threat to the exclusion restriction, we exclude all customers-supplier pairs with customers located within a 500 kilometer radius of the affected supplier from our analysis. Following the literature (e.g. Kale and Shahrur, 2007; Banerjee et al., 2008; Barrot and Sauvagnat, 2016; Campello and Gao, 2017; Cen, Maydew, Zhang, and Zuo, 2017; Phua, Tham, and Wei, 2018), we collapse our supplier-customer panel at the customer-year-quarter level and estimate OLS regressions of the following form at the quarterly frequency:

$$y_{ct} = \sum_{t=-3}^{0} \beta_t \times \mathrm{W}_{ct} + \mu_{cq(t)} + \gamma_{n(c)t} + \theta_{d(c)t} + \delta_{BS2016,t} + \epsilon_{ct} \tag{2}$$

where y_{ct} is either *Revenue/Assets* or *Operating Income/Assets* of customer c in period (i.e. year-quarter) t. W_{ct} is the sum of heat or flood days, respectively, across the locations of all suppliers of customer c in period t. Further, $\mu_{cq(t)}$ are customer by fiscal-quarter fixed effects, $\gamma_{d(c)t}$ are industry (of customer c) by year-quarter fixed effects, $\theta_{d(c)t}$ are country (of customer c)-specific quarterly trends. Similar to Equation (1), we add size, age, and profitability by year-quarter fixed effects ($\delta_{BS2016,t}$) to control for different firm profiles. Robust standard errors are clustered at the customer level. As in Section 3.1, we include 3 lags of W.

3.2.1 Results

The results show that both heat (Table 4a) and floods (Table 4b) in the locations of the suppliers negatively affect the financial performance of downstream customers. Specifically, we find that one additional day of heat across all supplier locations decreases customer revenues over assets by 0.0055 percentage points. Further, one additional day of flooding at supplier locations decreases customer revenues by 0.0229 percentage points.[23] Our results are similar for operating income. One additional day of heat and flooding at supplier locations decreases quarterly customer operating income over assets by 0.0007 and 0.004 percentage points, respectively.

[23] Similar to Section 3.1, these estimates are obtained by summing over the coefficient estimates for lags $t = -4, ..., 0$.

Compared to the the direct effects shown in Table 3, the indirect effects of climate-shock exposure on customers as documented in Table 4 are considerably smaller in magnitude. For flood days (heat days), the economic magnitude of the indirect effect on customers is equivalent to 31% (13.1%) of the direct effect on the supplier. The magnitude of the indirect effect on operating income is as large as 21% (7%) of the direct effect. Both, the significantly larger financial cost for customers and the higher relative spillover effect of floods compared to heat are consistent with the idea that floods represent more severe disruptions than heat days, affecting both human and physical capital through direct and indirect channels such as local transportation links, ports, and other infrastructure.

[Insert Table 4 here.]

The estimated effects are sizeable in economic terms: one day of supplier flood (heat) exposure decreases revenues over assets of a remote customer by 5.6% (1.3%) relative to the sample average per work day. The percentages translate into substantial absolute values, with a median downstream distortion of 91,000 (22,000) USD in revenue per affected flood (heat) *day*. Given standard deviations of flood days (heat days) of 11.5 (16.2) days conditional on occurrence, the downstream effect of a representative shock amounts to indirect costs of over 1 million and 350,000 USD, respectively. Hence, the observed shocks represent material disruptions for customers – particularly given that both heat days and inundations are projected to increase in frequency and severity.[24]

The operating income effects are consistently larger than the effects on revenues in percentage terms. This is consistent with the idea that customers are affected by supplier shocks through channels affecting both costs and productivity, as supply chain glitches may require costly short-run adaptations by customers. This is broadly in line with the literature on multi-sourcing and endogenous production networks (Du, Lu, and Tao, 2009; Antràs et al., 2017; Gervais, 2018), which highlights the trade-off between input cost minimization and risk diversification.

3.2.2 Robustness

To examine the robustness of our result, we use alternative measures of W to estimate Equation (2). We first replace continuous measures of heat and flood days with indicator variables taking the value of one, if at least one heatwave (i.e. seven consecutive days with temperatures above

[24] Given the fact that firms may have adapted their operations in this expectation already, these estimations are likely to represent a lower bound of the ex-ante costs of indirect shocks.

30° C) or flood occurred across suppliers per customer quarter in Appendix Table A3a. Second, while our heat measure follows the literature on temperatures and labor productivity (Graff-Zivin and Neidell, 2014; Burke et al., 2015b), concerns might remain that the effect of heat differs across locations depending on the local climate and existing adaptations. Hence, in Appendix Table A3b, we introduce an alternative measure of heat days combining an absolute and relative threshold. Specifically, for each customer-quarter, we count the number of days on which the temperature exceeded both 30°C *and* the 95th percentile of historical local temperatures across supplier locations. We also include tests retaining only severe flooding incidents in Appendix Table A3b, as defined by the NOAA. The results in both panels are similar to our main findings.

Next, we verify that our estimates do not exhibit any significant pre-trends to validate the identifying assumption that short-term weather shocks are drawn randomly from the underlying climate distribution. Figure 5 plots the coefficient estimates of β_t from Equation (2) for quarters $t \in [-4, ..., 6]$. As shown, the coefficient estimates are insignificant and close to zero before the occurrence of both heatwaves and floods. While the effect of supplier heatwaves on customer performance materializes with a lag of one quarter and reverts to pre-event levels within one to two quarters, we find an immediate effect of supplier floods that remains large and significant for three to four quarters. This is consistent with our previous findings in Table 4 and the idea that heatwaves and floods affect firm performance spillovers through different mechanisms.[25]

Next, we examine if particularly the shocks which are not intense enough to be captured by a disaster database, but projected to become much more frequent due to climate change, are economically relevant. Table A4 shows the estimates of Equation (2) using only weather shocks which are *not* recorded in the global disaster database EM-DAT. The results are similar to our main results, indicating that our findings are not solely driven by the very largest shocks.

3.2.3 Cross-Sectional Heterogeneity

We next explore cross-sectional differences in the propagation of weather shocks to study the economic mechanisms behind our findings in Section 3.2. First, all else equal, the effect of supplier climate shocks on customer firm performance should increase with the magnitude of supplier

[25] Consistent with Barrot and Sauvagnat (2016), both heat and flood shocks have a temporary effect. Barrot and Sauvagnat (2016) find a lag of three quarters studying the propagation effect of hurricanes from suppliers to customers, focusing on sales growth instead of operating income.

disruptions. Hence, we construct measures of supplier asset tangibility and industry vulnerability as outlined in Section 2.2 to test if the propagation effect is larger for more vulnerable suppliers.[26]

Second, we only expect to find a propagation effect of heat and floods if suppliers are able to (partially) pass on the related costs downstream, or if customers are unable to mitigate supply-chain disruptions. To test this idea, we collect the following proxies detailed in Section 2.2: 'supplier industry competitiveness' captures the relative supplier bargaining power, 'industry-level input concentration', 'customer inventory', and 'supplier diversification' are proxies for the dependence of the customer on the inputs of a given supplier, and 'sales correlation' and 'relationship length' capture the depth of integration between a supplier and customer.

We aggregate over the total number of heat and flood days across each customer's suppliers over the contemporaneous and previous three quarters, and interact this variable with the mean supplier, customer, and firm-pair characteristics listed above.[27] Table 5 shows the results.[28]

[Insert Table 5 here.]

We first consider differences in the nature of heat and flood events. Consistent with the literature, we find a significantly stronger propagation effect of high temperatures for suppliers in the agricultural, mining, and construction sectors in Column (2) of Table 5a. Further, we do not find a significant interaction effect of heat days and supplier asset tangibility. In contrast, the effect of flood-related supplier disruptions (Table 5b) is concentrated in customers with both high supplier capital intensity (Column 1) and high supplier labor intensity (Column 2), indicating that floods affect both labor and capital productivity.

Focusing on input substitutability and customer dependence, we find a statistically significant moderating effect of supplier industry competitiveness on the propagation of both heat and floods. This finding indicates that customers' ability to switch suppliers and low supplier bargaining power reduce customer exposure to suppliers' physical risk. Similarly, we find that shock propagation is exacerbated when the customer industry relies more heavily on inputs from a single supplier industry, and mitigated for high customer inventory holdings (heat and floods) and supplier

[26] The literature has documented that particularly firms with a large proportion of physical assets and labor-intensive (outdoor) activities are sensitive to heat and floods.

[27] All cross-sectional characteristics are lagged by one year to address concerns that our explanatory variables themselves are affected by the observed shocks.

[28] The dependent variables in Table 5 are scaled by 100 and the results for revenues are shown in Table A5.

diversification (heat). Last, while the results show that supplier-customer sales correlation increases shock propagation, we find the opposite, mitigating effect for supply-chain pairs with a long relationship length.

3.2.4 Other Outcomes

In our next set of tests, shown in Table 6, we further explore the underlying economic channels by examining other customer firm outcomes, including operating margin, supplier diversification, accounts payables, costs of goods sold, and inventory (all scaled by one-year lagged total assets).

[Insert Table 6 here.]

In line with the idea that heat- and flood-related disruptions may require costly adjustments, e.g. input sourcing from alternative suppliers, we find a significant negative effect of heat and flood days on customer operating margin in Column (1). For example, a one standard deviation increase in flood days (11.5 days conditional on occurrence) translates into a 2.7% decrease in customer operating margins relative to the sample mean. Further, in line with the idea that customers are unable to fully replace the inputs purchased from disrupted suppliers, we find a significant negative effect of supplier heat and flood days on the volume of inputs purchased (i.e. customer accounts payables and COGS), and customer inventory in Columns (3) to (5). Last, we find that customers increase their supplier-base, i.e. the number of suppliers scaled by one-year lagged assets, following weather shocks at their existing suppliers. The effect indicates an increase in supplier base by 0.5% relative to the sample mean for a one-standard deviation increase in supplier flood days.

4 Supply-Chain Adaptation

4.1 Realized and Expected Climate Risk

If weather shocks are financially material and change in frequency over time, firms may face incentives to adapt their production networks. In this section, we lay out conceptually how local trends in the frequency of climate events could affect firms' decisions to continue or terminate existing supply-chain relationships. Subsequently, we empirically estimate the magnitude of firms' responses to perceived changes in climate risk based on observable supply-chain adjustments.

4.1.1 Conceptual Framework

We study the decision $\mathbb{P}$ to either continue or terminate existing supply-chain relationships made by N identical customers producing output Q under perfect competition. We assume that the customers' production follows a Cobb-Douglas aggregate of capital K and labor L to yield a quantity Q, and requires a fixed set of inputs M besides labor and capital. This set of inputs is sourced from S identical suppliers, which are also subject to production under perfect competition. In this setting, capital investments are fixed in the short-run. This condition is important, as many types of supply chain relationships require substantial, relationship-specific investments (Dass, Kale, and Nanda, 2015; Dasgupta, Zhang, and Zhu, 2020). Customer managers carefully trade off supplier characteristics and input costs before placing initial orders in order to maximize profits, as profits depend on the quantities q_i and prices p_i of used inputs $i \in M$.

We define heat and flooding days conditional on location and season as shocks W. W in period t is randomly drawn from a normal distribution with possibly time varying mean ω_t and standard deviation σ_t, i.e. $W_t \sim \mathcal{N}(\omega_t, \sigma_t)$.[29] As in Barrot and Sauvagnat (2016), W can cause deviations in the availability of one input of production from its first-best level q_i^* to its constrained level $q_i < q_i^*$.[30] As documented in the previous section, these constraints can be costly even for shocks of relatively small magnitude.

Customers make input decisions and commit to relationship-specific investments before weather shocks are realized. Therefore, they consider the parameters of the distribution of W before committing to any supplier $s \in S$.[31] Inputs sourced by customers and outputs produced by suppliers are determined in equilibrium, yielding the matches of customers to suppliers, the prices p_i, and the quantities of inputs q_i. The resulting pairwise matches of customers and suppliers are such that customers would not be willing to accept an increase in the exposure of the supplier to physical climate risks without an adjustment of input prices. As is standard in the literature, we begin by assuming that both suppliers and customers are price takers in product markets. Therefore, we

[29] The intuition of our framework also applies if we assume alternative production functions or distributions for W.

[30] Alternatively, Kelly et al. (2005) model production as a function of input choices and an exogenous shocks in a multi-period model.

[31] For this purpose, managers may not have access to climate projections, a condition that we discuss more carefully below. However, we assume that there is wide access to information about past weather shocks. For instance, when choosing a supplier in a flood-prone area, managers may learn about past events from the suppliers' disclosures, internal information, or local news. Similarly, heatwaves and droughts may be discussed by regional, national, or international news outlets.

focus on customers' decisions $\mathbb{P}$ to terminate existing supplier relationships in a partial equilibrium, and study if customers respond to perceived changes in climate risks.[32]

We assume that customers estimate the parameters of the distribution of W before entering a new supply-chain relationship. As in Kelly et al. (2005), they form a prior about the mean of this distribution, ω_0, based on historical information.[33] Due to climate change, the parameters of the underlying distribution including ω_t may change over time. Since customers cannot directly observe ω_t, they assess their suppliers' shock exposure during the supply-chain relationship every period. They gradually learn about ω_t by calculating the average number of realized shocks per year in t since the beginning of the relationship at $k = 0$, i.e. $\bar{W}_t = \frac{\sum_{k=0}^{t} W_k}{t}$. Assuming that individual customers cannot influence market prices, increases from ω_0 to ω_t may hence render a previously optimal choice of a supplier sub-optimal. In contrast, when the realized shocks W_t are below or in line with the ex-ante expectation ω_0, customers have no incentive to reassess their choice of supplier. This intuition allows us to describe the relevant decision for customers as:

$$\mathbb{P}_t = \begin{cases} 0, & \text{if } \bar{W}_t \leq \omega_0 \\ 1, & \text{if } \bar{W}_t > \omega_0 \end{cases} \tag{3}$$

where $\mathbb{P}_t$ is the customers' decision to terminate the supply-chain relationship in year t, $\bar{W}_t$ is the average number of realized shocks per year in t since the beginning of the relationship, and ω_0 is the expected value of W based on historical information available at $k = 0$.

To make decisions about the adjustment of supplier networks, firms could use two types of information. First, firms could observe recent climate realizations and base decisions on perceived gradual changes. A large literature in finance and economics has proposed Bayesian updating to model how economic agents infer information about changing environments in general (i.e. Alevy et al., 2007; Chiang et al., 2011). In the context of climate change, this approach is not without difficulty: In the short- and medium-term, weather outcomes provide a noisy signal of potential changes in the underlying climate distribution. Nevertheless, empirical studies have shown that

[32] This choice is motivated by the fact that we cannot observe prices and quantities, and that it is ex-ante unclear if and how firms at large respond to (perceived) changes in supplier exposure. Beyond the scope of this paper, it is important to better understand effects in the general equilibrium. For instance, the question how increased risk of disruptions affects the value of access to international suppliers provides interesting avenues for future research.

[33] While we note that changes in other moments of the climate distribution may also affect supplier-customer matches, we choose to focus on changes in the mean ω.

individuals exhibit behavior consistent with Bayesian learning, i.e. in terms of efforts to understand changing climate distributions from their own experience (Deryugina, 2013; Moore, 2017; Kelly et al., 2005; Kala, 2019; Choi et al., 2020).

Alternatively, firms could use forward-looking models of climate change to assess expected changes, and interpolate expectations for future periods based on current and projected probabilities of weather events (Moore, 2017). As outlined by Fiedler et al. (2021), in practice this approach is impractical for most businesses: First, while numerous climate projections has been published by the IPCC in recent years, assessing the relative strengths of the various scientific models is challenging. Second, supply-chain managers typically make decisions for the short- and medium-run, and projecting climate change is particularly difficult at these horizons. Third, business decisions require granular information in spatial terms. However, the usefulness of downscaled regional or global models can be challenging to assess, despite the fact that their output offers numerical precision. Due to these challenges, it appears reasonable to assume that firms at large did not incorporate forward-looking information in their decision making in our sample period from 2003 to 2016. Hence, our empirical tests focus on firms' responses to experienced risk exposure.

We establish four testable hypotheses. First, under perfect competition, customer-supplier relationships in equilibrium reflect the expected exposure to physical climate risk which customers are willing to accept for a given set of other supplier characteristics and input prices. Hence, changes in the mean of the distribution may render previously optimal customer-supplier matches sub-optimal:

Hypothesis 1 *An increase in the number of realized shocks beyond what customers could have expected ex-ante increases the probability that a given supply-chain relationship is terminated.*

Since we do not observe whether supply-chain relationships were ended by customers or suppliers, our analysis is potentially confounded by supply-side disruptions. To investigate if the observed termination decisions can be attributed to demand-side effects, we test if the characteristics of the relation of supply-chain terminations and weather shocks are in line with patters of learning on behalf of customers. Namely, if customers behave consistently with models of Bayesian learning, we would expect that they respond more strongly when the observed deviations are larger in magnitude, or when the signal is repeated over multiple periods over time:

Hypothesis 2 *The relation of increases in the number of realized weather shocks beyond what customers could have expected ex-ante and the probability for a given supply-chain relationship to end is more pronounced when such deviations are larger in magnitude.*

Hypothesis 3 *The relation of increases in the number of realized weather shocks beyond what customers could have expected ex-ante and the probability for a given supply-chain relationship to end is more pronounced when such deviations persist over a prolonged period of time.*

Further, we note that it is unlikely for supply-side mechanisms to be the main driver of the results in our context, as the shocks are geographically concentrated events of limited magnitude. We also test this assumption explicitly. If supply-side disruptions were driving our results, we would expect that the effect of transitory shocks on supply-chain terminations is of a similar magnitude as the exceedance of ex-ante climate risk expectations:[34]

Hypothesis 4 *Transitory shocks to suppliers increase the probability that a given supply-chain relationship is terminated.*

Whereas we focus on demand-side adaptation, suppliers may also adapt to increasing frequencies of weather shocks. As we do not observe such adaptation investments, our results could represent a lower bound due to the fact that customers would not have to switch suppliers if suppliers became more resilient.

4.1.2 Assumptions

Before turning to the estimations, we consider two of our main assumptions in detail. First, our framework assumes that both customers and suppliers operate under perfect competition. However, product markets may be concentrated, allowing customers or suppliers to extract rents. Under imperfect competition, such rents can be represented as a latent variable, λ, which would increase the tolerance of customers to changes in climate risks as follows:

[34] The test is similarly subject to the challenge that it is impossible to cleanly disentangle demand- and supply-side driven terminations. Therefore, we might overestimate the magnitude of the effect of transitory shocks if customers over-respond to salient, transitory shocks despite the fact that those could have been anticipated. Previous studies have documented that firms are prone to availability bias in responding to salient events in related settings. For example, Dessaint and Matray (2017) find that managers adjust firms' cash holdings when nearby firms are hit by natural disasters, even if firms have not been directly exposed to these hazards.

$$\mathbb{P}_t = \begin{cases} 0, & \text{if } \bar{W}_t \leq \omega_0 + \lambda \\ 1, & \text{if } \bar{W}_t > \omega_0 + \lambda \end{cases} \tag{4}$$

Intuitively, maintaining existing relationships may be optimal for customers with market power even if average realized annual shocks $\bar{W}_t$ exceed ex-ante expected shocks ω_0. Since we cannot directly observe λ, this would lead us to underestimate the effect of an increase in ω_t on terminations, as our empirical measure captures only cases in which the historical mean of ω_0 but not the actual tolerance of the customer (i.e. $\omega_0 + \lambda$) is exceeded. Further, when suppliers benefit from concentrated input markets, customers may be bound to certain suppliers for a lack of alternatives. This would similarly increase the tolerance of customers to supplier climate risk and increase the threshold exposure to $\omega_0 + \gamma$. In addition to these considerations, we explicitly test the plausibility of our results using industry and firm characteristics as proxies for λ_0 and γ.

Second, we have thus far assumed that customers form a point prior of the expected risk exposure of suppliers. However, customers only observe an approximation of the true distribution at the beginning of the relationship. We think about the resulting additional uncertainty as a band around the mean of ω_0, increasing the threshold to $\omega_0 + \delta$. The magnitude of δ is unobservable and may vary by customer and supplier. Instead of imposing an arbitrary band around the point prior in our estimations, we therefore note that our measure may capture incidents where $\bar{W}_t$ exceeds ω_0 but not $\omega_0 + \delta$. In this case, our measure indicates an exceedance of the ex-ante expectations which does not lead customers to take action, resulting in a potential source of downward bias for our estimations.

4.1.3 Empirical Strategy

To test our hypotheses, we construct a measure to capture if weather shocks have increased beyond customers' ex-ante expectations, as illustrated in Figure 2. According to our conceptual framework, we assume that customers form a prior ω_0 (i.e. *expected* weather shocks) based on the historical number of shocks per year at the supplier location *before* the start of any given supplier-customer relationship.[35] Starting at the beginning of the relationship, customers then evaluate their experience and update their beliefs about whether the ex-ante expected exposure is exceeded every year based

[35] Since firms' time horizon for this benchmark period is unclear, we conduct robustness checks with different horizons over five, ten, and fifteen year periods.

on the average number of observed shocks $\bar{W}_t$ (i.e. *realized* weather shocks). Our main measure, $\mathbb{1}\left(Realized > Expected\ Shocks\right)_{sct}$, takes the value of one in year t if the average number of realized shocks per year since the beginning of the relationship sc exceeds the corresponding prior for supplier s, and zero otherwise.[36] As our outcome variable, we use the end dates of customer-supplier relationships from Factset Revere. In a panel of active customer-supplier-year observations, we set the indicator variable $\mathbb{1}\left(End\right)_{sct}$ to one in the last year of any reported supply-chain relationship. To address concerns about censoring, we drop all observations from the last year of our sample.

Our identification strategy is similar to the long-differences approach introduced by Burke and Emerick (2016), and relies on the fact that short-run climate realizations, in contrast to long-run changes, are quasi-randomly assigned across locations. Intuitively, our empirical design leverages the idea that managers can incorporate expected levels of climate risk exposure but not deviations from the expectation into their decision making. Figures 6a and 6b provide supporting evidence for this identifying assumption, by plotting the difference between *Realized* and *Expected Shocks*, and the residual variation of this difference after absorbing high dimensional time-varying regional fixed effects. As shown in Figures 6a and 6b, the distribution is largely unaffected by including the fixed effects, in line with the idea that the underlying short-term trends are quasi-randomly assigned and not determined at the country- and/or year-level. Based on this reasoning, we estimate the following linear probability model at the annual frequency:

$$\mathbb{1}\left(End\right)_{sct} = \beta \times \mathbb{1}\left(Realized > Expected\ Shocks\right)_{sct} + \gamma_{n(s)t} + \gamma_{n(c)t} + \theta_{d(s)d(c)t} + \epsilon_{sct} \tag{5}$$

To further control for potential confounding effects which may be correlated with both climate trends and other reasons for relationship terminations, we estimate this model with several dimensions of fixed effects. First, we include both supplier and customer industry-by-year fixed effects, $\gamma_{n(s)t}$ and $\gamma_{n(c)t}$, to account for industry trends, related for example to trends in make-or-buy choices. Second, we add supplier-country by customer-country by year fixed effects $\theta_{d(s)d(c)t}$ to account for changes in macroeconomic conditions, trade barriers, or import-related costs.[37] We cluster robust standard errors at the relationship level. To address concerns about a potential violation of

[36] In additional tests, we use the continuous difference, i.e. $\left(Realized - Expected\ Shocks\right)_{sct}$.

[37] Since our main variable of interest is differenced at the relationship-level, relationship or firm fixed effects would obscure the economic interpretation of the effect and are hence not included in this specification.

the exclusion restriction, we exclude all firm pairs with customers located within a 500 kilometer radius of the affected supplier to ensure that the observed trends affect suppliers only.[38] Hence, for any alternative explanations to be driving our results, unobservable characteristics would have to systematically change in those firm-pairs where realized shocks exceeded expectations, in a way that is unrelated to industry- or country-level trends.

4.1.4 Results

Table 7 reports the estimates obtained from Equation (5). Across all specifications, we find that existing suppliers are more likely to be terminated when the realized exposure to days with high temperatures or flooding exceeds customers' prior expectations, in line with Hypothesis (1). Under the most stringent specification, the coefficients of $\mathbb{1}(Realized > Expected)$ for both heat and flood days are positive and statistically significant at the 1% level. The linear probability model estimates presented in Panel 7a indicate a 0.004 to 0.009 (0.010 to 0.015) percentage point increase in the likelihood of supplier termination for heat days (flood days) exceedance of expectations, respectively. Compared to the unconditional sample mean of 0.26, this represents an increase of 3.5 to 5.8%.

[Insert Table 7 here.]

To facilitate the interpretation of the economic magnitudes of this effect, we also estimate conditional logistic regressions in Panel 7b. The results show that suppliers' exposure to flood days increases the likelihood of supply-chain relationship termination on average by 7.9 to 11.1%, significant at the 1%-level across all specifications. In comparison, the effect of increases in heat exposure over prior expectations on supplier termination is 6.1 to 7.8%. The difference in the magnitude between floods and heat is in line with the stronger direct and indirect effects of floods compared to heat documented in Sections 3.1 and 3.2.

4.1.5 Learning from Experienced Change

So far, we provide evidence that firms are more likely to terminate existing supplier relationships when weather shock experiences exceed expectations. To better understand if firms' behavior is in line with standard models of Bayesian updating, we test two related predictions. First, if firms use

[38] Tests with a 1000 kilometers radius yield very similar results.

Bayes rule to learn about potential changes in the climate risk exposure of their suppliers, we would also expect that the likelihood of terminations increases with the length of the periods during which these deviations persist (Moore, 2017), i.e. Hypothesis (2). Second, we should observe that stronger deviations lead to more pronounced effects (Deryugina, 2013), i.e. Hypothesis (3).

[Insert Table 8 here.]

In Table 8a, we first estimate changes in the likelihood of supplier termination as a function of the number of years during which realized weather shocks exceed customers' priors.[39] In line with Hypothesis (2), we find that the effect on the likelihood of supplier termination increases when the condition persists for multiple years, and is particularly strong for the second signal. After two years, a prolonged observation of the deviation continues to increase the probability of supplier termination, but with a decreasing marginal effect.[40]

Moreover, we test if firms' responses increase with the magnitude of the signal. We estimate Equation (5) using the continuous measure $Realized - Expected\ Shocks_{sct}$ instead of an indicator variable and present results in Panel 8b. Consistent with Bayesian learning and Hypothesis (3), we find that the likelihood of supplier terminations increases with the magnitude of the deviation, measured in heat and flood days.

4.1.6 Supply-side Disruptions

For clarity of the exposition, we started by describing the observable outcome of supply-chain terminations as a function of customers' decision making. In reality, the outcome could be driven by both supply- and demand-side dynamics. If supply-side disruptions caused by transitory heat and flood shocks drive our results, we would expect that the effect of such transitory shocks is of a similar magnitude as the exceedance of ex-ante climate risk expectations. Further, availability bias could influence customers' decisions about replacing suppliers if firms react to recent, salient events (Dessaint and Matray, 2017). In this case, we would expect the likelihood of supplier termination to increase with recent weather shocks, i.e. Hypothesis (4). We test this hypothesis by replacing

[39] We collapse relationships with more than five signal and impose no functional form on the marginal effect of the first five repetitions of the signal $\mathbb{1}\,(Realized > Expected)$.

[40] This decrease in effect size is consistent with the idea that some relationships may not be terminated for structural reasons, and hence a high number of repetitions may indicate the resilience of the relationship.

our measures of climate-risk exceedance in Equation (5) with contemporaneous weather shocks, i.e. *Realized Heat Days* and *Realized Flood Days*, as our main independent variables.

[Insert Table 9 here.]

Our results, presented in Table 9, show a statistically significant, positive effect of contemporary heat and flood events on supply-chain termination in columns (1) and (5). However, compared to the effect of climate-risk exceedance, i.e. *Realized* − *Expected* heat and flood days in Columns (2), (4), (6), and (8), the effect is economically small. For example, the coefficient estimate of *Realized* − *Expected Heat Days* (significant at the 1% level) is about seven times larger than the corresponding coefficient for *Realized Heat Days* (significant at the 10% level). Tests for differences in coefficients between contemporary shocks to climate-risk exceedance are statistically significant across all specifications. This finding further supports our interpretation that supply-chain relationships are not primarily terminated because of (temporary) disruptions of supplier operations and input availability, but due to changes in customers' perceptions of climate-change related risks.

To further address concerns about supply-side terminations, we also test if the effects are driven by suppliers which cease operations following a weather shock. The findings, presented in Appendix Table A7a, remain similar when we exclude suppliers which were delisted within two years of the relationship end date from the sample.

4.1.7 Robustness

We conduct several robustness tests. First, our main test uses a ten-year benchmark period before the start of any given relationship to estimate customers' priors. To test the sensitivity of our results to this choice, we estimate Equation (5) using alternative benchmark periods of 5 and 15 years. As shown in Appendix Table A6, all estimates remain similar in magnitude and statistical significance.

Second, we set our main independent variable to zero in the first year of the supply chain relationship. Since we estimate priors as the expected exposure prior to the start of the relationship, there is a 50% chance of exceeding this prior in the first relationship year. Hence, the first signal might not be particularly informative to managers. In line with this idea, our results increase in magnitude when we set the first year to zero in Appendix Table A7b.

Third, 6.37% of supply-chains in our sample are terminated, but eventually re-established at some point. As Appendix Table A7c shows, our results are unaffected when excluding these observations.

Fourth, we consider the duration of supplier-customer relationships as an alternative measure of supply-chain stability, as in Fee, Hadlock, and Thomas (2006) and Phua et al. (2018). In this test, the dependent variable is the number of years from the beginning to the end of a given supplier-customer relationship. We drop relationships that were terminated and subsequently restarted at some point in our sample, and code observations that are active in the last year of our sample as right censored, following the literature. The main independent variable is defined as $max\,[1(Realized > Expected\ Shocks)]$ within each supplier-customer relationship. Instead of including fixed effects as in our OLS estimations, we stratify regressions with the first year of each relationship (FY), customer- and supplier-by-industry-by-FY and supplier-country-by-FY. Appendix Table A8 shows Cox proportional hazard model estimates of the effect of increases in supplier climate-risk exposure on relationship duration. In line with the previously presented results, the estimates indicate that relationship duration decreases by 0.23 to 0.46 years (0.32 to 0.4 years) when the realized number of days affected by heat (floods) exceeds expectations.

4.1.8 Cross-Sectional Heterogeneity

To test the plausibility of our main result, we explore the effect of cross-sectional differences at the supplier, customer, and relationship level. In particular, we interact our main variable of interest in Equation (5) with proxies of supplier-industry competitiveness, customer input dependence, and supply-chain integration to study the role of these characteristics for the effect of climate-risk exceedance on supplier termination. Table 10 reports the results.

[Insert Table 10 here.]

If our findings are driven by customers who substitute potentially risky suppliers, we would expect to find a stronger effect when competition in the supplier industry is high, i.e. when γ in our conceptual framework is small. Similar to Table 5, we use the number of firms in the SIC 2-digit supplier industry as a proxy for the number of potential replacement suppliers and find results consistent with this conjecture. As shown in Column (1) of Table 10, a one-standard deviation increase in supplier-industry competitiveness more than doubles the effect of climate-risk exceedance

on supplier-termination, relative to the average effect ($[0.006 + 0.009 \times 0.807]/0.006 = 2.2$), for flood days. Consistent with this result we find a negative, albeit statistically imprecise, effect of industry-input concentration, i.e. customers who procure a larger proportion of their total inputs from one industry in Column (2).

We next study the role of relationship length and sales correlation on the effect of shock exceedance on supplier termination. Focusing on floods, we find negative coefficient estimates (significant at the 1% level) for the interaction terms of both relationship length and supplier-customer sales correlation with flood related 'climate-risk exceedance'. We find qualitatively similar results, albeit statistically insignificant estimates for sales correlation, when considering heat. This finding is in line with the notion that relationship-specific investments increase switching costs of customers. As supply-chains become more closely integrated, the cost of terminating existing relationships increases and hence modulates customers' reactions to experienced weather shocks in excess of expectation.

4.2 Experienced Heat Days and Temperature Projections

Our previous tests indicate that firms form expectations about climate risks based on backward-looking historical information. However, this approach is not without difficulty as weather outcomes provide a noisy signal of persistent changes. As the plots illustrating the identifying variation in Figures 6a and 6b show, the perceived changes in exposure are not necessarily representative of trends in the mean of local distributions of weather shocks. To investigate possible limitations of firms' learning processes based on experienced change, we examine how firms respond when experienced changes differ from future projections.

To do so, we focus on cases where the change in local heat days until mid-century is projected to be close to zero. If projections indicate minimal change in local climate going forward, relationship-specific investments to adopt new suppliers in response to short-term trends may be undesirable. We again implement Equation (5), but estimate the regression model for subsamples in which there is little projected change in long-term temperatures according to the RCP 2.6 (column 1), RCP 4.5 (column 2), and RCP 8.5 (column 3) scenarios. Specifically, we focus on observations for which the projected difference in number of heat days comparing the periods 2006–2019 and 2049–2060 is smaller than 7 days per year under the respective scenario. The three scenarios represent three of

the main trajectories adopted by the IPCC, with the RCP 2.6 representing a very stringent scenario with strong policy intervention. RCP 8.5 is closest to a business as usual scenario, assuming very limited policy interventions directed at emissions reduction.

[Insert Table 11 here.]

Table 11 presents the results for these estimations. Panel 11a shows the results when we estimate priors over a 10 year period before the start of each relationship, Panel 11b uses a 15 year formation period. Across all climate scenarios and specifications, we find that the magnitude of responses to deviations of expected and experienced climate risk are indistinguishable from our main results in Section 7. One possible interpretation of this result is that firms respond to experienced changes regardless of whether these changes are indicative of projected trends. As Moore (2017) points out, adaptation will only occur at the speed at which economic agents learn about climate change. If investments are based on perceived short-term changes, adaptation may insufficiently reflect long-term projections and progress slower than necessary.

5 Climate Risk Exposure and Supplier Replacement

In the last part of our analysis, we examine how climate risk exposure affects replacement choices and the selection of new suppliers. This helps us address two questions raised by our previous analyses: First, do firms deliberately manage climate risk factors? If customers observe the adverse financial effects of indirect weather shocks, but are agnostic about the underlying driver, we would not expect to see permanent decreases in the risk exposure of 'new' (i.e. replacement) compared to 'old' (i.e. terminated) suppliers.

Second, how do firms assess noisy climate signals obtained from short-run climate realizations? We generally assume that customers evaluate existing suppliers and potential replacements during the initial supplier-relationship. Hence, if firms primarily respond to experienced shocks, but do not take into account that these signals are noisy in the short-run, replacement suppliers may have experienced more favorable conditions during the initial supplier-relationship despite having a similar underlying climate distribution as the 'old' suppliers.

To address these questions, we limit our dataset to supplier-customer links with a known end

date. For each supplier whose relationship with a customer ends throughout our sample period (i.e. 'replaced' supplier), we identify likely 'replacement' suppliers who enter a new supply-chain relationship with the same customer in the following year. We require replacement candidates to have the same 4-digit SIC code as the 'old' supplier. As before, we drop customer-supplier pairs located in the same geographic region, and exclude customers and suppliers in the financial industry and firms with a concentration of facilities around the headquarters below 10%. After applying these filters, we identify replacement suppliers for 16,900 customer-supplier pairs in our sample.

As illustrated in Figure 3, we first compare the climate exposure of the replaced suppliers to the exposure that their replacements would have had *during* the 'initial' relationship. Second, we compare 'new' and 'old' suppliers over the time period *after* the initial (i.e. during the new) supplier relationship. For each comparison, we estimate the following linear probability model to study the effect of increases in climate-risk exposure on the selection of new suppliers:

$$\begin{aligned} \mathbb{1}(Exposure\ New < Old)_{sc} = \beta \times \mathbb{1}\left(Realized > Expected\ Shocks\right)_{st} \\ + \gamma_{n(s)t} + \gamma_{n(c)t} + \theta_{d(s)t} + \theta_{d(c)t} + \epsilon_{sc} \end{aligned} \tag{6}$$

where $\mathbb{1}(Exposure\ New < Old)_{sc}$ takes the value of one if the 'new' supplier has a lower climate risk exposure than the 'old' supplier, and zero otherwise. $\mathbb{1}(Realized > Expected\ Shocks)_{st}$ indicates the exceedance of climate risk expectations at the location of supplier s in the last relationship year t before termination to identify supplier which were more likely to be terminated due to climate risk reasons. We include industry- and country-by-year fixed effects (γ_{nt}, θ_{ct}) for suppliers s and customers c. Table 12 summarizes the results.

[Insert Table 12 here.]

We find a strong positive effect of climate risk exceedance on the likelihood that replacement suppliers had a lower ex-post exposure to heat shocks than terminated suppliers *during* the initial relationship, as shown in Columns (1) and (2) of Panel 12a and Panel 12b. The likelihood that new suppliers had a lower heat exposure than old suppliers is 12.1 percentage points higher for suppliers that were more likely terminated due to climate risk (i.e. $\mathbb{1}\left(Realized > Expected\ Shocks\right) = 1$). This finding is consistent with the idea that customers choose replacement suppliers which exhibited lower climate exposure in the past when the perceived climate-risk has changed in the location of

the 'old' supplier.

At the same time, even if customers disregard climate risks and on average switch to replacement suppliers in ex-ante similar climate zones, we might find a difference in climate exposure *during* the initial relationship, as the 'old' supplier by construction experienced a high number of shocks drawn randomly from the underlying distribution. However, we would expect no difference in climate exposure between 'old' and 'new' suppliers *after* the initial relationship, as both firms in this case would have similar ex-ante climate expectations. Importantly, we find that a large proportion of the documented effect remains when we consider the period *after* the initial relationship ended. As shown in Columns (3) and (4) of Panel 12a, we find that 'new' suppliers were 6 to 10 percentage points more likely (statistically significant at the 5% and 1% level) to experience a decrease in actual heat shocks compared to 'old' suppliers *going forward*. This result indicates that customers on average choose replacement suppliers with an ex-ante different local climate distribution. In contrast, these findings are inconsistent with a purely statistical effect, under which 'old' and 'new' suppliers' climate realizations revert to the mean after switching suppliers.

We further consider long-term heat projections for 'old' and 'new' suppliers in Columns (5) and (6).[41] We find a small, less precisely estimated positive effect of climate-risk exceedance on the difference in heat projections between 'new' and 'old' suppliers. Regarding flood risk in Panels 12c and 12d, we find qualitatively similar results. We document a large difference in ex-post flood exposure of 'new' and 'old' suppliers *during* the initial relationship, but a smaller, less precisely estimated difference in the period *after* compared to our results for heat exposure. This result is potentially due to the fact that floods occur less frequently. Hence, when we consider the period after which the initial supplier was affected by a flood, the substitution of suppliers with firms located in areas with less flood risk may only lead to identifiable decreases in exposure after longer periods of time.

Taken together, our results indicate that climate risk exposure affects not only the termination but also the formation of new supply-chain relationships, as customers switch from suppliers which experienced more weather shocks than expected to replacements in less exposed areas. This effect is more precisely estimated for heat compared to flood events, and weaker when considering heat

[41] We use projections of future heat days between 2040 and 2069 under the RCP 4.5 scenario as modelled by the Max Planck Institute for Meteorology.

projections from long-term climate models.

6 Conclusion

This paper studies if firms adjust their supply-chain networks as a result of perceived changes in their suppliers' exposure to physical climate risks. To address this question, we combine granular data on global supply-chain relationships from FactSet Revere with meteorologic records of high temperatures from the ECMWF, spatial information on floods from the DFO, and daily temperature projections from the CMIP5. Our final sample includes 5,628 (8,200) supplier (customer) firms across 92 (74) countries from 2003 to 2017. We document three main insights.

First, we find that the financial performance of suppliers is negatively affected by heat and flooding incidents, and show that the financial consequences of these shocks propagate to customers through existing supply chain links. Second, we show that firms adapt their supply-chain organizations when weather shocks at the locations of their supplier firms become more frequent. Consistent with models of experience-based Bayesian updating, this effect increases with signal strength and repetition, cannot be explained by transitory shocks, and is stronger for suppliers in competitive industries and weaker for closely integrated supply-chain relationships. Third, we document that customers choose replacement suppliers with lower expected climate risks.

Our findings have potentially important implications. The adaptation efforts of internationally diversified firms could have meaningful consequences for international economic development. As developing countries are likely to experience the most pronounced increases in the frequency of weather shocks, firms in less developed countries might be more likely to be substituted by customers in favor of suppliers in less vulnerable locations. As a result, the outlined effects could further economically weaken the areas most vulnerable to climate change. Further, our findings could be relevant for estimations of the social cost of carbon, as current estimations do not take indirect negative performance effects of heat and flood events into account.

Taken together, our study contributes to the rapidly growing academic literature on the financial economics of climate change, and is among the first studies to provide evidence on how firms adapt to climate change.

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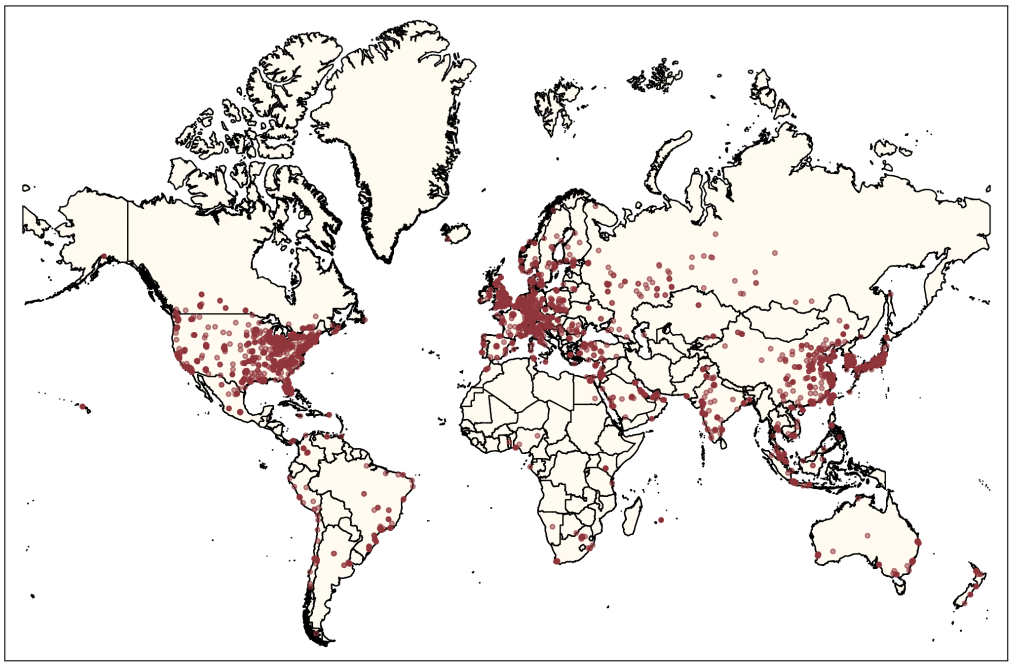
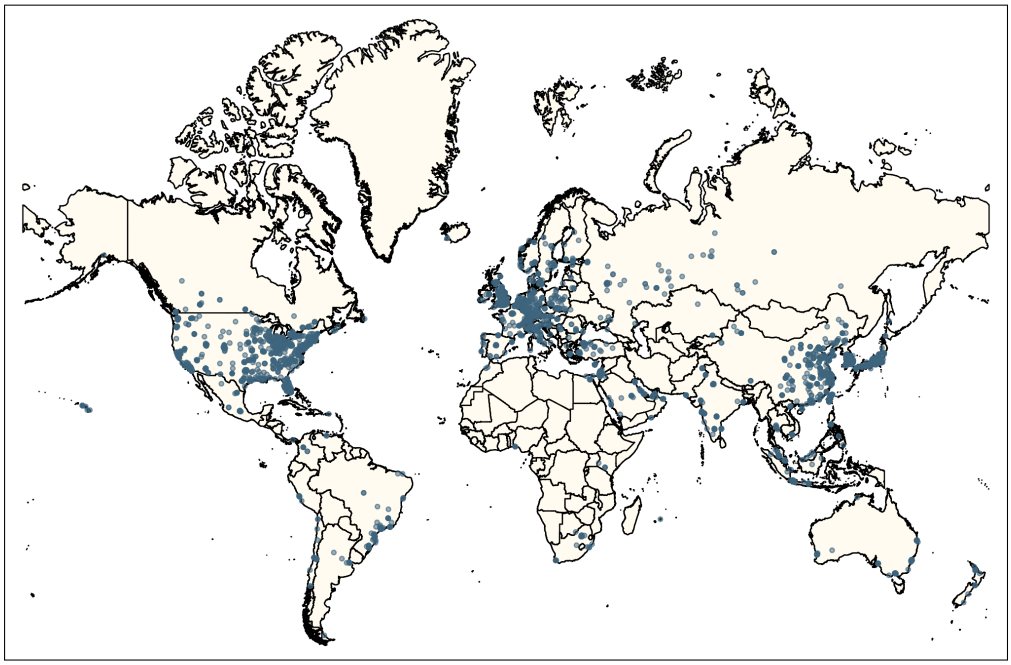
Tables and Figures

Figure 1: Geographic Distribution of Customers and Suppliers



(a) Distribution of Customers

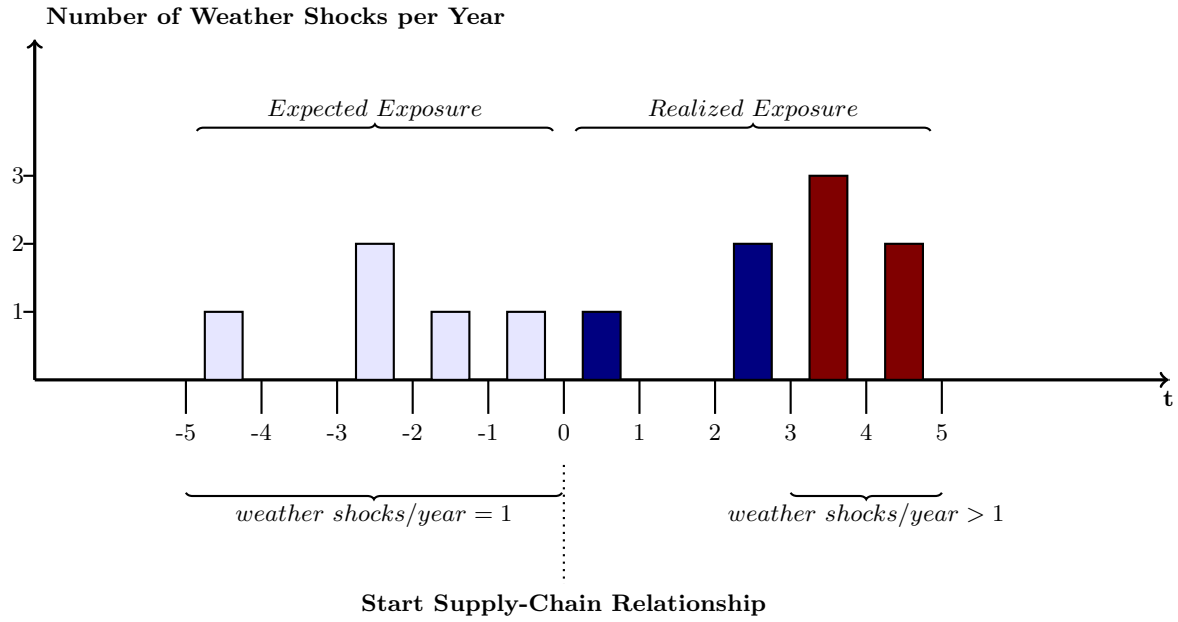


(b) Distribution of Suppliers

This figure shows the geographical distribution of the customers and suppliers in our sample. Supply-chain relationships and firm locations are obtained from FactSet Revere and FactSet Fundamentals, respectively. The corresponding Table 1 reports the number of customers by geographic regions.

Verbal Description This figure shows two maps of the world to illustrate the geographical distribution of the customers and suppliers the sample. Panel (a) shows a map with the country boundaries and red dots marking the location of supplier headquarters. Panel (b) shows the same map with blue dots marking the location of customer locations. Supply-chain relationships and firm locations are obtained from FactSet Revere and FactSet Fundamentals, respectively. The sample is global and both suppliers and customers are distributed over a large number of countries, with stronger concentration in the Eastern United States, along the West Coast of the Unites States, in Northern and Western Europe, in East Asia, and Japan. The corresponding Table 1 reports the exact number of suppliers and customers by geographic regions.

Figure 2: Variable Construction — Expected vs. Realized Climate Risk

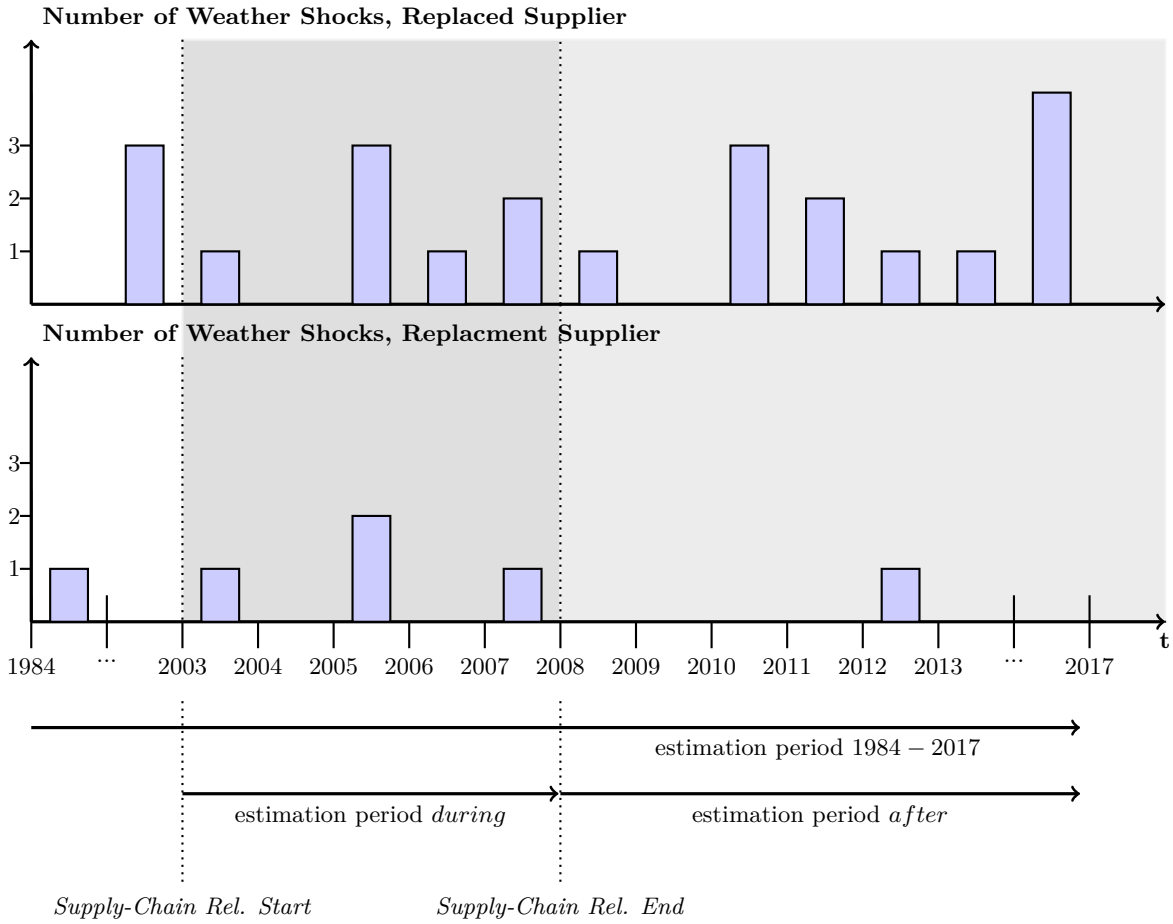


This figure illustrates the construction of our main measure capturing the discrepancy between realized and expected climate risk based on the exposure of a hypothetical supplier to heat and flood days over time, i.e. $\mathbb{1}\left(Realized > Expected\ Shocks\right)\ (t)$. This indicator variable is constructed by first estimating the historical prior as the average number of weather shocks per year in the supplier location over a benchmark period of five years *before* the establishment of a given supplier-customer relationship. In robustness tests we use alternative estimation horizons of seven, ten, and fifteen years. $\mathbb{1}\left(Realized > Expected\ Shocks\right)\ (t)$ then takes the value of one in a given year t, if the difference between the realized number of climate shocks per year since the beginning of the supplier-customer relationship exceeds the corresponding expected number of shocks, and zero otherwise. For example, in the case illustrated above, the average number of weather shocks over the five-year benchmark period before the beginning of the supply-chain relationship is one, i.e. $climate\ shocks/year = 1$ (*illustrated in light blue*). In year 1, the realized number of shocks is 1 and hence does not exceed the expected value from the benchmark period. Similarly, in year 3 the number of shocks is 2, bringing the average number of annual shocks since the beginning of the supply-chain relationship to 1 (i.e. $(1 + 0 + 2)/3 = 1$), which also does not exceed the prior (*highlighted in dark blue*). In years 4 and 5, the average number of realized annual shocks increases above 1 and exceeds the expected value from the benchmark period (*highlighted in red*). $\mathbb{1}\left(Realized > Expected\ Shocks\right)\ (t)$ would be zero in $t = 1$ through $t = 3$, and one in $t = 4$ and $t = 5$ in the illustrated example.

Verbal Description This figure illustrates an example of the construction of our main measure. It captures the discrepancy between realized and expected climate risk based on the exposure of a hypothetical supplier to heat and flood days over time, i.e. $\mathbb{1}\left(Realized > Expected\ Shocks\right)\ (t)$. This indicator variable is constructed by first estimating the historical prior as the average number of weather shocks per year in the supplier location over a benchmark period of five years *before* the establishment of a given supplier-customer relationship. In robustness tests we use alternative estimation horizons of seven, ten, and fifteen years. $\mathbb{1}\left(Realized > Expected\ Shocks\right)\ (t)$ then takes the value of one in a given year t, if the difference between the realized number of climate shocks per year since the beginning of the supplier-customer relationship exceeds the corresponding expected number of shocks, and zero otherwise.

In the figure, the y-axis shows the number of weather shocks per year at the location of a hypothetical supplier firm. The x-axis shows the timeline of a customer relationship for this supplier, starting five years before the supply chain relationship (t=-5) and ending five years into the relationship (t=5). In the example in the figure, the average number of weather shocks over the five-year benchmark period before the beginning of the supply-chain relationship [-5,0] is one on average, i.e. $climate\ shocks/year = 1$ (*illustrated in light blue*), with 1 shock in t=-5, two shocks in t=-3, and 1 shock in t=-2 and t=-1, respectively. In the benchmark period, the customer-supplier relationship is not active yet, and the customer assesses the average annual exposure of the supplier, *Expected Shocks*. In the first year of the relationship t=1, the realized number of shocks is 1. Hence, the expected value of shocks from the benchmark period is not exceeded, $\mathbb{1}\left(Realized > Expected\ Shocks\right)\ (t)$ would be zero in $t = 1$. There are no shocks in t=2. In t=3, the number of shocks is 2, increasing the average number of annual shocks since the beginning of the supply-chain relationship to 1 (i.e. $(1 + 0 + 2)/3 = 1$), which also does not exceed the prior (*highlighted in dark blue*). Therefore, $\mathbb{1}\left(Realized > Expected\ Shocks\right)\ (t)$ would still be zero in $t = 3$. In t=4 and t=5, 3 and 4 shocks occur. The average number of annual shocks increases above 1 and now exceeds the expected value from the benchmark period (*highlighted in red*). $\mathbb{1}\left(Realized > Expected\ Shocks\right)\ (t)$ switches to 1 in $t = 4$ and $t = 5$.

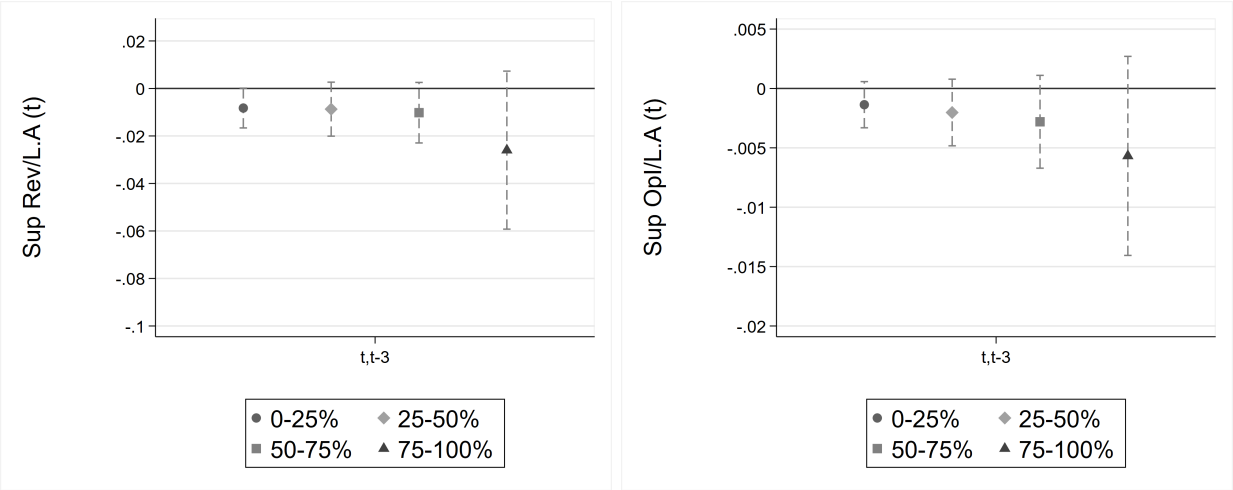
Figure 3: Variable Construction – Exposure of Replaced and Replacement Suppliers



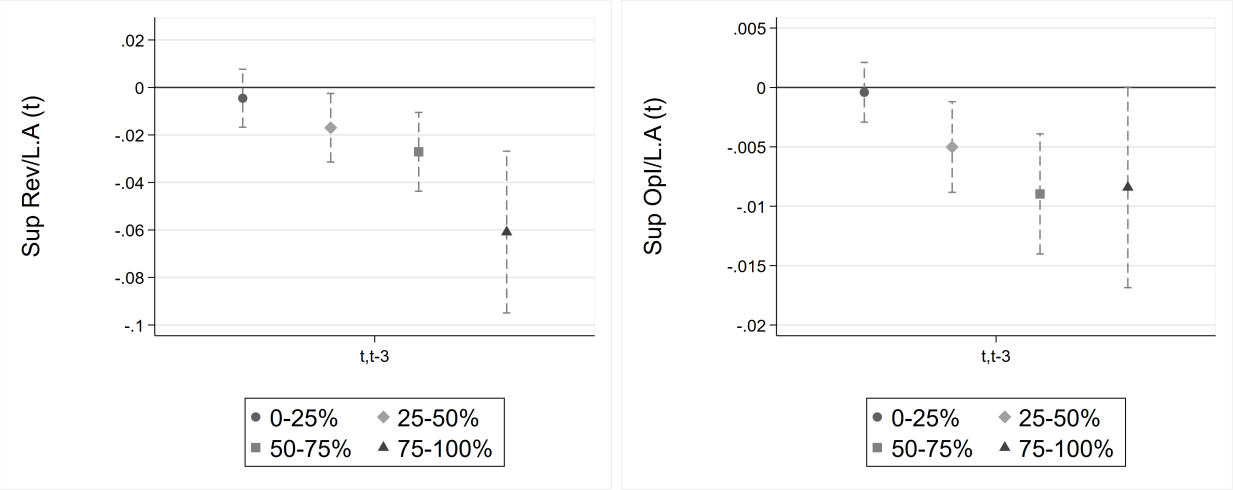
This figure illustrates the construction of the comparison of the climate exposure of replaced and replacement suppliers (Table 12) based on an example of a hypothetical replaced supplier and the replacement. We compare the heat and flood days of old and new suppliers based on three time periods. First, we estimate and compare the climate risk exposure of the replaced and replacement supplier based on the years (*in dark grey*) during which the initial supply-chain relationship was active. Second, we compare the exposure of both suppliers after the initial supplier has been replaced (*in light grey*). Third, we compare the exposure of both suppliers according to long-term forecasts from scientific climate change models.

Verbal Description This figure illustrates the construction of the comparison of the climate exposure of replaced and replacement suppliers (Table 12) based on an example of a hypothetical replaced supplier and the replacement. The figure has two panels. In the first panel, the y-axis shows the number of weather shocks (annual heat and flood days) for the replaced supplier. In the second panel, the y-axis shows the number of shocks for the new replacement supplier. The x-axis tracks the timeline of the sample from 1984 to 2017. We compare the heat and flood days of old and new suppliers based on three time periods. First, we estimate and compare the climate risk exposure of the replaced and replacement supplier based on the years during which the initial, hypothetical supply-chain relationship was active. For the example, we choose a relationship lasting from 2003 to 2007. In both panels, the region of these years is shaded in in dark grey. The start (t=2003) is labeled 'supply-chain relationship start', the end (t=2008) is labeled 'supply-chain relationship end', and the period is named 'estimation period during'. In the first panel of the replaced supplier, the number if shocks is 1 in 2003, 3 in 2005, 1 in 2006, and 2 in 2007. In the second panel of the replacement supplier, the average number of shocks is lower, with one shock occurring in 2003, 2 shocks in 2005, and 1 shock in 2007. Second, we compare the exposure of both suppliers after the initial supplier has been replaced from 2008 to 2017. The region of shocks in these years is shaded (*in light grey*). The start(t=2008) is labeled 'supply-chain relationship end', and the period is named 'estimation period after'. In this period and in the first panel of the replaced supplier, the number if shocks is 1 in 2008, 3 in 2010, 2 in 2011, 1 in 2012, 1 in 2013, and 4 in 2016. In the second panel of the replacement supplier, the average number of shocks is lower, with one shock occurring in 2012. Third, we compare the exposure of both suppliers during the full sample period from 1984 to 2017, labeled 'estimation period 1984 - 2017'.

Figure 4: Direct Effects of Weather Shocks By Firm Geographic Concentration



(a) Effect of Heat Days, Supplier Geographic Concentration



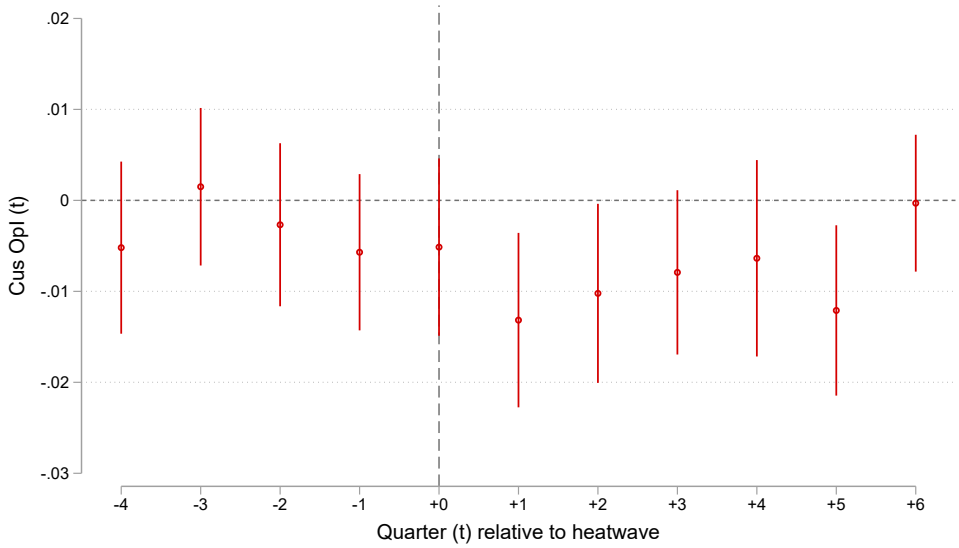
(b) Effect of Flood Days, Supplier Geographic Concentration

This figure shows the effect of heat days and flood days on suppliers' revenues (Rev) and operating income (OpI), both scaled by firm assets lagged by one year with 95% confidence intervals. The effects are estimated as outlined in Equation 1 for subsamples of the data based on the percentage of firms within 30km of the supplier's headquarters. The main variable of interest is the sum of days on which heat or flooding occurred during the financial quarters $t-3$ to t. The number of firms by concentration is 3,514 (0-25%), 2,412 (25-50%), 1,861 (50-75%), 484 (75-100%). We exclude firms in the financial industry. All regressions include firm-by-fiscal quarter fixed effects, industry-by-year-by-quarter fixed effects, controls for country-specific linear trends, and interaction terms of terciles of firm size, age, and ROA with year-by-quarter fixed effects to control for firm characteristics, following Barrot and Sauvagnat (2016) (BS2016).

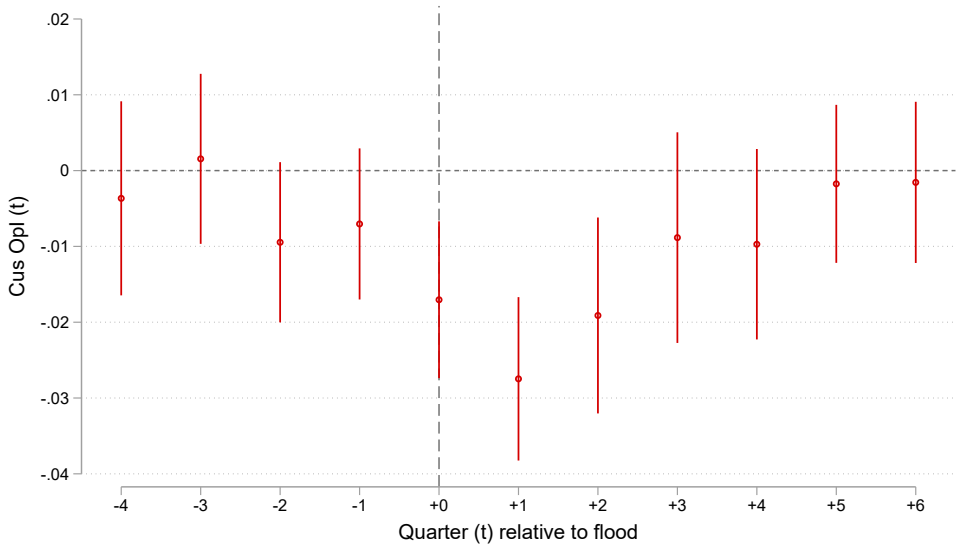
Verbal Description This figure shows the effect of heat days and flood days on suppliers' revenues and operating income by geographic concentration. The figure consists of four individual charts. The effect of heat days on revenues over assets is shown in the top left and the effect of heat on operating income over assets is shown in the top right. The effect of floods on revenues is shown in the bottom left and the effect of floods on operating income is shown in the bottom right. All individual charts show four different estimations for subsamples of the data based on the percentage of firms' locations obtained from Orbis that lie within 30km of the supplier's headquarters. The first susample consists of firms with 0-25% of locations concentrated within a 30km radius of the headquarters. The second subsample contains firms with 25-50%, the third contains firms with 50-75%, and the fourth contains firms with 75-100% concentration. The number of firms by concentration is 3,514 (0-25%), 2,412 (25-50%), 1,861 (50-75%), 484 (75-100%). For each of the four subsamples, the effects are estimated as outlined in Equation 1. The individual charts plot the coefficient of the sum of days on which heat or flooding occurred during the financial quarters $t-3$ to t together with 95% confidence intervals. We exclude firms in the financial industry. All regressions include firm-by-fiscal quarter fixed effects, industry-by-year-by-quarter fixed effects, controls for country-specific linear trends, and interaction terms of terciles of firm size, age, and ROA with year-by-quarter fixed effects to control for firm characteristics, following Barrot and Sauvagnat (2016) (BS2016).

The charts show the effects on the outcomes, revenues and operating income over assets, on the y-axis, and the coefficients ordered by concentration category along the x-axis. First, on the top left, we find similar coefficients sizes for the first three concentration categories (approximately -0.01 for 0-25%, 25-50%, and 50-75%) and a more negative effect for the most concentrated firms (75-100%) (approximately -0.023). The effect for the first category is significant, and insignificant for all other categories with the confidence interval just crossing the x-axis. Second, on the top right, the effect of heat days on operating income becomes larger with firm concentration in absolute terms (0-25%: $\approx$ -0.002, 25-50%: $\approx$ -0.0025, 50-75%: $\approx$ -0.0025, 75-100%: $\approx$ -0.006). All effects are insignificant with the confidence interval just crossing the x-axis. Third, on the bottom left, the effects of floods on revenues over assets also become more negative with firm concentration (0-25%: $\approx$ -0.005, 25-50%: $\approx$ -0.02, 50-75: $\approx$ -0.03, 75-100: $\approx$ -0.06). The effects for the three categories with concentrations of 25% and higher are significantly different from zero. Fourth, on the bottom right, the effects of flood days on operating income become more negative with concentration except for the most concentrated category (0-25%: $\approx$ 0, 25-50%: $\approx$ -0.005, 50-75: $\approx$ -0.009, 75-100: $\approx$ -0.008). Except for the estimation on the subsample of firms with 0-25% concentration, the coefficients are significantly different from zero.

Figure 5: Dynamics Plots – Weather Shocks to Suppliers and Customer Performance



(a) Customer operating income around supplier heatwaves



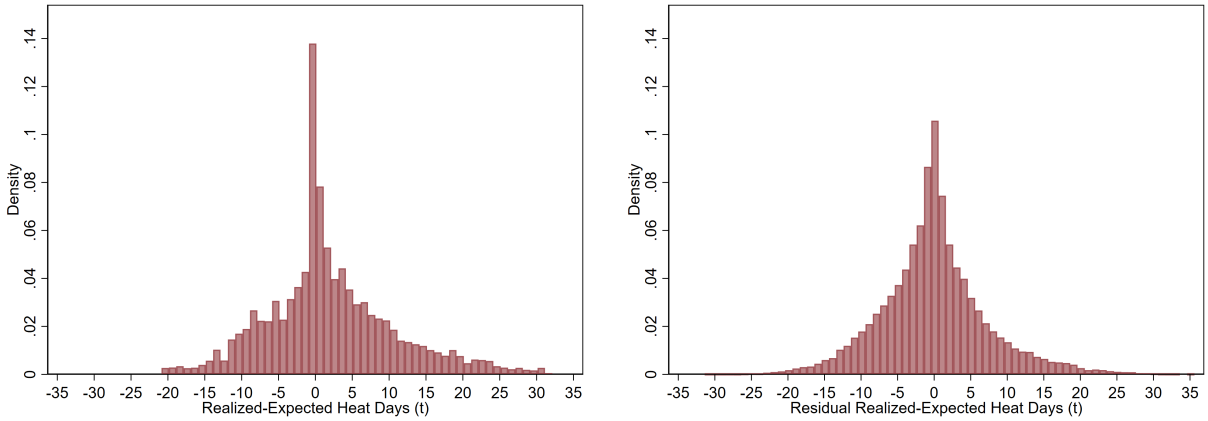
(b) Customer operating income around supplier floods

This figure shows the effect of heatwaves and floods at the supplier firm locations on customer operating income in the 11 quarters around weather shocks on suppliers. Specifically, the plots in Fig. 5a and 5b show the coefficient estimates and corresponding 95% confidence intervals for β_t from Equation (2) with $t \in [-4; 6]$ for heatwaves and floods, respectively. As in Appendix Table A3, we use indicator variables of heatwaves and floods in this figure. Each model includes customer-by-quarter fixed effects, industry-by-year-by-quarter (SIC 2 digit) fixed effects, country-specific time-trends, and size, age, and profitability by time fixed effects as in Barrot and Sauvagnat (2016).

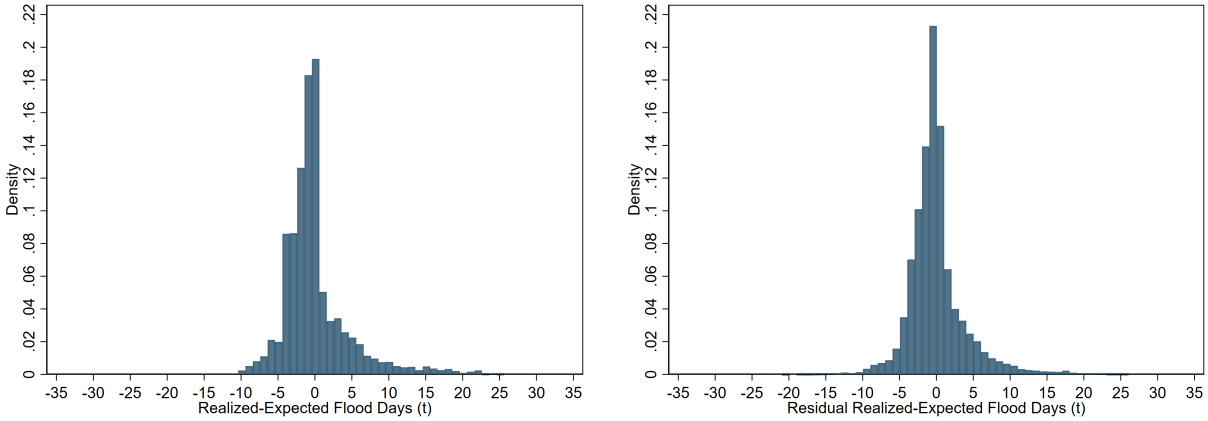
Verbal Description This figure shows the effect of heatwaves and floods at the supplier firm locations on customer operating income in the 11 quarters around weather shocks on suppliers. It consists of two parts, first the plot of the effects of heat on operating income in Figure 5a and second the plot of the effects of floods on operating income in Figure 5b. Both subfigures show the coefficient estimates and corresponding 95% confidence intervals for β_t from Equation (2) with $t \in [-4; 6]$ for heatwaves and floods, respectively. The y-axis plots the effect size, the x-axis shows the coefficients for each of the lags for $t \in [-4; 6]$. As in Appendix Table A3, we use indicator variables of heatwaves and floods in this figure. Each model includes customer-by-quarter fixed effects, industry-by-year-by-quarter (SIC 2 digit) fixed effects, country-specific time-trends, and size, age, and profitability by time fixed effects as in Barrot and Sauvagnat (2016).

In Figure 5a, the effect of heat on operating income is insignificant from zero up until t=0 and in t=3, t=4, and t=6. In t=1, t=2, and t=3, the effects are negative and significantly different from zero (t=1 $\approx$ -0.0125, t=2 $\approx$ -0.01, t=5 $\approx$ -0.011). In Figure 5b, the effects are insignificant except for t=0 ($\approx$ -0.019), t=1 ($\approx$ -0.025), and t=2 ($\approx$ -0.02).

Figure 6: Identifying Variation in Realized vs. Expected Climate Risk



(a) Identifying Variation, Realized-Expected Heat Days



(b) Identifying Variation, Realized-Expected Flood Days

This figure shows the distribution of our main measure of interest, (*Realized* > *Expected Shocks*) (t), capturing the discrepancy between realized and expected climate risk both before and during the supply-chain relationship. The construction of the variable is illustrated in Figure 2. First, we estimate the historical prior as the expected number of heat and flood days per year in the supplier location over a benchmark period of ten (in robustness tests seven, ten, and fifteen) years *before* the establishment of a given supplier-customer relationship. Then we calculate the difference between this prior and the average realized number of climate shocks per year since the beginning of the supplier-customer relationship. Figure 6a shows the distribution of the absolute deviation of realized and expected exposure to heat *(left)* as well as the residual after absorbing customer industry-year, supplier industry-year, and customer country-supplier country-year fixed effects *(right)*. Figure 6b presents the corresponding distributions for floods.

Verbal Description This figure shows the distribution of the variation underlying our main measure of interest, (*Realized* > *Expected Shocks*) (t). The construction of the variable is illustrated in Figure 2. It shows the difference between the realized heat days and flood days during the relationship and the expected climate shocks before the supply-chain relationship. We estimate the expected number of heat and flood days per year in the supplier location over a benchmark period of ten (in robustness tests seven, ten, and fifteen) years *before* the establishment of a given supplier-customer relationship. It consists of four charts. In each of the four charts, the y-axis shows the density, the x-axis shows the difference between realized and expected heat or flood days. The top left shows the density for the difference of realized and expected heat days, and the bottom left shows the density for the difference of realized and expected flood days. The top right shows the density of the residual variation of the difference of realized and expected heat days after absorbing customer industry-year, supplier industry-year, and customer country-supplier country-year fixed effects. The bottom right shows the density for the residual of the difference of realized and expected flood days.

First, the distribution of realized and expected heat days on the top left is close to symmetric. It is unimodal and peaks around 0 with a density of ≈0.14, but somewhat more dense and skewed to the right. The difference in realized and expected days ranges from ≈-20 to ≈30 days per year. Second, the distribution of the residual of realized and expected heat days on the top left is even more symmetric. It is unimodal and peaks around 0 with a density of ≈0.11, but somewhat more dense left of the center. It is slightly skewed to the right, with the difference in realized and expected days ranging from ≈-20 to ≈25 days per year. Third, the distribution of realized and expected flood days on the bottom left is close to symmetric. It is unimodal and peaks around 0 with a density of ≈0.2, but more dense left of the center and skewed to the right. The difference in realized and expected days ranges from ≈-10 to ≈22 days per year. Fourth, the distribution of the residual of realized and expected flood days on the bottom right is also close to symmetric. It is unimodal and peaks around 0 with a density of ≈0.21. It is more dense left of the center and skewed to the right. The difference in realized and expected days ranges from ≈-10 to ≈17 days per year.

Table 1: Sample Composition

Notes. This table shows the industry and geographic distribution of customers and suppliers in our sample. We retain supplier and customer firms from the FactSet Revere universe of supply chain relationships if more than 50% of the supplier's assets are in their home country and at least one complete record of financial performance data and climate hazard records is available during the period from 2003 to 2017. We drop firms that operate in the financial industry (one-digit SIC code of 6). The number of observations refers to unique firms.

Customers

SIC Code	No.	%
Manufacturing (3)	2,310	28.2
Manufacturing (2)	1,500	18.3
Transport/Utilities	1,175	14.3
Retail/Wholesale	1,070	13.0
Services (7)	931	11.4
Mining/Construction	807	9.8
Services (8)	337	4.1
Administration	36	0.4
Agriculture	34	0.4
Total	8,200	100.0

Suppliers

SIC Code	No.	%
Manufacturing (3)	1,693	30.1
Manufacturing (2)	1,054	18.7
Services (7)	825	14.7
Transport/Utilities	693	12.3
Mining/Construction	646	11.5
Retail/Wholesale	394	7.0
Services (8)	278	4.9
Agriculture	26	0.5
Administration	19	0.3
Total	5,628	100.0

Customers

UN Regions (long)	No.	%
Asia	3,200	39.0
Americas	2,981	36.4
Europe	1,666	20.3
Oceania	250	3.0
Africa	103	1.3
Total	8,200	100.0

Suppliers

UN Regions (long)	No.	%
Asia	2,268	40.3
Americas	2,185	38.8
Europe	978	17.4
Oceania	148	2.6
Africa	49	0.9
Total	5,628	100.0

Customers

UN Regions (short)	No.	%
Northern America	2,633	32.1
Eastern Asia	2,140	26.1
Northern Europe	703	8.6
Western Europe	589	7.2
South-Eastern Asia	496	6.0
Western Asia	292	3.6
South America	282	3.4
Southern Asia	267	3.3
Australia and New Zealand	250	3.0
Southern Europe	192	2.3
Eastern Europe	182	2.2
Central America	65	0.8
Southern Africa	61	0.7
Northern Africa	27	0.3
Eastern Africa	9	0.1
Central Asia	5	0.1
Western Africa	5	0.1
Caribbean	1	0.0
Middle Africa	1	0.0
Total	8,200	100.0

Suppliers

UN Regions (short)	No.	%
Northern America	1,944	34.5
Eastern Asia	1,647	29.3
Northern Europe	401	7.1
Western Europe	332	5.9
South-Eastern Asia	323	5.7
South America	204	3.6
Western Asia	192	3.4
Australia and New Zealand	148	2.6
Eastern Europe	128	2.3
Southern Europe	117	2.1
Southern Asia	104	1.8
Central America	37	0.7
Southern Africa	34	0.6
Northern Africa	7	0.1
Eastern Africa	4	0.1
Western Africa	4	0.1
Central Asia	2	0.0
Total	5,628	100.0

Table 2: Summary Statistics

Notes. This table presents summary statistics of the suppliers (Panel A), customers (Panel B), customer-supplier pairs (Panel C), and weather shocks (Panel D) in our sample. The sample period is 2003 to 2017. The number of observations refers to unique firm-year-quarters in Panels A, B, and D and pair-year-quarters in Panel C. Data on market capitalization ("MCap"), book value of assets ("Assets"), revenue, operating income ("Op. Income"), asset tangibility ("Tangibility"), inventory, operating margin, accounts payable ("AccPay")), and cost of goods sold ("COGS") are from Worldscope, all measured at the quarterly frequency, and scaled by one-year lagged total assets. "Tangibility" is the ratio of property, plants, and equipment (PPE) to total assets. "% of locations <30km from HQ" refers to the number of company facilities within 30km of the headquarter as obtained from Orbis. "Industry Competitiveness" is the number of firms (in thousands) per SIC 2-digit industry. "Asset4 ESG Score" is the firm's ESG score from the Thomson Reuters Asset4 database. "BEA Input-Ind. Concentration" is the Herfindahl-Hirschman Index (HHI) of inputs per industry from the BEA Input-Output matrices. "Supplier Diversification" is the ratio of the number of suppliers to unique supplier SIC 2-digit industries. "Sales Correlation" is the running correlation of supplier and customer sales over the previous 9 quarters. The number of suppliers and percentage of sales (COGS) are from Factset Revere. "Heatwave 30°C/7 (0/1)" indicates the occurrence of a heatwave as seven consecutive days above 30°C. The sample excludes observations with missing records on revenue and/or operating income, missing lagged climate variables, as well as records of firms that operate in the financial industry (SIC 1-digit code of 6).

	N	Mean	StDev	p25	Median	p75
Revenue / Assets (%)	226085	26.884	20.141	13.125	22.392	34.926
Op. Income / Assets (%)	225085	1.274	4.397	0.201	1.583	3.172
% Locations <30km from HQ	222031	29.598	24.568	7.755	22.222	50.000
Asset Tangibility (%)	192319	22.291	20.564	6.544	15.404	32.117
Ind. Vulnerability (%)	222031	5.433	22.666	0.000	0.000	0.000
Ind. Competitiveness	193251	1.201	0.807	0.489	1.048	1.923

(a) Unique Supplier-Year-Quarter Observations

	N	Mean	StDev	p25	Median	p75
Revenue / Assets (%)	125359	25.757	20.339	11.788	21.137	33.914
Op. Income / Assets (%)	125359	1.802	3.132	0.472	1.665	3.203
BEA Input-Ind. Concentration	55111	0.051	0.101	0.011	0.022	0.054
Inventory / Assets (%)	114785	10.688	11.122	1.611	7.937	15.936
Supplier Diversification	124023	1.060	0.747	0.500	1.000	1.250
Asset4 ESG Score	65814	50.621	19.509	35.102	50.475	66.083
Op. Margin (%)	124605	6.645	24.848	2.850	8.260	15.940
No. Suppliers / Assets (B. USD)	123944	3.176	6.901	0.407	1.025	2.733
AccPay / Assets (%)	103663	10.247	9.239	3.714	7.498	13.738
COGS / Assets (%)	114206	17.564	16.129	6.094	13.199	23.432

(b) Unique Customer-Year-Quarter Observations

	N	Mean	StDev	p25	Median	p75
Sales Correlation (%)	500046	16.116	44.091	-16.700	18.600	51.300
Relationship Age (Years)	746432	2.431	2.820	0.000	1.000	3.000
Pct. Sales Sup (%)	72651	18.571	17.091	10.000	13.900	21.600
Pct. COGS Cus (%)	60828	2.605	7.331	0.105	0.413	1.695
Sales Sup to Cus (M. USD)	62647	265.669	670.965	13.190	51.585	181.905
MCap Cus / MCap Sup	577941	317.660	1110.934	2.972	19.372	118.769
Assets Cus / Assets Sup	592222	490.463	1758.379	4.556	27.911	175.762

(c) Unique Firm-Pair-Year-Quarter Observations

	N	Mean	StDev	p25	Median	p75
Heat Days 30° C	202439	14.091	23.624	0.000	1.000	18.000
Heat Days (within-location)	202439	-0.000	16.170	-8.967	-1.128	3.571
Heat Days (conditional)	102526	27.823	26.830	5.000	18.000	46.000
Heatwave 30° C/7 (0/1)	202439	0.243	0.429	0.000	0.000	0.000
Heatwaves Count	202439	0.503	1.048	0.000	0.000	0.000
Average Temperature	202439	19.292	5.591	15.016	19.197	22.325
Flood Days	202439	0.696	3.954	0.000	0.000	0.000
Flood Days (conditional)	13113	10.738	11.554	4.000	6.000	12.000
Flood (0/1)	202439	0.065	0.246	0.000	0.000	0.000
Flood Count	202439	0.064	0.262	0.000	0.000	0.000
EMDAT Heat Days	202439	2.060	7.848	0.000	0.000	0.000
EMDAT Heatwave (0/1)	202439	0.124	0.329	0.000	0.000	0.000
EMDAT Flood (0/1)	202439	0.442	0.497	0.000	0.000	1.000
EMDAT Flood Days	202439	7.345	13.617	0.000	0.000	9.000

(d) Supplier Exposure to Weather Shocks

Table 3: Physical Climate Risk and Supplier Firm Performance

Notes. This table presents OLS regression estimates on the impact of heat and flooding at the location of the sample supplier firms on their revenues (Rev) and operating income (OpI), both scaled by assets lagged by one year. *Heat Days* (t) and *Flood Days* (t) indicate the number of days on which heat and floods occur during the financial quarter t and the three preceding quarters ($t-3$ to $t-1$). The number of observations refers to supplier firm year-quarters, and the sample period is 2003 to 2017. We exclude firms in the financial industry as well as firms with less than 10% of firm locations within 30 kilometers of the company headquarter. All regressions include firm-by-fiscal quarter fixed effects to control for time invariant firm characteristics and firm-specific seasonal effects, industry-by-year-by-quarter fixed effects, as well as controls for country-specific linear trends. Columns (2) and (4) additionally include interaction terms of terciles of firm size, age, and ROA with year-by-quarter fixed effects to control for firm characteristics (BS2016 FE), following Barrot and Sauvagnat (2016). Standard errors are clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

(a) Heat

	Sup Rev/L.A (t)		Sup OpI/L.A (t)	
	(1)	(2)	(3)	(4)
Heat Days (t)	-0.016***	-0.015***	-0.003**	-0.003**
	(0.005)	(0.005)	(0.001)	(0.001)
Heat Days (t-1)	-0.003	-0.002	-0.002*	-0.003*
	(0.005)	(0.005)	(0.001)	(0.001)
Heat Days (t-2)	-0.015***	-0.014***	-0.003**	-0.003**
	(0.005)	(0.005)	(0.001)	(0.001)
Heat Days (t-3)	-0.011**	-0.011**	-0.001	-0.001
	(0.005)	(0.005)	(0.001)	(0.001)
Firm × Fiscal-Qtr FE	Yes	Yes	Yes	Yes
Ind × Year-Qtr FE	Yes	Yes	Yes	Yes
Ctry-Linear-Trends	Yes	Yes	Yes	Yes
BS2016 FE	No	Yes	No	Yes
R^2	0.7626	0.7668	0.6258	0.6311
Observations	202,438	202,438	202,438	202,438
Suppliers	5,628	5,628	5,628	5,628

(b) Floods

	Sup Rev/L.A (t)		Sup OpI/L.A (t)	
	(1)	(2)	(3)	(4)
Flood Days (t)	-0.023***	-0.020***	-0.006***	-0.006***
	(0.007)	(0.007)	(0.002)	(0.002)
Flood Days (t-1)	-0.025***	-0.023***	-0.006***	-0.006***
	(0.006)	(0.006)	(0.002)	(0.002)
Flood Days (t-2)	-0.024***	-0.023***	-0.004**	-0.004**
	(0.006)	(0.006)	(0.002)	(0.002)
Flood Days (t-3)	-0.009	-0.008	-0.003	-0.003
	(0.007)	(0.008)	(0.002)	(0.002)
Firm × Fiscal-Qtr FE	Yes	Yes	Yes	Yes
Ind × Year-Qtr FE	Yes	Yes	Yes	Yes
Ctry-Linear-Trends	Yes	Yes	Yes	Yes
BS2016 FE	No	Yes	No	Yes
R^2	0.7626	0.7668	0.6258	0.6311
Observations	202,438	202,438	202,438	202,438
Suppliers	5,628	5,628	5,628	5,628

Table 4: Downstream Propagation of Weather Shocks

Notes. This table presents OLS regression estimates on the impact of heat and flooding at the location of the supplier firms on their *customers'* revenues (Rev) and operating income (OpI), both scaled by assets lagged by one year. *Heat Days* (t) and *Flood Days* (t) indicate the number of days on which heat (in excess of 30 degrees Celsius) and floods occurred during the financial quarter t and the three preceding quarters across all supplier firms of a given customer. The number of observations refers to customer firm-quarters, and the sample period is 2003 to 2017. We exclude customer and supplier firms in the financial industry, supplier firms with less than 10% of firm locations within 30 kilometers of the headquarters, and customer-supplier pairs with headquarters located within 500 kilometers of each other. All regressions include firm-by-fiscal quarter fixed effects, industry-by-year-by-quarter fixed effects, and country-specific linear trends. Columns (2) and (4) additionally include interaction terms of terciles of firm size, age, and ROA with year-by-quarter fixed effects to control for firm characteristics (BS2016 FE), following Barrot and Sauvagnat (2016). Standard errors are clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

(a) Heat

	Cus Rev (t)		Cus OpI (t)	
	(1)	(2)	(3)	(4)
Sup Heat Days (t-0)	-0.0012***	-0.0012***	-0.0002***	-0.0001*
	(0.000)	(0.000)	(0.000)	(0.000)
Sup Heat Days (t-1)	-0.0017***	-0.0019***	-0.0003***	-0.0003***
	(0.000)	(0.000)	(0.000)	(0.000)
Sup Heat Days (t-2)	-0.0009**	-0.0011***	-0.0001*	-0.0001**
	(0.000)	(0.000)	(0.000)	(0.000)
Sup Heat Days (t-3)	-0.0010***	-0.0013***	-0.0002***	-0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)
Firm × Fiscal-Qtr FE	Yes	Yes	Yes	Yes
Ind × Year-Qtr FE	Yes	Yes	Yes	Yes
Ctry-Linear-Trends	Yes	Yes	Yes	Yes
BS2016 FE	No	Yes	No	Yes
Observations	123700	123700	123700	123700
R^2	.884	.886	.707	.711

(b) Floods

	Cus Rev (t)		Cus OpI (t)	
	(1)	(2)	(3)	(4)
Sup Flood Days (t-0)	-0.0069***	-0.0066***	-0.0014***	-0.0012***
	(0.001)	(0.001)	(0.000)	(0.000)
Sup Flood Days (t-1)	-0.0056***	-0.0055***	-0.0011***	-0.0010***
	(0.001)	(0.001)	(0.000)	(0.000)
Sup Flood Days (t-2)	-0.0059***	-0.0061***	-0.0013***	-0.0012***
	(0.001)	(0.001)	(0.000)	(0.000)
Sup Flood Days (t-3)	-0.0040***	-0.0047***	-0.0007**	-0.0006*
	(0.001)	(0.001)	(0.000)	(0.000)
Firm × Fiscal-Qtr FE	Yes	Yes	Yes	Yes
Ind × Year-Qtr FE	Yes	Yes	Yes	Yes
Ctry-Linear-Trends	Yes	Yes	Yes	Yes
BS2016 FE	No	Yes	No	Yes
Observations	123700	123700	123700	123700
R^2	.884	.886	.707	.711

Table 5: Downstream Propagation of Weather Shocks – Cross Section

Notes. This table presents OLS regression estimates on cross-sectional differences in the impact of heat and flooding at the location of the suppliers on customer performance. The dependent variable in both panels is customer operating income, scaled by one-year lagged assets. For easier readability, all dependent variables are scaled by multiplying with 100. *Heat Days* $(t, t-3)$ (Panel 5a) and *Flood Days* $(t, t-3)$ (Panel 5b) measures the total number of heat and flood days at all suppliers of a given customer during the contemporaneous and previous three quarters. The data is organized at the customer-year-quarter level and the sample period is 2003 to 2017. We apply similar data filters as in Table 4. "Sup Tangibility" is the ratio of property, plants, and equipment (PPE) to total assets of the supplier. "Sup Ind Vulnerability" takes the value of one for a given supplier if the firm is in the agriculture, mining, or construction sector (SIC 1-digit of 1, 2, or 3). "Sup Ind. Competitiveness" is the number of firms (in thousands) per SIC 2-digit industry. "Input-Ind. Concentration" is the HHI of inputs per industry from the BEA Input-Output matrices. "Sup Diversification" is the ratio of the number of suppliers to unique supplier SIC 2-digit industries. "Sales Correlation" is the running correlation of supplier and customer sales over the previous 9 quarters. "Relationship Length" is the time in years since the beginning of the relationship for the current period t. All regressions include firm-by-fiscal quarter fixed effects, industry-by-year-by-quarter fixed effects, for country-specific linear trends. Columns (2) and (4) additionally include interaction terms of terciles of firm size, age, and ROA with year-by-quarter fixed effects to control for firm characteristics (BS2016 FE), following Barrot and Sauvagnat (2016). Standard errors are clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Cus OpI (t)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Heat Days (t,t-3)	-0.0067	-0.0015	-0.0439***	0.0000	-0.0290***	-0.0182*	-0.0206***	-0.0331***
	(0.012)	(0.006)	(0.008)	(0.007)	(0.006)	(0.011)	(0.005)	(0.006)
Heat Days (t,t-3) × Sup Tangibility	-0.0005							
	(0.000)							
Heat Days (t,t-3) × Sup-Ind Vuln.		-0.0012***						
		(0.000)						
Heat Days (t,t-3) × Sup-Ind Comp.			0.0213***					
			(0.007)					
Heat Days (t,t-3) × Input-Ind Conc.				-0.0569***				
				(0.020)				
Heat Days (t,t-3) × Cus Inventory					0.0013***			
					(0.000)			
Heat Days (t,t-3) × Sup Divers.						0.0009		
						(0.005)		
Heat Days (t,t-3) × Sales Corr.							-0.0000	
							(0.000)	
Heat Days (t,t-3) × Rel. Length								0.0051***
								(0.001)
Sup Tangibility	0.1110							
	(0.137)							
Sup-Ind Vuln.		0.2369**						
		(0.117)						
Sup-Ind Comp.			-7.2028					
			(4.423)					
Cus Inventory					1.0956*			
					(0.597)			
Sup Divers.						-10.9024***		
						(3.939)		
Sales Corr.							-0.0817*	
							(0.048)	
Rel. Length								0.2317
								(1.374)
Firm × Fiscal-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind × Year-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ctry-Linear-Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BS2016 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	117039	123700	102762	54188	114095	122162	93025	123700
R^2	0.709	0.711	0.714	0.718	0.709	0.711	0.713	0.711

(a) Heat

	Cus OpI (t)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Flood Days (t,t-3)	0.0145	-0.0262	-0.2379***	-0.0361	-0.1815***	-0.1034	-0.0650**	-0.2289***
	(0.055)	(0.030)	(0.060)	(0.045)	(0.031)	(0.069)	(0.028)	(0.052)
Flood Days (t,t-3) × Sup Tangibility	-0.0040**							
	(0.002)							
Flood Days (t,t-3) × Sup-Ind Vuln.		-0.0043***						
		(0.001)						
Flood Days (t,t-3) × Sup-Ind Comp.			0.1385***					
			(0.048)					
Flood Days (t,t-3) × Input-Ind Conc.				-0.1513				
				(0.126)				
Flood Days (t,t-3) × Cus Inventory					0.0093***			
					(0.002)			
Flood Days (t,t-3) × Sup Divers.						0.0092		
						(0.032)		
Flood Days (t,t-3) × Sales Corr.							-0.0016*	
							(0.001)	
Flood Days (t,t-3) × Rel. Length								0.0428***
								(0.016)
Sup Tangibility	0.0753							
	(0.131)							
Sup-Ind Vuln.		0.0921						
		(0.112)						
Sup-Ind Comp.			-5.4896					
			(4.325)					
Cus Inventory					1.2976**			
					(0.584)			
Sup Divers.						-12.3944***		
						(3.786)		
Sales Corr.							-0.0668	
							(0.045)	
Rel. Length								0.7714
								(1.355)
Firm × Fiscal-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind × Year-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ctry-Linear-Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BS2016 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	117039	123700	102762	54188	114095	122162	93025	123700
R^2	0.709	0.711	0.713	0.718	0.709	0.710	0.713	0.711

(b) Floods

Table 6: Downstream Propagation of Weather Shocks – Other Outcomes

Notes. This table presents OLS regression estimates on the impact of heat and flooding at the location of the suppliers on several customer firm-level outcomes. The dependent variables in both Panels 6a and 6b are the customer operating margin, number of suppliers, accounts receivables, cost of goods sold, and inventory in quarter t in columns (1) through (5), respectively, all scaled by one-year lagged total assets. The data is organized at the customer-year-quarter level. The independent variables capturing the number of heat days and flood days across the suppliers of a given customer in quarters t to $t-3$, data filters, as well as fixed effects specifications are similar to Table 4. Standard errors are clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) Op. Margin (t)	(2) No. Suppliers (t)	(3) AccPay(t)	(4) COGS (t)	(5) Inventory (t)
Sup Heat Days (t-0)	-0.0005	0.0003***	-0.0005**	-0.0007***	-0.0002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sup Heat Days (t-1)	-0.0010*	0.0003***	-0.0005**	-0.0014***	-0.0005***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Sup Heat Days (t-2)	-0.0002	0.0003***	-0.0001	-0.0007**	-0.0002
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Sup Heat Days (t-3)	-0.0007	0.0005***	-0.0001	-0.0008***	-0.0003**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm × Fiscal-Qtr FE	Yes	Yes	Yes	Yes	Yes
Ind × Year-Qtr FE	Yes	Yes	Yes	Yes	Yes
Ctry-Linear-Trends	Yes	Yes	Yes	Yes	Yes
BS2016 FE	Yes	Yes	Yes	Yes	Yes
Observations	122947	122070	101949	112582	111637
R^2	.745	.912	.887	.913	.936

(a) Heat

	(1) Op. Margin (t)	(2) No. Suppliers (t)	(3) AccPay(t)	(4) COGS (t)	(5) Inventory (t)
Sup Flood Days (t-0)	-0.0034*	0.0010***	-0.0013**	-0.0039***	-0.0009*
	(0.002)	(0.000)	(0.001)	(0.001)	(0.001)
Sup Flood Days (t-1)	-0.0046***	0.0010***	-0.0013**	-0.0036***	-0.0014**
	(0.002)	(0.000)	(0.001)	(0.001)	(0.001)
Sup Flood Days (t-2)	-0.0032*	0.0011***	-0.0014**	-0.0043***	-0.0011*
	(0.002)	(0.000)	(0.001)	(0.001)	(0.001)
Sup Flood Days (t-3)	-0.0042**	0.0010***	-0.0001	-0.0025**	-0.0012*
	(0.002)	(0.000)	(0.001)	(0.001)	(0.001)
Firm × Fiscal-Qtr FE	Yes	Yes	Yes	Yes	Yes
Ind × Year-Qtr FE	Yes	Yes	Yes	Yes	Yes
Ctry-Linear-Trends	Yes	Yes	Yes	Yes	Yes
BS2016 FE	Yes	Yes	Yes	Yes	Yes
Observations	122947	122070	101949	112582	111637
R^2	.745	.912	.887	.913	.936

(b) Floods

Table 7: Expected vs. Realized Climate Risk and Relationship Termination

Notes. This table presents linear probability model (Panel 7a) and logit (Panel 7b) estimates on the effect of $\mathbb{1}(Realized > Expected\ Shocks)(t)$ on the likelihood of supply-chain relationships to end. This measure takes a value of one in year t if the difference between the realized number of heat and flood days per year since the beginning of the supply-chain relationship exceeds the corresponding expected number of heat and flood days, and zero otherwise. The construction is illustrated in Figure 2. The unit of observation is at the supplier-customer pair-year level. The dependent variable is a dummy variable taking the value of one if a given supplier-customer relationship ends after the current year t, and zero otherwise. As in previous analyses, customer or supplier firms in the financial industry, supplier firms with less than 10% of locations within a radius of 30km from the headquarters, and pairs with less than 500km distance between headquarters' are excluded from the tests. The regressions include year fixed effects, supplier and customer-industry-by-year, as well as supplier-country-by-customer-country-by-year fixed effects as indicated. Robust standard errors are clustered on the relationship level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	OLS - *Dependent Variable:* Last Relationship Year (0/1)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}Realized > Expected\ HeatDays$	0.005**	0.004*	0.009***			
	(0.002)	(0.002)	(0.002)			
$\mathbb{1}Realized > Expected\ FloodDays$				0.015***	0.014***	0.010***
				(0.002)	(0.002)	(0.003)
Year FE	Yes	No	No	Yes	No	No
Sup Ind-Year FE	No	Yes	Yes	No	Yes	Yes
Cus Ind-Year FE	No	Yes	Yes	No	Yes	Yes
Cus Ctry-Sup Ctry-Year FE	No	No	Yes	No	No	Yes
Observations	126205	126205	126205	126205	126205	126205
R^2	0.313	0.320	0.380	0.314	0.320	0.380

(a) Linear Probability: Expected > Realized Exposure to Heat or Floods

	Logit - Dependent Variable: Last Relationship Year (0/1)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}Realized > Expected\ HeatDays\ (t)$	0.050***	0.061***	0.078***			
	(0.016)	(0.017)	(0.017)			
$\mathbb{1}Realized > Expected\ FloodDays\ (t)$				0.087***	0.111***	0.079***
				(0.018)	(0.018)	(0.019)
Year FE	Yes	No	No	Yes	No	No
Cus Ind-Year-Qtr FE	No	Yes	No	No	Yes	No
Sup Ind-Year-Qtr FE	No	Yes	No	No	Yes	No
Cus Country-Sup Country-Year FE	No	No	Yes	No	No	Yes
Observations	106293	102784	106293	106293	102784	106293

(b) Logit Regression: Realized − Expected Exposure to Heat or Floods

Table 8: Strength of the Signal – Expected vs. Realized Climate Risk

Notes. This table presents linear probability model estimates on the effect of weather shock exceedance, i.e. $\mathbb{1}$ (*Realized* > *Expected Shocks*), on supply-chain relationship termination, taking into account how often realized heat and flood days have exceeded expectations (Panel 8a) as well as the magnitude of the deviation of realization and expectation (Panel 8b). The construction of the measure is shown in Figure 2. The unit of observation is at the supplier-customer pair-year level. The dependent variable is a dummy variable taking the value of one if a given supplier-customer relationship ends after the current year t, and zero otherwise. As in previous analyses, customer or supplier firms in the financial industry, supplier firms with less than 10% of locations within a radius of 30km from the headquarters, and pairs with less than 500km distance between headquarters' are excluded from the tests. The regressions include supplier and customer-industry-by-year, as well as supplier-country-by-customer-country-by-year fixed effects as indicated. Robust standard errors are clustered on the relationship level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	DV: Last Relationship Year (0/1)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$*Realized* > *Expected HeatDays*=1	-0.020***	-0.021***	-0.013***			
	(0.002)	(0.002)	(0.003)			
$\mathbb{1}$*Realized* > *Expected HeatDays*=2	0.076***	0.075***	0.082***			
	(0.003)	(0.003)	(0.004)			
$\mathbb{1}$*Realized* > *Expected HeatDays*=3	0.051***	0.049***	0.057***			
	(0.004)	(0.004)	(0.004)			
$\mathbb{1}$*Realized* > *Expected HeatDays*=4	0.059***	0.055***	0.045***			
	(0.006)	(0.006)	(0.006)			
$\mathbb{1}$*Realized* > *Expected HeatDays*=5	0.008**	0.008**	0.009**			
	(0.004)	(0.004)	(0.004)			
$\mathbb{1}$*Realized* > *Expected FloodDays*=1				0.020***	0.019***	0.016***
				(0.003)	(0.003)	(0.003)
$\mathbb{1}$*Realized* > *Expected FloodDays*=2				0.041***	0.039***	0.042***
				(0.004)	(0.004)	(0.005)
$\mathbb{1}$*Realized* > *Expected FloodDays*=3				0.023***	0.022***	0.019***
				(0.005)	(0.005)	(0.005)
$\mathbb{1}$*Realized* > *Expected FloodDays*=4				0.046***	0.045***	0.021***
				(0.007)	(0.007)	(0.007)
$\mathbb{1}$*Realized* > *Expected FloodDays*=5				-0.001	-0.000	-0.001
				(0.004)	(0.004)	(0.004)
Year FE	Yes	No	No	Yes	No	No
Sup Ind-Year FE	No	Yes	Yes	No	Yes	Yes
Cus Ind-Year FE	No	Yes	Yes	No	Yes	Yes
Cus Ctry-Sup Ctry-Year FE	No	No	Yes	No	No	Yes
Observations	126205	126205	126205	126205	126205	126205
R^2	0.319	0.326	0.384	0.314	0.321	0.380

(a) Functional Form: Effect of Realized > Expected Exposure on Relationship Termination

	DV: Last Relationship Year (0/1)					
	(1)	(2)	(3)	(4)	(5)	(6)
$Realized - Expected\ HeatDays(t)$	0.0003**	0.0001	0.0003**			
	(0.000)	(0.000)	(0.000)			
$Realized - Expected\ FloodDays(t)$				0.0017***	0.0017***	0.0005*
				(0.000)	(0.000)	(0.000)
Year FE	Yes	No	No	Yes	No	No
Sup Ind-Year FE	No	Yes	Yes	No	Yes	Yes
Cus Ind-Year FE	No	Yes	Yes	No	Yes	Yes
Cus Ctr-Sup Ctr-Year FE	No	No	Yes	No	No	Yes
Observations	120805	120805	120805	120805	120805	120805
R^2	0.312	0.319	0.381	0.312	0.319	0.381

(b) Continuous Measure: Expected > Realized Exposure to Heat or Floods

Table 9: Transitory Shocks and Relationship Termination

Notes. This table presents linear probability model estimates on the effect of transitory weather shocks on the likelihood of supply-chain relationship termination. *Realized Heat Days* and *Realized Flood Days* measure the number of heat and flood days at the supplier locations in a given year. ($Realized - Expected\ Shocks$) is the continuous difference between the realized and expected number of heat and flood days per year since the beginning of the supplier-customer relationship. The variable construction is illustrated in Figure 2. The unit of observation is at the supplier-customer pair-year level. The dependent variable is a dummy variable taking the value of one if a given supplier-customer relationship ends after the current year t, and zero otherwise. As in previous analyses, customer or supplier firms in the financial industry, supplier firms with less than 10% of locations within a radius of 30km from the headquarters, and pairs with less than 500km distance between headquarters' are excluded from the tests. Fixed effects are included as indicated in the table. Robust standard errors are clustered on the relationship level. *z-test* indicates the p-value from a z-test, testing the hypothesis that the difference between coefficient estimates in adjacent models (i.e. Columns (1) and (2), (3) and (4), etc.) are zero. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	DV: Last Relationship Year (0/1)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Realized\ HeatDays(t)$	0.0002*		0.0001					
	(0.000)		(0.000)					
$Realized - Expected\ HeatDays(t)$		0.0014***		0.0007**				
		(0.000)		(0.000)				
$Realized\ FloodDays(t)$					0.0005***		-0.0003*	
					(0.000)		(0.000)	
$Realized - Expected\ FloodDays(t)$						0.0037***		0.0005
						(0.000)		(0.000)
Sup Ind-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cus Ind-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cus Ctr-Sup Ctry-Year FE	No	No	Yes	Yes	No	No	Yes	Yes
Observations	127313	123384	123884	119946	127313	124424	123884	121022
Z-test	.	0.000	.	0.027	.	0.000	.	0.076
R^2	0.566	0.564	0.618	0.616	0.566	0.564	0.618	0.616

Table 10: Expected vs. Realized Climate Risk – Cross-Section

Notes. This table shows the cross-sectional heterogeneity in the impact of weather shock exceedance on supply-chain relationship termination. The measure $\mathbb{1}\,(Realized > Expected\ Shocks)\,(t)$ takes the value of one in year t if the difference between the realized number of heat and flood days per year since the beginning of the supplier-customer relationship exceeds the corresponding expected number of heat and flood days, and zero otherwise. The construction is shown in Figure 2. The unit of observation is at the supplier-customer pair-year level. The dependent variable is a dummy variable taking the value of one if a given supplier-customer relationship ends after the current year t, and zero otherwise. Similar to Table 5, "Sup-Ind Competitiveness" is the number of firms (in thousands) per SIC 2-digit industry of the supplier. "Input-Ind. Concentration" is the HHI of inputs per customer industry from the BEA Input-Output matrices. "Relationship Length" is the time in years since the beginning of the supply-chain relationship for the current period t. "Sales Correlation" is the running correlation of supplier and customer sales over the previous 9 quarters. We apply similar data filters as in Table 7. Each regression includes supplier and customer-industry-by-year fixed effects, as well as supplier-country-by-customer-country-by-year fixed effects as indicated. Robust standard errors are clustered on the relationship level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	DV: Last Relationship Year (0/1)			
	(1)	(2)	(3)	(4)
$\mathbb{1}\,(Realized > Exp.\ Heat\ Days)\ (t)$	0.006*	0.013***	0.019***	0.013***
	(0.004)	(0.004)	(0.003)	(0.003)
$\mathbb{1}\,(Realized > Exp.\ Heat\ Days)\ (t)$ × Sup-Ind Comp.	0.006*			
	(0.003)			
$\mathbb{1}\,(Realized > Exp.\ Heat\ Days)\ (t)$ × Input-Ind Conc.		-0.003		
		(0.063)		
$\mathbb{1}\,(Realized > Exp.\ Heat\ Days)\ (t)$ × Rel. Length			-0.004***	
			(0.001)	
$\mathbb{1}\,(Realized > Exp.\ Heat\ Days)\ (t)$ × Sales Corr.				-0.005
				(0.006)
Sup-Ind Comp.	-0.157			
	(0.279)			
Input-Ind Conc.		0.140		
		(0.091)		
Rel. Length			0.007***	
			(0.001)	
Sales Corr.				0.007
				(0.005)
Sup-Ind × Year FE	Yes	Yes	Yes	Yes
Cus-Ind × Yr FE	Yes	Yes	Yes	Yes
Cus-Ctry × Sup-Ctry × Yr FE	Yes	Yes	Yes	Yes
Observations	126140	50163	126145	78844
R^2	0.398	0.465	0.399	0.398

(a) Heat, Cross-Sectional Heterogeneity

	DV: Last Relationship Year (0/1)			
	(1)	(2)	(3)	(4)
$\mathbb{1}$ (*Realized* > *Exp. Flood Days*) (t)	0.006	0.019***	0.043***	0.002
	(0.004)	(0.005)	(0.004)	(0.003)
$\mathbb{1}$ (*Realized* > *Exp. Flood Days*) (t) × Sup-Ind Comp.	0.009**			
	(0.004)			
$\mathbb{1}$ (*Realized* > *Exp. Flood Days*) (t) × Input-Ind Conc.		-0.044		
		(0.073)		
$\mathbb{1}$ (*Realized* > *Exp. Flood Days*) (t) × Rel. Length			-0.011***	
			(0.001)	
$\mathbb{1}$ (*Realized* > *Exp. Flood Days*) (t) × Sales Corr.				-0.014**
				(0.007)
Sup-Ind Comp.	-0.154			
	(0.279)			
Input-Ind Conc.		0.152*		
		(0.086)		
Rel. Length			0.008***	
			(0.001)	
Sales Corr.				0.009**
				(0.004)
Sup-Ind × Year FE	Yes	Yes	Yes	Yes
Cus-Ind × Yr FE	Yes	Yes	Yes	Yes
Cus-Ctry × Sup-Ctry × Yr FE	Yes	Yes	Yes	Yes
Observations	126140	50163	126145	78844
R^2	0.398	0.465	0.400	0.398

(b) Floods, Cross-Sectional Heterogeneity

Table 11: Experienced Exposure, Projections, and Relationship Termination

Notes. This table presents linear probability model estimates on the effect of $\mathbb{1}(Realized > Expected\ Shocks)$ on the likelihood of supply-chain relationship termination. The construction of the measure is illustrated in Figure 2. Estimates are presented separately for the full sample (column 4), as well as subsets of suppliers located in areas which are projected to experience limited change in temperatures. The projected change is estimated as the difference between the number of days over 30° Celsius from 2006-2019 and 2040-2049. Projections are obtained from the MPI-ESM-LR model, and averaged across all available ensemble members for the RCP 2.6, 4.5, and 8.5 scenario. We exclude observations before the issue of the IPCC 4th assessment report in 2007. In Panel 11a (11b) the expected exposure is estimated over 10 (15) years prior to the relationship. The unit of observation is at the supplier-customer pair-year level. The dependent variable is a dummy variable taking the value of one if a given supplier-customer relationship ends after the current year t, and zero otherwise. As in previous analyses, customer or supplier firms in the financial industry, supplier firms with less than 10% of locations within a radius of 30km from the headquarters, and pairs with less than 500km distance between headquarters' are excluded from the tests. The regressions include supplier and customer-industry-by-year fixed effects and supplier-country-by-customer-country-by-year fixed effects as indicated. Robust standard errors are clustered on the relationship level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	≈0 RCP2.6	≈0 RCP4.5	≈0 RCP8.5	Full Sample
	(1)	(2)	(3)	(4)
$\mathbb{1}(Realized > Expected\ HeatDays)(t)$	0.011***	0.012**	0.017**	0.017***
	(0.004)	(0.005)	(0.007)	(0.002)
Sup Ind-Year FE	Yes	Yes	Yes	Yes
Cus Ind-Year FE	Yes	Yes	Yes	Yes
Cus Ctr-Sup Ctr-Year FE	Yes	Yes	Yes	Yes
Observations	49932	33122	20147	102975
R^2	0.431	0.455	0.471	0.427

(a) Exceeded Expected Exposure and Projections, prior formed over 10-year benchmark period.

	≈0 RCP2.6	≈0 RCP4.5	≈0 RCP8.5	Full Sample
	(1)	(2)	(3)	(4)
$\mathbb{1}(Realized > Expected\ HeatDays)(t)$	0.022***	0.014***	0.021***	0.021***
	(0.004)	(0.005)	(0.007)	(0.003)
Sup Ind-Year FE	Yes	Yes	Yes	Yes
Cus Ind-Year FE	Yes	Yes	Yes	Yes
Cus Ctr-Sup Ctr-Year FE	Yes	Yes	Yes	Yes
Observations	49932	33122	20147	102975
R^2	0.431	0.455	0.471	0.427

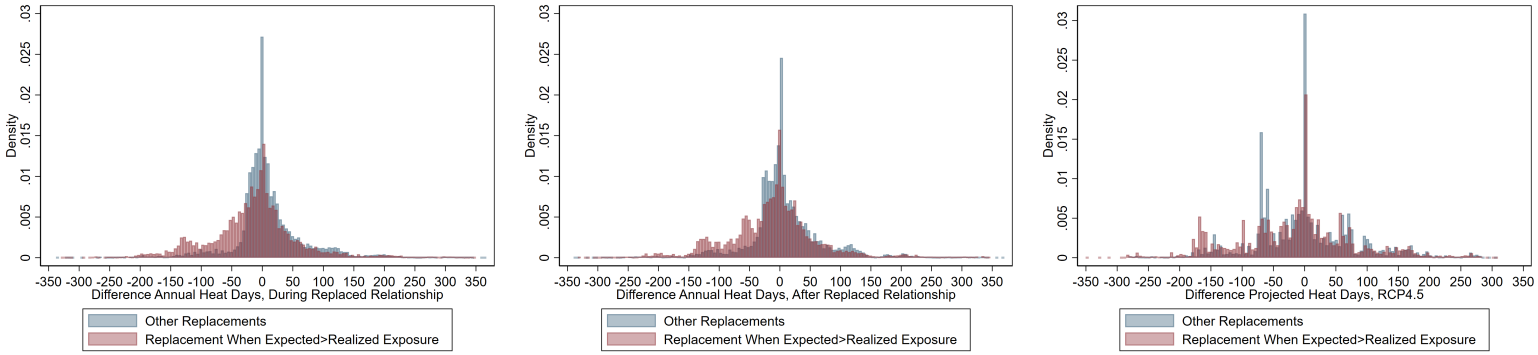
(b) Exceeded Expected Exposure and Projections, prior formed over 15-year benchmark period.

Table 12: Physical Climate Risk and Supplier Substitution

Notes. This table shows the effect of physical climate risk on supplier substitution. We match supplier firms for which the supplier-customer relationship is terminated during the sample period (i.e. *old suppliers*) with their likely replacements (i.e. *new suppliers*). Replacements are identified as firms with identical 4-digit SIC codes, which enter a new supply-chain relationship with the given customer within one year of the previous Panels 12a and 12c show linear probability model estimates on the likelihood that the exposure to weather shocks of *new* replacement suppliers is lower than the exposure of *old* replaced suppliers as a function of $\mathbb{1}(Realized > Expected\ Shocks)$. The dependent variable takes the value of one if new suppliers are exposed to fewer heat and flood days than old suppliers, during and after the initial supply-chain relationship, respectively. In Columns (5) and (6) of Panel 12a, the dependent variable takes the value of one if there are fewer shocks projected at the location of the new compared to the old supplier. Standard errors are clustered at the relationship level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. The figures in Panels 12b and 12d show the corresponding distribution of the difference (continuous measure) in exposure between new and old suppliers, measured during and after the relationship, and according to IPCC projections, respectively.

	Decrease Dur. Initial Rel.(0/1)		Decrease Aft. Initial Rel. (0/1)		Decrease Projected Days (0/1)	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}Realized > Expected\ HeatDays(t)$	0.149***	0.121***	0.095***	0.057**	0.053**	-0.022
	(0.026)	(0.023)	(0.026)	(0.025)	(0.025)	(0.024)
Sup Ind and Cus Ind-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cus Ctry-Sup Ctry-Year FE	No	Yes	No	Yes	No	Yes
Observations	16900	16526	16900	16526	16900	16526
R^2	0.076	0.232	0.067	0.224	0.055	0.227

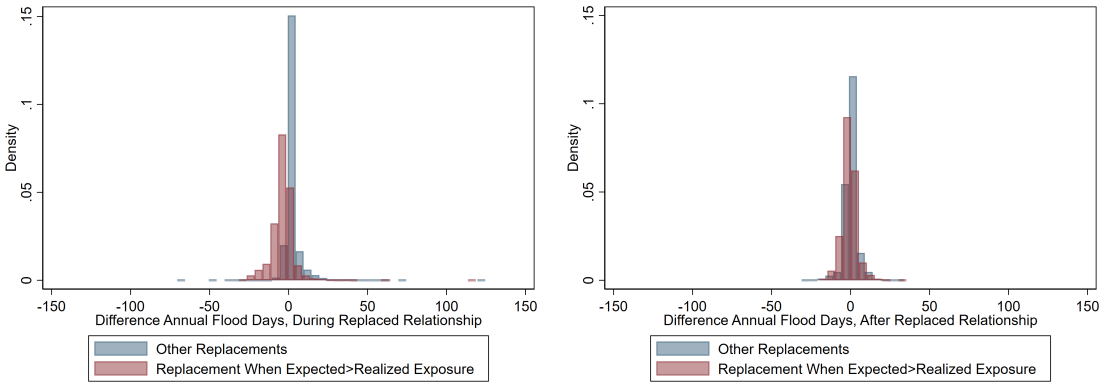
(a) Expected and Actual Decrease in Exposure to Heat



(b) Distribution in Heat Exposure: During the Initial Relationship | After the Initial Relationship | IPCC Projections

	Decrease Dur. Initial Rel.(0/1)		Decrease Aft. Initial Rel. (0/1)	
	(1)	(2)	(3)	(4)
$\mathbb{1}\,(Realized > Expected\ FloodDays)\,(t)$	0.614***	0.613***	0.073**	0.008
	(0.023)	(0.020)	(0.029)	(0.029)
Sup Ind and Cus Ind-Year FE	Yes	Yes	Yes	Yes
Cus Ctry-Sup Ctry-Year FE	No	Yes	No	Yes
Observations	16900	16526	16900	16526
R^2	0.403	0.513	0.054	0.246

(c) Expected and Actual Decrease in Exposure to Floods



(d) Distribution in Flood Exposure: During the Initial Relationship | After the Initial Relationship

Verbal Description Table 12 describes the difference in climate exposure of old and new suppliers after supply-chain relationships are terminated. It combines two tables and two figures. This description covers the figures in Panel (b) and (d).

Figure 12b consists of three charts. Each of the charts plots the distribution of the difference in the number of heat days per year between a replaced supplier and the replacement to learn about the extent to which customers seek replacement suppliers with less exposure to climate shocks. Moreover, each of the charts overlays the distributions of two subsamples to compare the changes in climate exposure for terminations that (1) may have been related to climate change in red and (2) are less likely to have been affected by considerations about climate-related risks in blue. We assume that the terminations may be related to suppliers' climate exposure when the exposure of the supplier to heat days during the supply-chain relationship exceeded what the customer could have expected ex-ante based on historical priors (red distribution). In contrast, we assume that terminations are less likely to be related to climate change-related concerns when the exposure to heat days was lower than or equal to historical expectations before the start of the supply-chain relationship (blue distribution).

The first graph (left) shows the difference in annual heat days per year for old and new suppliers, calculating the average number of heat days per year in the time period of the initial supply-chain relationship. The second chart (middle) shows the distributions of the difference when we calculate the average heat exposure for the time period starting after the initial relationship ends until the end of the sample period. The third chart (right) shows the distributions of the differences based on future expected number of heat days per year based on IPCC projections (CMIP5 RCP 4.5).

In the left chart of Panel (b), the blue and red distribution of the difference in heat exposure during the initial supply-chain relationship are similar in shape but differ noticeably left of their center. Both distributions are unimodal and centered around 0. However, the red distribution has a density of $\approx$0.015 at the center, whereas the density at the center of the blue distribution is $\approx$0.0275. The red distribution is denser left of its center and has a longer and thicker left tail. The blue distribution is more concentrated right around its center. Right of the center, the red and blue distribution are hard to distinguish. This pattern is consistent with the idea that customers may seek new suppliers with a relatively lower exposure to climate shocks when the terminations are motivated by concerns about climate change. In the middle chart of Panel (b), both distributions also show a similar shape. Both distributions are centered around zero, with a higher density of the blue distribution (peak in density around 0.025 compared to 0.015 for the red distribution). Again, the red distribution is denser left of its center and has a longer and thicker left tail. Right of the center, the red and blue distribution are hard to distinguish. Compared to the chart on the left which measures the difference in heat days during the initial relationship, the difference in density left of the center is less pronounced when the difference in annual heat days is calculated after the end of the initial relationship. In the right chart of Panel (b), we compare the distributions for the future expected number of heat days using IPCC projections. Once again, both distributions are similar in shape with their center close to zero and with a higher density around the peak of the blue distribution (peak in density around 0.0125 compared to 0.01 for the red distribution). The tails are difficult to distinguish, with a slightly higher density of the red distribution right of the center but a longer left tail of the blue distribution. The corresponding table in Panel (a) shows the statistical significance of the difference of the means of the blue and red distribution for each of the charts.

The charts in Panel (d) correspond to Panel (b) but show the distribution of the differences for flood days. The figure consists are two charts. Since the IPCC projections are specific to temperatures, we only compare the differences in flood days based on observed data during the initial relationship (left) and after the initial relationship is terminated (right). In the left chart, the

blue and red distribution are both unimodal but differ in their center, with the blue distribution centered just above and the red distribution centered just below 0. The blue distribution has a density of ≈0.15 at the center, whereas the density at the center of the red distribution is ≈0.09. The red distribution is denser left of its center and has a thicker left tail. The blue distribution is more concentrated right of its center. In the right chart of Panel (d), both distributions are again unimodal and show the same difference in centers, with the blue distribution peaking just above and the red distribution peaking just below zero. The difference in density is less noticeable (peak in density around 0.12 for the blue and 0.09 for the red distribution). The red (blue) distribution is slightly denser left (right) of its center. Compared to the left chart which measures the difference in heat days during the initial relationship, the difference of the red and blue distribution is less pronounced in the right chart. The corresponding table in Panel (c) shows the statistical significance of the difference of the means of the blue and red distribution for both of the charts.

A Appendix

Table A1: Robustness – Physical Climate Risk and Supplier Firm Performance

Notes. This table shows robustness tests analogous to Table 3 on the impact of weather shocks at the location of the supplier firms on their revenues (Rev) and operating income (OpI), using alternative heat and flood measures. Both dependent variables are scaled by one-year lagged assets. The main independent variables, $Heatw$ $(30/7)(t)$ and $Flood$ (t), indicate the occurrence of heatwaves (i.e. $>= 7$ consecutive days with temperatures above 30° Celsius) and floods (indicator variable if the firm is affected by a flood) during the financial quarter as well as the three preceding quarters ($t-3$ to t). The number of observations refers to supplier firm-quarters, and the sample period is 2003 to 2017. We exclude firms in the financial industry as well as firms with less than 10% of firm locations within 30 kilometers of the headquarters. All regressions include firm-by-fiscal quarter fixed effects, industry-by-year-by-quarter fixed effects, as well as controls for country-specific linear trends. Columns (2) and (4) additionally include interaction terms of terciles of firm size, age, and ROA with year-by-quarter fixed effects (BS2016 FE), following Barrot and Sauvagnat (2016). Standard errors are clustered on the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level.

	Sup Rev/L.A (t)		Sup OpI/L.A (t)	
	(1)	(2)	(3)	(4)
Heat Days (30/95) (t)	-0.012**	-0.009	-0.003**	-0.004**
	(0.006)	(0.006)	(0.002)	(0.002)
Heat Days (30/95) (t-1)	-0.002	-0.001	-0.003	-0.003*
	(0.006)	(0.006)	(0.002)	(0.002)
Heat Days (30/95) (t-2)	-0.008	-0.006	-0.002	-0.001
	(0.006)	(0.006)	(0.002)	(0.002)
Heat Days (30/95) (t-3)	-0.002	-0.002	-0.002	-0.002
	(0.005)	(0.006)	(0.002)	(0.002)
Firm × Fiscal-Qtr FE	Yes	Yes	Yes	Yes
Ind × Year-Qtr FE	Yes	Yes	Yes	Yes
Ctry-Linear-Trends	Yes	Yes	Yes	Yes
BS2016 FE	No	Yes	No	Yes
R^2	0.7626	0.7667	0.6257	0.6310
Observations	202,438	202,438	202,438	202,438
Suppliers	5,628	5,628	5,628	5,628

(a) Direct Effects of Heat - Severity

	Sup Rev/L.A (t)		Sup OpI/L.A (t)	
	(1)	(2)	(3)	(4)
Flood Severity (t)	-0.067	-0.078	-0.038*	-0.037*
	(0.070)	(0.071)	(0.020)	(0.020)
Flood Severity (t-1)	-0.195***	-0.226***	-0.044**	-0.047**
	(0.071)	(0.071)	(0.020)	(0.020)
Flood Severity (t-2)	-0.087	-0.093	-0.024	-0.021
	(0.070)	(0.070)	(0.019)	(0.019)
Flood Severity (t-3)	-0.113*	-0.144**	-0.047**	-0.049**
	(0.069)	(0.069)	(0.021)	(0.021)
Firm × Fiscal-Qtr FE	Yes	Yes	Yes	Yes
Ind × Year-Qtr FE	Yes	Yes	Yes	Yes
Ctry-Linear-Trends	Yes	Yes	Yes	Yes
BS2016 FE	No	Yes	No	Yes
R^2	0.7626	0.7667	0.6257	0.6311
Observations	202,438	202,438	202,438	202,438
Suppliers	5,628	5,628	5,628	5,628

(b) Direct Effects of Floods - Severity

	Sup Rev/L.A (t)		Sup OpI/L.A (t)	
	(1)	(2)	(3)	(4)
Count Heatw (30/7) (t)	-0.028	-0.025	-0.029**	-0.030**
	(0.047)	(0.048)	(0.012)	(0.012)
Count Heatw (30/7) (t-1)	-0.019	-0.013	-0.018	-0.018
	(0.049)	(0.049)	(0.014)	(0.014)
Count Heatw (30/7) (t-2)	-0.115**	-0.115**	-0.011	-0.011
	(0.048)	(0.048)	(0.013)	(0.013)
Count Heatw (30/7) (t-3)	-0.003	0.004	0.001	-0.002
	(0.048)	(0.049)	(0.013)	(0.013)
Firm × Fiscal-Qtr FE	Yes	Yes	Yes	Yes
Ind × Year-Qtr FE	Yes	Yes	Yes	Yes
Ctry-Linear-Trends	Yes	Yes	Yes	Yes
BS2016 FE	No	Yes	No	Yes
R^2	0.7626	0.7667	0.6257	0.6310
Observations	202,438	202,438	202,438	202,438
Suppliers	5,628	5,628	5,628	5,628

(c) Direct Effects of Heat - Shock

	Sup Rev/L.A (t)		Sup OpI/L.A (t)	
	(1)	(2)	(3)	(4)
Count Floods (t)	-0.149	-0.135	-0.050*	-0.045
	(0.102)	(0.103)	(0.029)	(0.030)
Count Floods (t-1)	-0.442***	-0.452***	-0.053*	-0.055*
	(0.103)	(0.104)	(0.029)	(0.029)
Count Floods (t-2)	-0.244**	-0.233**	-0.031	-0.024
	(0.102)	(0.103)	(0.028)	(0.028)
Count Floods (t-3)	-0.297***	-0.307***	-0.069**	-0.067**
	(0.101)	(0.102)	(0.029)	(0.029)
Firm × Fiscal-Qtr FE	Yes	Yes	Yes	Yes
Ind × Year-Qtr FE	Yes	Yes	Yes	Yes
Ctry-Linear-Trends	Yes	Yes	Yes	Yes
BS2016 FE	No	Yes	No	Yes
R^2	0.7626	0.7668	0.6257	0.6310
Observations	202,438	202,438	202,438	202,438
Suppliers	5,628	5,628	5,628	5,628

(d) Direct Effects of Floods - Shock

Table A2: Robustness – Heterogeneity of Direct Effects of Physical Climate Risk

Notes. This table shows OLS regression estimates on the effects of heat and floods on supplier revenues (Rev) and operating income (OpI) by industry. Both dependent variables are scaled by lagged assets. Industry classifications are based on SIC 1-digit codes. The independent variables *Heat Days* (t) and *Flood Days* (t) indicate the number of days on which heat and floods occur during the financial quarter as well as the three preceding quarters ($t-3$ to t). The column *Joint Test* indicates if the effects of heat or flood days on Revenues or Income is significant at or above the 10%-level for a given industry (+ for revenues, /+ for operating income). The number of observations refers to supplier firm-quarters, and the sample period is 2003 to 2017. We exclude firms in the financial industry as well as firms with less than 10% of firm locations within 30 kilometers of the headquarters. All regressions include firm-by-fiscal quarter fixed effects, industry-by-year-by-quarter fixed effects, and interaction terms of terciles of firm size, age, and ROA with year-by-quarter fixed effects to control for firm characteristics (BS2016 FE). Standard errors are clustered on the firm level. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Joint Test	Sup Rev/L.A (t)	Sup OpI/L.A (t)
		(1)	(2)
Heat Days		0.023**	0.003
		(0.010)	(0.002)
Heat Days × Mining/Constr	+	-0.042***	-0.006**
		(0.014)	(0.003)
Heat Days × Services	+/+	-0.053***	-0.008**
		(0.015)	(0.003)
Heat Days × Manufacturing	/+	-0.031***	-0.005**
		(0.012)	(0.003)
Heat Days × Wholes/Retail		-0.042**	-0.005
		(0.018)	(0.003)
Heat Days × Transport	/+	-0.023	-0.007**
		(0.014)	(0.003)
Heat Days × Agriculture		-0.107*	-0.019
		(0.059)	(0.013)
Heat Days × Administr		-0.107	0.012
		(0.071)	(0.030)
Firm × Fiscal-Qtr FE		Yes	Yes
Ctry-Linear-Trends		Yes	Yes
BS2016 FE		Yes	Yes
R^2		0.7622	0.6248
Observations		202,438	202,438
Suppliers		5,628	5,628

Direct Effects of Heat by Industry

	Joint Test	Sup Rev/L.A (t)	Sup OpI/L.A (t)
		(1)	(2)
Flood Days		-0.070***	-0.009***
		(0.014)	(0.002)
Flood Days × Mining/Constr	/+	0.059***	-0.001
		(0.017)	(0.003)
Flood Days × Services		0.060***	0.007*
		(0.021)	(0.004)
Flood Days × Manufacturing	+/+	0.048***	0.006*
		(0.016)	(0.003)
Flood Days × Wholes/Retail		0.062**	0.006
		(0.029)	(0.004)
Flood Days × Transport		0.075***	0.009**
		(0.020)	(0.004)
Flood Days × Agriculture	+/+	-0.116	-0.021*
		(0.081)	(0.012)
Flood Days × Administr		0.042	0.088*
		(0.118)	(0.049)
Firm × Fiscal-Qtr FE		Yes	Yes
Ctry-Linear-Trends		Yes	Yes
BS2016 FE		Yes	Yes
R^2		0.7623	0.6249
Observations		202,438	202,438
Suppliers		5,628	5,628

Direct Effects of Floods by Industry

Table A3: Robustness – Downstream Propagation of Weather Shocks

Notes. This table shows OLS regression estimates analogous to Table 4 on the effect of weather shocks at the supplier locations on their customers' revenues over assets (Rev) and operating income over assets (OpI), using indicator variables for heatwaves and floods. Both dependent variables are scaled by one-year lagged assets. *Sup Heatwaves* (t) and *Sup Floods* (t) are the total number of heatwaves or floods that occurred at the locations of a given customer's suppliers in quarter t. The unit of observation is at the supplier-customer pair-quarter level. In Panel A3a the independent variables represent dummy variables indicating the occurrence of a heatwave (at least seven consecutive days over 30°C) and flood, respectively. In Panel A3b, *Sup Heat Days* (30/95) measures the number of days across suppliers in a quarter with local temperatures both above 30°C and above the local 95th percentile. *Sup Flood Severity* is an indicator variable for the occurrence of a severe flood across supplier locations. We apply similar data filters as in Table 4. All regressions include relationship-by-quarter fixed effects as well as year-by-quarter fixed effects. In both Panels, Columns (2) and (4) additionally include terciles of size, age, and ROA interacted with year-by-quarter fixed effects (BS2016 FE) as in Table 4. Standard errors are clustered on the customer level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

(a) Weather Shocks – Indicator Variables

	Cus Rev (t)		Cus OpI (t)	
	(1)	(2)	(3)	(4)
Sup Heatw (30/7) (t-0)	-0.0693***	-0.0704***	-0.0142***	-0.0110***
	(0.015)	(0.016)	(0.003)	(0.004)
Sup Heatw (30/7) (t-1)	-0.0902***	-0.0960***	-0.0187***	-0.0151***
	(0.020)	(0.020)	(0.004)	(0.004)
Sup Heatw (30/7) (t-2)	-0.0490***	-0.0693***	-0.0086***	-0.0095***
	(0.015)	(0.016)	(0.003)	(0.003)
Sup Heatw (30/7) (t-3)	-0.0442***	-0.0567***	-0.0087***	-0.0082**
	(0.015)	(0.015)	(0.003)	(0.003)
Firm × Fiscal-Qtr FE	Yes	Yes	Yes	Yes
Ind × Year-Qtr FE	Yes	Yes	Yes	Yes
Ctry-Linear-Trends	Yes	Yes	Yes	Yes
BS2016 FE	No	Yes	No	Yes
Observations	123700	123700	123700	123700
R^2	.884	.886	.707	.711

	Cus Rev (t)		Cus OpI (t)	
	(1)	(2)	(3)	(4)
Sup Flood Dummy (t-0)	-0.0799***	-0.0712***	-0.0192***	-0.0145***
	(0.021)	(0.022)	(0.004)	(0.005)
Sup Flood Dummy (t-1)	-0.0702***	-0.0636***	-0.0148***	-0.0123***
	(0.021)	(0.023)	(0.004)	(0.004)
Sup Flood Dummy (t-2)	-0.0734***	-0.0759***	-0.0186***	-0.0163***
	(0.020)	(0.020)	(0.004)	(0.004)
Sup Flood Dummy (t-3)	-0.0616***	-0.0552***	-0.0113***	-0.0069*
	(0.019)	(0.021)	(0.004)	(0.004)
Firm × Fiscal-Qtr FE	Yes	Yes	Yes	Yes
Ind × Year-Qtr FE	Yes	Yes	Yes	Yes
Ctry-Linear-Trends	Yes	Yes	Yes	Yes
BS2016 FE	No	Yes	No	Yes
Observations	123700	123700	123700	123700
R^2	.884	.886	.707	.711

(b) Weather Shocks – Alternative Definitions

	Cus Rev (t)		Cus OpI (t)	
	(1)	(2)	(3)	(4)
Sup Heat Days (30/95) (t-0)	-0.0042***	-0.0043***	-0.0008***	-0.0006**
	(0.001)	(0.001)	(0.000)	(0.000)
Sup Heat Days (30/95) (t-1)	-0.0043***	-0.0044***	-0.0008***	-0.0006**
	(0.001)	(0.001)	(0.000)	(0.000)
Sup Heat Days (30/95) (t-2)	-0.0029***	-0.0037***	-0.0005***	-0.0005**
	(0.001)	(0.001)	(0.000)	(0.000)
Sup Heat Days (30/95) (t-3)	-0.0019**	-0.0028***	-0.0004*	-0.0004*
	(0.001)	(0.001)	(0.000)	(0.000)
Firm × Fiscal-Qtr FE	Yes	Yes	Yes	Yes
Ind × Year-Qtr FE	Yes	Yes	Yes	Yes
Ctry-Linear-Trends	Yes	Yes	Yes	Yes
BS2016 FE	No	Yes	No	Yes
Observations	123700	123700	123700	123700
Customers	6299	6299	6299	6299
R^2	.884	.886	.707	.711

	Cus Rev (t)		Cus OpI (t)	
	(1)	(2)	(3)	(4)
Sup Flood Severity (t-0)	-0.0539***	-0.0495***	-0.0133***	-0.0100***
	(0.013)	(0.013)	(0.003)	(0.003)
Sup Flood Severity (t-1)	-0.0489***	-0.0458***	-0.0112***	-0.0093***
	(0.013)	(0.014)	(0.003)	(0.002)
Sup Flood Severity (t-2)	-0.0507***	-0.0513***	-0.0128***	-0.0110***
	(0.012)	(0.013)	(0.003)	(0.003)
Sup Flood Severity (t-3)	-0.0414***	-0.0390***	-0.0071***	-0.0042*
	(0.012)	(0.013)	(0.002)	(0.002)
Firm × Fiscal-Qtr FE	Yes	Yes	Yes	Yes
Ind × Year-Qtr FE	Yes	Yes	Yes	Yes
Ctry-Linear-Trends	Yes	Yes	Yes	Yes
BS2016 FE	No	Yes	No	Yes
Observations	123700	123700	123700	123700
Customers	6299	6299	6299	6299
R^2	.884	.886	.707	.711

Table A4: Robustness – Propagation of Weather Shocks over EM-DAT

Notes. This table presents OLS regression estimates on the impact of weather shocks at the supplier locations on the financial performance of their customers. Financial performance is measured as revenues (Rev) and operating income (OpI), both scaled by one-year lagged assets. The unit of observation is at the customer-quarter level. The sample period is from 2003 to 2017. *Heat Days* (t) (*ex. EMDAT*) and *Flood Days* (t) (*ex. EMDAT*) are count variables indicating the number of heat and flood days in the supplier's location in quarter t, in excess of shocks recorded by the EM-DAT international disaster database. We apply similar data filters as in Tables 3 and 4. All regressions include firm-by-fiscal quarter fixed effects as well as industry-by-year-by-quarter fixed effects and country-specific linear trend fixed effects. Columns (2) and (4) in each panel additionally include terciles of size, age, and ROA interacted with year-by-quarter fixed effects (BS2016 FE) as in Tables 3 and 4. Standard errors are clustered at the customer-firm level. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Cus Rev (t)		Cus OpI (t)	
	(1)	(2)	(3)	(4)
Sup Heat Days (t-0) (ex. EMDAT)	-0.0011***	-0.0012***	-0.0002***	-0.0002**
	(0.000)	(0.000)	(0.000)	(0.000)
Sup Heat Days (t-1) (ex. EMDAT)	-0.0012***	-0.0014***	-0.0002***	-0.0002**
	(0.000)	(0.000)	(0.000)	(0.000)
Sup Heat Days (t-2) (ex. EMDAT)	-0.0012***	-0.0016***	-0.0002***	-0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)
Sup Heat Days (t-3) (ex. EMDAT)	-0.0006**	-0.0009***	-0.0002***	-0.0002**
	(0.000)	(0.000)	(0.000)	(0.000)
Firm × Fiscal-Qtr FE	Yes	Yes	Yes	Yes
Ind × Year-Qtr FE	Yes	Yes	Yes	Yes
Ctry-Linear-Trends	Yes	Yes	Yes	Yes
BS2016 FE	No	Yes	No	Yes
Observations	123700	123700	123700	123700
R^2	.884	.886	.707	.711

	Cus Rev (t)		Cus OpI (t)	
	(1)	(2)	(3)	(4)
Sup Flood Days (t-0) (ex. EMDAT)	-0.0103*	-0.0092*	-0.0032***	-0.0028***
	(0.005)	(0.005)	(0.001)	(0.001)
Sup Flood Days (t-1) (ex. EMDAT)	-0.0092*	-0.0093*	-0.0031***	-0.0032***
	(0.005)	(0.005)	(0.001)	(0.001)
Sup Flood Days (t-2) (ex. EMDAT)	-0.0111**	-0.0120**	-0.0032***	-0.0032***
	(0.005)	(0.005)	(0.001)	(0.001)
Sup Flood Days (t-3) (ex. EMDAT)	-0.0157***	-0.0155***	-0.0032***	-0.0029***
	(0.005)	(0.005)	(0.001)	(0.001)
Firm × Fiscal-Qtr FE	Yes	Yes	Yes	Yes
Ind × Year-Qtr FE	Yes	Yes	Yes	Yes
Ctry-Linear-Trends	Yes	Yes	Yes	Yes
BS2016 FE	No	Yes	No	Yes
Observations	123700	123700	123700	123700
R^2	.884	.886	.707	.711

Table A5: Robustness – Downstream Propagation – Cross Section

Notes. Analogous to Table 5, this table presents OLS regression estimates on cross-sectional differences in the impact of heat and flooding at the location of the suppliers on customer performance. The dependent variable in both panels is customer revenue (Rev), scaled by one-year lagged assets. *Heat Days* $(t, t-3)$ (Panel A5a) and *Flood Days* $(t, t-3)$ (Panel A5b) measures the total number of heat and flood days at all suppliers of a given customer during the contemporaneous and previous three quarters. The data is organized at the customer-year-quarter level and the sample period is 2003 to 2017. All other variables are defined as in Table 5. We apply similar data filters as in Table 5. All regressions include firm-by-fiscal quarter fixed effects, industry-by-year-by-quarter fixed effects, and for country-specific linear trends. Columns (2) and (4) additionally include interaction terms of terciles of firm size, age, and ROA with year-by-quarter fixed effects to control for firm characteristics (BS2016 FE). Standard errors are clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Cus Rev (t)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Heat Days (t,t-3)	-0.1018*	-0.0649**	-0.2367***	-0.0703*	-0.1306***	-0.2059***	-0.1247***	-0.1817***
	(0.060)	(0.028)	(0.046)	(0.039)	(0.034)	(0.051)	(0.026)	(0.032)
Heat Days (t,t-3) × Sup Tangibility	-0.0013							
	(0.002)							
Heat Days (t,t-3) × Sup-Ind Vuln.		-0.0048***						
		(0.001)						
Heat Days (t,t-3) × Sup-Ind Comp.			0.0810**					
			(0.038)					
Heat Days (t,t-3) × Input-Ind Conc.				-0.0893				
				(0.074)				
Heat Days (t,t-3) × Cus Inventory					-0.0007			
					(0.003)			
Heat Days (t,t-3) × Sup Divers.						0.0396*		
						(0.020)		
Heat Days (t,t-3) × Sales Corr.							-0.0005	
							(0.001)	
Heat Days (t,t-3) × Rel. Length								0.0161**
								(0.008)
Sup Tangibility	0.4888							
	(0.672)							
Sup-Ind Vuln.		0.2961						
		(0.568)						
Sup-Ind Comp.			-4.9306					
			(19.664)					
Cus Inventory					56.0093***			
					(3.991)			
Sup Divers.						-77.2286***		
						(18.155)		
Sales Corr.							-0.6969***	
							(0.211)	
Rel. Length								-9.2461
								(5.920)
Firm × Fiscal-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind × Year-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ctry-Linear-Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BS2016 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	117039	123700	102762	54188	114095	122162	93025	123700
R^2	0.887	0.886	0.886	0.878	0.882	0.887	0.893	0.886

(a) Heat

	Cus Rev (t)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Flood Days (t,t-3)	-0.0880	-0.2049	-1.3050***	-0.5523**	-0.5444***	-1.1313***	-0.4261***	-1.1484***
	(0.297)	(0.159)	(0.295)	(0.233)	(0.192)	(0.298)	(0.131)	(0.265)
Flood Days (t,t-3) × Sup Tangibility	-0.0172*							
	(0.009)							
Flood Days (t,t-3) × Sup-Ind Vuln.		-0.0218***						
		(0.007)						
Flood Days (t,t-3) × Sup-Ind Comp.			0.7156***					
			(0.276)					
Flood Days (t,t-3) × Input-Ind Conc.				-0.1054				
				(0.425)				
Flood Days (t,t-3) × Cus Inventory					-0.0050			
					(0.020)			
Flood Days (t,t-3) × Sup Divers.						0.3128**		
						(0.137)		
Flood Days (t,t-3) × Sales Corr.							-0.0064	
							(0.005)	
Flood Days (t,t-3) × Rel. Length								0.1873**
								(0.084)
Sup Tangibility	0.3776							
	(0.646)							
Sup-Ind Vuln.		-0.2846						
		(0.558)						
Sup-Ind Comp.			0.5088					
			(19.420)					
Cus Inventory					56.1943***			
					(3.921)			
Sup Divers.						-85.1009***		
						(17.932)		
Sales Corr.							-0.6886***	
							(0.203)	
Rel. Length								-7.2855
								(5.853)
Firm × Fiscal-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind × Year-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ctry-Linear-Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BS2016 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	117039	123700	102762	54188	114095	122162	93025	123700
R^2	0.887	0.886	0.885	0.878	0.882	0.886	0.892	0.886

(b) Floods

Table A6: Robustness: Alternative Estimation Periods, Relationship Termination

Notes. Analogous to Panel 7a of Table 7, this table presents linear probability model estimates on the impact of the exceedance of weather shock expectations on the likelihood of supply-chain relationship termination. The sample and variables are constructed similarly as in Table 7. The main difference to Table 7 is that Panels A6a and A6b use benchmark periods of five and fifteen years before the establishment of a supply-chain relationship to construct our main variables of interest, $\mathbb{1}\left(Realized > Expected\ Shocks\right)(t)$, as illustrated in Figure 2. We apply similar data filters as in Table 7. The regressions include relationship fixed effects, year fixed effects, supplier and customer-industry-by-year, as well as supplier-country-by-customer-country-by-year fixed effects as indicated. Robust standard errors are clustered on the relationship level. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	OLS - *Dependent Variable:* Last Relationship Year (0/1)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}Realized > Expected\ HeatDays$	0.007***	0.006***	0.010***			
	(0.002)	(0.002)	(0.002)			
$\mathbb{1}Realized > Expected\ FloodDays$				0.018***	0.017***	0.010***
				(0.002)	(0.002)	(0.002)
Year FE	Yes	No	No	Yes	No	No
Sup Ind-Year FE	No	Yes	Yes	No	Yes	Yes
Cus Ind-Year FE	No	Yes	Yes	No	Yes	Yes
Cus Ctry-Sup Ctry-Year FE	No	No	Yes	No	No	Yes
Observations	126205	126205	126205	126205	126205	126205
R^2	0.313	0.320	0.380	0.314	0.320	0.380

(a) Alternative Expected Exposure Estimates, 5 Years Before Relationship

	OLS - *Dependent Variable:* Last Relationship Year (0/1)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}Realized > Expected\ HeatDays$	0.010***	0.008***	0.011***			
	(0.002)	(0.002)	(0.002)			
$\mathbb{1}Realized > Expected\ FloodDays$				0.011***	0.010***	0.007***
				(0.002)	(0.002)	(0.002)
Year FE	Yes	No	No	Yes	No	No
Sup Ind-Year FE	No	Yes	Yes	No	Yes	Yes
Cus Ind-Year FE	No	Yes	Yes	No	Yes	Yes
Cus Ctry-Sup Ctry-Year FE	No	No	Yes	No	No	Yes
Observations	126205	126205	126205	126205	126205	126205
R^2	0.313	0.320	0.380	0.313	0.320	0.380

(b) Alternative Expected Exposure Estimates, 15 Years Before Relationship

Table A7: Robustness – Initial Years and Restarts, Relationship Termination

Notes. Analogous to Panel 7a, this table presents linear probability model estimates on the impact of the exceedance of weather shock expectations on the likelihood of supply-chain relationship termination. The sample and variables are constructed similarly as in Table 7. In Panel A7a, we exclude supplier firms that were delisted within one year of the end of the supply-chain relationship. In Panel A7b, we set the independent variable $\mathbb{1}\,(Realized > Expected\ Shocks)\,(t)$ to zero in the first year of the relationship. In Panel A7c, we exclude relationships which are only temporarily interrupted. These observations account for 6.37% of the observations in our sample. We apply similar data filters as in Table 7. The regressions include year fixed effects, supplier-industry-by-year, supplier-country-by-year, and supplier-country-by-customer-country-by-year fixed effects as indicated. Robust standard errors are clustered on the relationship level. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Dependent Variable: Last Relationship Year (0/1)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}Realized > Expected\ HeatDays$	0.004*	0.002	0.007***			
	(0.002)	(0.002)	(0.002)			
$\mathbb{1}Realized > Expected\ FloodDays$				0.016***	0.015***	0.014***
				(0.002)	(0.002)	(0.003)
Year FE	Yes	No	No	Yes	No	No
Sup Ind-Year FE	No	Yes	Yes	No	Yes	Yes
Cus Ind-Year FE	No	Yes	Yes	No	Yes	Yes
Cus Ctry-Sup Ctry-Year FE	No	No	Yes	No	No	Yes
Observations	120106	120106	120106	120106	120106	120106
R^2	0.303	0.311	0.374	0.304	0.311	0.374

(a) Excluding Delisted Suppliers

	Dependent Variable: Last Relationship Year (0/1)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}Realized > Expected\ HeatDays$	0.065***	0.064***	0.068***			
	(0.002)	(0.002)	(0.003)			
$\mathbb{1}Realized > Expected\ FloodDays$				0.039***	0.039***	0.035***
				(0.003)	(0.003)	(0.003)
Year FE	Yes	No	No	Yes	No	No
Sup Ind-Year FE	No	Yes	Yes	No	Yes	Yes
Cus Ind-Year FE	No	Yes	Yes	No	Yes	Yes
Cus Ctry-Sup Ctry-Year FE	No	No	Yes	No	No	Yes
Observations	126205	126205	126205	126205	126205	126205
R^2	0.318	0.325	0.384	0.315	0.322	0.381

(b) Excluding Signal in the First Year of the Relationship

	Dependent Variable: Last Relationship Year (0/1)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}Realized > Expected\ HeatDays$	0.009***	0.007***	0.014***			
	(0.002)	(0.002)	(0.002)			
$\mathbb{1}Realized > Expected\ FloodDays$				0.019***	0.018***	0.013***
				(0.002)	(0.002)	(0.003)
Year FE	Yes	No	No	Yes	No	No
Sup Ind-Year FE	No	Yes	Yes	No	Yes	Yes
Cus Ind-Year FE	No	Yes	Yes	No	Yes	Yes
Cus Ctry-Sup Ctry-Year FE	No	No	Yes	No	No	Yes
Observations	117919	117919	117919	117919	117919	117919
R^2	0.305	0.312	0.375	0.305	0.312	0.375

(c) Excluding Temporarily Interrupted Relationships (6.37% of Sample)

Table A8: Robustness – Weather Shocks and Relationship Duration

Notes. This table presents Cox proportional hazard model regression estimates on the impact of realized vs. expected weather shocks on supply-chain relationship duration. The dependent variable is the number of years from the beginning to the end of a given supplier-customer relationship. The start of a supplier-customer relationship is the first year the relationship is documented in the Factset Revere database, the end is the year a relationship is terminated. We drop relationships that were terminated and subsequently restarted at some point in our sample. Following Fee et al. (2006), if a relationship lasts until the final year of the sample period, we treat the duration of relationship as being right-censored. The main independent variable is defined as $max\left[\mathbb{1}\left(Realized > Expected\ Shocks\right)\ (t)\right]$ for each supplier-customer relationship, i.e. the maximum of an indicator variable that takes the value of one in year t if the difference between the realized number of heat and flood days per year since the beginning of the supply-chain relationship exceeds the corresponding expected number of days, and zero otherwise, across all years t in which the relationship is active. We apply similar data filters as in Table 7. The unit of observation is at the supplier-customer pair level. Strata for the first year of each relationship (FY), and customer-by-industry-by-FY, supplier-by-industry-by-FY and supplier-country-by-FY are included as indicated. The table reports coefficient estimates, not hazard ratios. Robust standard errors are clustered on the relationship level. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Dependent Variable: Duration of the Relationship					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}(Realized > Expected\ HeatDays)(t)$	-0.273***	-0.332***	-0.464***			
	(0.021)	(0.018)	(0.024)			
$\mathbb{1}(Realized > Expected\ FloodDays)(t)$				-0.318***	-0.305***	-0.401***
				(0.022)	(0.018)	(0.024)
Observations	34945	34455	34455	34945	34455	34455
First Year (FY)	Yes	No	No	Yes	No	No
Cus Ind-FY, Sup Ind-FY	No	Yes	Yes	No	Yes	Yes
Cus Ind-FY, Sup Ind-FY, Sup Ctr-FY	No	No	Yes	No	No	Yes