Climate Change and Adaptation in Global Supply-Chain Networks

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Abstract

This paper examines how firms adapt to climate-change risks resulting from their supply-chain networks. Combining a large sample of global supplier-customer relationships with granular data on local temperatures, floods, and climate projections, we first document that the occurrence of climate-related shocks at the locations of supplier firms has significant negative direct and indirect effects on the operating performance of suppliers and their customers. Second, we demonstrate that customers respond to changes in this exposure. When realized climate risks at supplier locations exceed ex-ante expectations, customers are 6 to 11% more likely to terminate existing supplier-relationships. Consistent with models of experience-based Bayesian updating, this effect increases with signal strength and repetition, cannot be explained by salient, transitory shocks, and is stronger for suppliers in competitive industries and weaker for closely integrated supply-chain relationships. Customers subsequently choose replacement suppliers with lower expected climate-risk exposure. Moreover, we find that both supplier termination and replacement decisions are insensitive to long-term climate projections – even when experienced and projected change diverge substantially. Our findings indicate that climate change related risks affect the formation of global production networks.

Keywords: Climate Change, Adaptation, Firm Performance, Production Networks.
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1 Introduction

Climate change is one of the greatest challenges of our time. The average global surface temperature has increased by 0.85°C since the industrial revolution, leading to more frequent extreme weather events such as heatwaves, forest fires, and catastrophic floods, with serious social and economic consequences (Carleton and Hsiang, 2016). The academic literature has studied the effects of climate change on firms with respect to labor and capital productivity (Graff-Zivin, Hsiang, and Neidell, 2018; Zhang, Deschenes, Meng, and Zhang, 2018), earnings (Addoum, Ng, and Ortiz-Bobea, 2020), stock returns (Kumar, Xin, and Zhang, 2019), and capital structure (Ginglinger and Moreau, 2019), among others. However, while managers and investors are increasingly looking for ways to mitigate climate change risks by adapting their operations (Lin, Schmid, and Weisbach, 2018) and investments (Krueger, Sautner, and Starks, 2020), much less is known about how firms learn about and adapt to climate change.

Understanding and adapting 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 climate change risks due to their suppliers and customers.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 outcomes provide a noisy signal of potential changes in the underlying climate distribution (Deryugina, 2013; Kala, 2019). Further, indirect exposure to climate-related risks due to suppliers and customers can be challenging to identify. In this environment, it is unclear how climate-related shocks affect firms' expectations of climate risks and, as a consequence, the adjustment of their supply-chain networks.

In this paper, we study if firms adjust their supply-chain networks as a result of perceived changes in their suppliers' exposure to climate-related risks. Specifically, we first establish that the effects of climate-related extreme weather events at supplier locations propagate to their corporate customers around the world. Next, we investigate whether 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 climate-related shocks affect the continuation of existing and initiation of new supply-chain relationships. Our main contribution is to show that customers terminate suppliers when climate-related shocks increase beyond historical expectations, and switch to replacements in less exposed climate zones. Thereby, this study provides novel evidence on how changes in the perceived level of climate-related risks affect the formation of production networks.

We combine detailed global, firm-level supply-chain data from FactSet Revere with 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 71 countries around the world, over the period from 2003 to 2017.

We focus on two types of risks related to climate change – extreme temperatures and floods – for the following reasons. First, the literature in physiology and economics has documented several channels through which heat can affect firm productivity. For example, extreme heat reduces human capital (Graff-Zivin et al., 2018), labor provision (Graff-Zivin and Neidell, 2014), and productivity (Zhang et al., 2018), with sharp declines typically observed at temperatures over 30°C. Given current emissions and policy inertia, 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 (Graff-Zivin and Neidell, 2014). Second, flooding incidents can cause enormous economic damage. According to FEMA, the United States 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).

We begin by examining if customer firms face financial incentives to adapt their supply-chain organizations due to heat and flood exposure of their suppliers. Whereas Barrot and Sauvagnat (2016), Seetharam (2018), and Carvalho, Nirei, Saito, and Tahbaz-Salehi (2020) show that the effect of large-scale natural disasters can propagate through firm-level production networks, it is unclear whether climate-related shocks – which are projected to change heterogeneously around the world and do not match the magnitudes required to be classified as disasters – cause similar distortions.[1] While extreme temperatures and floods might be costly to supplier firms, for example by increasing energy consumption for air conditioning or clean-up costs, customer firms would be unaffected by such shocks if suppliers cannot pass on the incurred costs downstream. Further, even if heat or floods reduce supplier productivity, customers' operational risk management strategies could insulate them against heat and flood-related disruptions. On the other hand, increased costs and lower output could propagate downstream along the supply-chain, especially if frictions such as relationship-specific investments prevent customer firms from making operational adjustments, or from switching to alternative suppliers.

Following the literature (e.g. Carleton and Hsiang, 2016; Auffhammer, 2018; Dell, Jones, and Olken, 2014; Burke, Hsiang, and Miguel, 2015a), 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 the firms' production facilities. Consistent with Somanathan et al. (2015), Zhang et al. (2018), and Pankratz et al. (2019), we document a significant negative effect of high temperatures and floods on supplier firm operating performance. 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 climate change-related shocks to supplier firms have a negative effect on 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.[2] Further, we find that a customer's ability to source inputs from alternative sources mitigates the propagation of climate-related supplier disruptions.

Our main analysis focuses on the question how firms learn about climate change and adapt their supply-chains when global climate risk exposure changes. Given that short- and medium-term

[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; Custódio, Ferreira, Garcia-Appendini, and Lam, 2020).

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

weather observations provide noisy signals for the underlying climate 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; 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 this setting, adverse climate shocks in line with the expected climate distribution would not affect the longevity of supply chain relations. However, if firms change their beliefs about the underlying distribution of climate events due to experienced climate realizations, the original supplier choice may no longer be optimal. In this case, 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) percentage points 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. We further document a stronger effect for suppliers in competitive industries and a weaker effect for closely integrated supply-chains. We find similar results implementing our tests as linear probability models, logistic regressions, and as Cox proportional hazard models.

Further, consistent with models of Bayesian updating (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 climate-related shocks exceeded prior expectations. Importantly, when we consider the effect of heat and floods without comparing them to ex-ante expectations, i.e. models of updating consistent with availability heuristics, we find a much smaller effect. This result is consistent with the notion that managers are taking climate risks into consideration when entering a supply-chain relationship.

While our main tests reflect the idea that firms form priors and update their beliefs based on observable climate-related shocks, we also study the role of long-term climate projections. Using model output from the Max Plack Institute for Meteorology, we obtain projections for the number of average heat days between 2040 and 2059.[3] We then estimate our main tests for subsamples of suppliers for which long-term climate models project minimal changes under various climate change scenarios. Indicating potential challenges in trading-off experience and forward looking information, we find that customers strongly respond to short-run increases in climate-related risks beyond ex ante expectations even when long-run projections indicate little to no change.[4]

Last, we examine if firms consider climate exposure when switching to new suppliers. For this purpose, we identify 'replacement' suppliers as firms with identical 4-digit SIC codes as previously terminated suppliers which entered a new supplier-relationship with the same customer within one year. We then estimate linear probability models on the likelihood that the 'replacement' suppliers have a lower climate exposure than the terminated supplier as a function of realized vs. expected climate-related 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 climate risk observed both *during* as well as *after* the initial relationship. An unexpectedly high number of climate-related shocks during the initial supplier-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. Together, these results are consistent with our previous findings, which indicate that firms mainly rely on experience-based learning when forming climate-risk expectations.

Our paper contributes to the literature on climate change in economics along several dimensions. First, our results indicate that climate change risks affect the formation of global firm-level production networks as firms adapt their supply-chain organizations to climate-related shock experiences.

[3]This dataset is computed in the framework of the CMIP5 project, which is the primary source of climate data for the Intergovernmental Panel on Climate Change (IPCC) Assessment Reports. Daily projections are made accessible by the ECMWF, and we obtain projections for the Representative Concentration Pathways (RCP) 2.6, 4.5, and 8.5. For all projections, we download and average across all available ensemble members.

[4]To minimize the necessary number of assumptions about the way customers use climate projections and which scenarios would be most relevant, we focus on cases where experienced climate shocks far exceed long-term projections.

Previous research on the endogenous formation of production networks has studied the role of ownership rights and contract enforcement practices (Antràs and Helpman, 2004; Antràs and Chor, 2013; Boehm and Oberfield, 2020), technological progress (Acemoglu and Azar, 2020), and their effect on aggregate growth and business cycles (Oberfield, 2018; Lim, 2018).

Second, we contribute to the literature on learning about climate change. Deryugina (2013) uses survey data on beliefs about global warming to document that local temperature fluctuations affect these beliefs in a Bayesian framework and Choi et al. (2020) show that people revise their beliefs about climate change when experiencing unusual weather using Google search data. Moore (2017) proposes a hierarchical Bayesian model in which agents learn from experiences and anticipated future changes to study adjustment costs of climate change adaptation. Kala (2019) examines how farmers in India update their decisions to plant crops based on rainfall observations. In contrast to these studies, our paper focuses on learning and adaptation of firms, combining both observed signals and climate projections in a novel supply-chain setting.

Third, 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 climate 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 (Bansal, Kiku, and Ochoa, 2016; 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 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. (2020), who document the propagation of natural disasters along firm linkages. The key difference between our study and these papers is that we focus on heat and flood incidents, which are closely tied to global climate change and hence allow us – in contrast to natural disasters such as earthquakes and hurricanes – to explicitly examine long-run projections and changes in the underlying distribution of events.

Our main finding on the adaptation of supply chains to climate change-related 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, Hsiang, and Miguel, 2015b; Carleton and Hsiang, 2016).

2 Data Sources and Descriptive Statistics

We combine data on global supply-chain relationships, firm financial performance, and granular data on local climate exposure from four main sources. In the following sections we describe the data sources, explain how we link the individual datasets, and provide summary statistics for our main sample. The summary statistics presented in Table 2 refer to the sample used to study the propagation of climate-related shocks in Section 3.1. Throughout the rest of the paper, we provide relevant summary statistics and details in the context of the respective empirical tests.

2.1 Global Supply Chains

We start by obtaining information on customer-supplier relationships from FactSet Revere. Previous research on supply-chains in finance (e.g. Hertzel, Li, Officer, and Rodgers, 2008; Cohen and Frazzini, 2008; Banerjee, Dasgupta, and Kim, 2008; Barrot and Sauvagnat, 2016) has relied primarily on SEC regulation S-K, which requires U.S. firms to disclose the existence and names of customer firms representing at least 10% of their total sales, to identify customer-supplier links. In contrast, the Revere supply-chain data has two important advantages that are particularly important for this paper. First, while the SEC regulation does not apply to firms outside of the U.S., Factset Revere includes both U.S. and foreign supplier and customer firms. This is important because many of the regions most vulnerable to global climate change are located outside of the United States. Second, and more importantly, previous research relying on the SEC regulation has been unable to study the initiation and termination of supplier-customer relationships, since the appearance and disappearance of a given supply-chain link in the data might either be due to a customer starting/ending a relationship with a given supplier, or because a customer firm was above/below the 10% reporting threshold in a given year. In contrast, 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, providing us with precise information on the beginning and end of a given supplier-customer relationship.

In total, our sample includes 8,200 unique customer firms and 5,769 unique supplier firms across 71 different countries, comprising almost 595,000 supplier-customer pair-year-quarter observations over the sample period from 2003 to 2017. The geographical and industry distribution of the suppliers and customers in our sample is summarized in Table 1 and visually illustrated in Figures 1a and 1b. As documented in Table 1, 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). Geographically, the majority of suppliers are located in Asia (40.3%), North Americas (38.8%), and Europe (17.4%). The regional distribution of customers is similar to the geographic distribution of the suppliers.

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. Similar to prior research (e.g. Banerjee et al., 2008; Cen, Maydew, Zhang, and Zuo, 2017), we document an asymmetric mutual importance between customers and their suppliers in our sample. First, sample customer firms are typically 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. This relationship asymmetry suggests that customers on average have higher bargaining power in the relationship with their suppliers.

2.2 Accounting Performance and Firm Characteristics

Next, we obtain quarterly financial performance records for the firms in our sample from 2000 to 2017 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 to financial performance data, we obtain information on firms' financial reporting schedules to ensure that we correctly match climate records 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 measures of 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

To study climate-related shocks affect financial performance, downstream propagation, and supply-chain formation we require data on the precise geographic location of the firms in our sample. For this purpose, we obtain information on the location of firms' operations from two different sources, FactSet Fundamentals and Orbis. First, we use the addresses (City, Zip Code, Street Name) of firm headquarters from FactSet Fundamentals as our primary measure for firm location.

Of course, firms' plants and establishments are not always located in the same location as firms' headquarters. Hence, we collect facility-level location data for our sample firm from Orbis. In total, we obtain 1.1 million addresses of locations of incorporated subsidiaries, branches, and establishments. Transforming these addresses into geographic coordinates, we calculate the share of firm locations located within a 30 kilometer radius of the firm's headquarters.

We then apply two additional 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.[5] Second, we drop all supplier-customer firm-pairs with headquarter locations within 500km of each other to rule out that both firms are affected simultaneously by the same climate-related shocks.[6]

2.4 Temperatures, Floods, and Climate Projections

We study two different types of climate related shocks – extreme heat and floods – for two reasons. First, both heat and floods are two of the most pervasive types of climate change-related events

[5]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. As a result, our measures of heat and flood exposure after filtering out dispersed firms are likely to be identified with noise. However, the direction of the potential resulting measurement error is likely to bias our estimates in Sections 3.1 and 4 against finding significant effects.

[6]Excluding supplier-customer firm-pairs with headquarters within 1000km does not affect our results.

which are projected to become more frequent and severe in the near future (CSSR, 2017), making them a particularly important subject of study.[7] While both extreme heat and floods can cause significant economic damage (see e.g. Graff-Zivin et al., 2018; Graff-Zivin and Neidell, 2014; Zhang et al., 2018), the two types of climate-related shocks possibly affect firms' operating performance and the results propagation effects through different channels. Studying two different types of hazards allows us to compare the way climate-related shocks affect supply-chain formation, and use the heterogeneity in the magnitudes and channels to test the plausibility of our results. To capture both the occurrence and intensity of these climate-related shocks, we use the number of days on which firms were affected by high heat or floods per financial quarter as our main measures.

2.4.1 Temperatures

First, we construct indicators capturing 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 data set[8] from the European Center for Medium-term Weather Forecasts (ECMWF). The dataset provides global, daily coverage of a $0.25 \times 0.25°$ latitude-longitude grid, and is available starting in 1979.[9]

We match daily maximum temperatures to customer and supplier firms using the closest ERA5 latitude-longitude grid node and convert temperatures from Kelvin to Celsius. Following the literature on temperatures, labor productivity, and economic output, we use 30° Celsius as our main temperature threshold[10] to define days as hot.[11] Taking differences in firms reporting schedules into account, we sum the number of days on which firms are affected by high temperatures per financial quarter as our main measure heat exposure. In addition, we construct a measure of heatwaves by identifying spells of seven or more consecutive days with daily maximum temperatures over 30° Celsius by firm location. Table 2d shows all related summary statistics.

[7]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.

[8]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.

[9]Hersbach 2016 provide a detailed description of the dataset.

[10]In robustness tests, we combine this absolute threshold with relative definitions of high temperatures based on season- and location-specific historical temperature distributions.

[11]For instance, Sepannen, Fisk, and Lei (2006) find that worker performance decreases significantly above 30° C in an experimental setting. The National Weather Service defines heatwaves based sequence of days during which temperatures exceed a threshold of 90° F/32° C.

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, which uses satellite images and remote sensing sources to identify inundated areas. In addition, the Dartmouth Observatory collects information on floods from news and governmental sources, and spatially maps materially affected areas. The dataset includes start and end dates for each flood and detailed geographical information on the inundated areas from 1984 until today. The dataset further provides information on the floods such as the associated damages, size of the affected area, and deaths. Based on flood polygons provided by the Dartmouth Observatory, 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 a given firm location was inundated at a given point in time.

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. Conditional on their occurrence, floods in our sample last 10.74 days on average.

2.4.3 Temperature Projections

Third, we use data on daily climate projections, which are computed in the framework of 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 the 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

[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).

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', with very limited policy interventions directed at emissions reduction. To capture cross-sectional variation in the projected change of temperatures, we obtain data for the 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 Climate-Related Shocks and Firm Performance

3.1 Direct Exposure to Climate-Related Shocks

To validate our identifying assumption that heat and flood events have economically important direct and indirect effects, we first study how climate-related shocks affect supplier performance. Our two main variables for measuring firm operating performance are sales turnover and profitability. Specifically, we use quarterly 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. 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.

If firms organize production to maximize profits and climate-related shocks affect financial performance, managers may choose (not) to produce in certain locations based on the existing climatic conditions. Consequently, climate exposure and firm financial performance are likely to be

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

endogenous in the cross-section. However, 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. Hence, our empirical strategy relies on the assumption that variation in climate-related shocks over time is plausibly exogenous and randomly distributed conditional on firm locations.

We isolate this variation by estimating OLS regressions with firm-by-fiscal quarter fixed effects. This empirical strategy 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 any time-invariant and potentially endogenous firm-level characteristics. Second, controlling for firm-specific seasonality is important because firm operating performance varies seasonally by firm throughout the year, which could be correlated with the incidence of climate-related shocks. Further, we follow the related literature and include industry-by-year-by-quarter fixed effects to absorb industry-specific time trends. We also include country-specific linear trends to control for confounding simultaneous trends in temperatures and firm performance. Moreover, to address the possibility that climate-related shocks randomly coincide with changes in firm characteristics over time, we additionally 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 in our main specification, following Barrot and Sauvagnat (2016). Specifically, we estimate models of the following form:

$$y_{iqt} = \sum_{t=-k}^{0} \beta_t \times \ Climate - Related\ Shocks_{iqt} + \mu_{iq} + \gamma_{nqt} + \delta_{BS2016} + \epsilon_{iqt} \tag{1}$$

where y_{iqt} is either $Revenue/Assets$ (Rev/AT) or $Operating\ Income/Assets$ (OpI/AT) of firm i in quarter q of year t, $Days\ Climate - Related\ Shock_{iqt}$ measures the number of days on which firms i are exposed to heat or floods in year-quarter qt, μ_{iq} are firm-by-quarter fixed effects, γ_{nqt} are industry-by-year-by-quarter fixed effects based on 2-digit SIC codes, and δ_{BS2016} are firm size, age, and profitability by time fixed effects. Following Barrot and Sauvagnat (2016), we cluster robust standard errors at the firm level. In robustness tests, we also use indicators as well as count variables of climate events by financial quarter as alternative specifications. As it is ex-ante unclear if the financial impact of climate-related shocks manifests immediately or with some delay throughout the financial year, we include three lags of climate-related shocks, i.e. $k = 3$.

[Insert Table 3 here.]

Table 3 reports the regression results for Equation (1). The results in both panels indicate that 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.[14] 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 similar to the effects documented in studies on heat and worker performance in an office environment: According to Sepannen et al. (2006), an increase in temperatures from 25 to 30° C decreases task performance 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).[15]

Given our economically larger effects on operating income compared to revenues, supplier profitability is likely affected both through cost and revenue channels. Focusing on heat, the applied microeconomics 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 worker performance are compromised (Sepannen et al., 2006; Xiang, Bi, Pisaniello, and Hansen, 2014). These channels have been studied less extensively with regards to floods. The observed net effect could be due to damages to equipment and infrastructure or production distortions during flooding events.[16]

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

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

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

Table A2 further examines the heterogeneity of these effects by industry. For heat, we observe particularly pronounced effects in agriculture, transportation, manufacturing, mining and construction, and services. Overall these effects are in line with evidence documented in the literature on the negative effect of heat on crop yields, outdoors industries, and labor and capital productivity.[17] For floods, we observe the strongest effects in industries with high asset tangibility, including mining and construction, manufacturing, and agriculture.

We further test the validity of our choice to match climate-related shocks and 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.[18] 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.[19]

3.2 Indirect Exposure to Climate-Related Shocks

Next, we examine if climate-related shocks propagate along the supply-chain affecting the operations of downstream firms. Previous research (e.g. Barrot and Sauvagnat, 2016; Carvalho et al., 2020) has documented performance spillovers from customers to suppliers following large-scale natural disasters. In comparison to the shocks examined in these studies, 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 due to climate change. This may allow firms to observe climate-related shocks, update their beliefs, and adjust their supply-chain networks, which is not possible focusing on earthquakes or tsunamis.

The downstream effects of climate-related 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 vis-a-vis their customers is small, their ability to pass on higher costs due to heat or flood

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

[18] 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.

[19] 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.

exposure may be limited. In both cases, neither heat- nor flood-related distortions would propagate along the supply-chain, and we should be unable to document a significant impact of climate shocks to suppliers on customer financial performance. On the other hand, even small environmental shocks resulting from heat exposure or floods could cause supply-chain glitches and lower production output and/or increased costs at the supplier and customer level, particularly given modern just-in-time production and inventory management systems. These disruptions are particularly likely if the provided 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 are affected by climate-related shocks to their suppliers. In line with Section 3.1, we use sales turnover and profitability, measured by revenue over assets and operating income over assets, as our two main dependent variables. As climate-related shocks to suppliers may distort supply-chain operations in ways that do not affect financial performance but strain the relationship between customers and suppliers, our tests may understate the extent to which supply-chain relationships are challenged by floods and high temperatures.

Our tests require two identifying assumptions. First, we assume that realizations from the underlying climate distribution (i.e. climate-related shocks) are drawn randomly over short horizons, and rely on this variation for causal interpretation of the observed effects.[20] Second, to satisfy the exclusion restriction, we ensure that customer firms are not directly affected by the same climate-related shocks as their suppliers. To rule out simultaneous demand-side effects, 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 et al., 2017; Phua, Tham, and Wei, 2018), we collapse our supplier-customer panel at the customer-year-quarter level. For our main test, we estimate OLS regressions of the following form,

$$y_{cqt} = \sum_{t=-3}^{0} \beta_t \times Climate - Related\ Shocks_{cqt} + \mu_{cq} + \gamma_{n(c)t} + \delta_{BS2016} + \epsilon_{cqt} \quad (2)$$

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

where y_{cqt} is either *Revenue/Assets* or *Operating Income/Assets* of customer c in quarter q of year t. *Climate Shocks*$_{cqt}$ is the sum of heat or flood days across the locations of all suppliers of customer c in year-quarter qt. Further, μ_{cq} are customer-by-quarter fixed effects and customer country-specific time trends, $\gamma_{n(c)qt}$ are customer industry-by-year-by-quarter fixed effects, and δ_{BS2016} are customer firm size, age, and profitability $\times$ year-quarter fixed effects similar to Equation (1). Robust standard errors are clustered at the customer level. In line with Section 3.1, we include lags of $k = 3$ periods for the climate-related shocks.

Our identifying assumptions imply that besides existing supplier-customer relationships, customer characteristics are not systematically correlated with both firm performance outcomes and the occurrence of floods and heat days at related suppliers. In line with the related literature, we hence do not include firm-level controls in our main specification, but add size, age, and profitability by quarter fixed effects (δ_{BS2016}) to control for different firm profiles, analogous to Equation (2).

3.2.1 Results

The results show that both heat (Table 4a) and floods (Table 4b) in the locations of the supplier firms 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. In line with the idea that floods represent more severe disruptions than heat days, one additional day of flooding at supplier locations decreases customer revenues by 0.0229 percentage points.[21] We find similar effects of high temperatures and floods on operating income. One additional day of heat (flooding) at supplier locations decreases customer operating income over assets by 0.004 and 0.0007 percentage points, respectively.

[Insert Table 4 here.]

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.

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

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 customer firms – particularly given that both heat days and inundations are projected to increase in frequency and severity.[22]

The operating income effects are consistently larger than the effects on revenues in percentage terms, consistent with the hypothesis that customers may be affected by indirect shocks both through channels affecting costs and productivity. For instance, while shocks to suppliers may cause supply chain glitches, the relatively larger effects on profitability could be due to costly adaptive behavior in the short run. This is broadly in line with the literature on multi-sourcing and endogenous production networks (Du, Lu, and Tao, 2009; Antràs, Fort, and Tintelnot, 2017; Gervais, 2018), which highlights the trade-off between input cost minimization and risk diversification.

3.2.2 Robustness

To test the robustness of our result, we estimate Equation (2) using alternative measures of climate-related shocks. We first replace heat and flood days with indicator variables taking the value of one if at least one heatwave (defined as seven consecutive days on which temperatures exceeded 30° C) or flood occurred across suppliers per customer quarter in Appendix Table A3a. Further, in Appendix Table A3b, we define days on which the local temperature in the supplier location exceeded both 30°C and the 95th percentile of historical local temperatures as supplier heat days, and count the number of heat days across suppliers per customer-quarter. This alternative measure helps address concerns that the effect of heat may differ across locations depending on the local climate. We also include tests retaining only severe flooding incidents in Appendix Table A3b, as defined by the NOAA. The results of both tests are similar to our main findings.

Next, we verify that our estimates do not exhibit any significant pre-trends to validate the iden-

[22]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.

tifying assumption that short-term climate-related shocks are drawn randomly from the underlying climate distribution. For this purpose, 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.[23]

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.[24] Table A4 shows the estimates of Equation (2) using only local flood and heat-related shocks which are *not* recorded in the global disaster database EM-DAT. The results are very similar to our main results, indicating that our findings are not solely driven by the largest climate-related shocks.

3.2.3 Cross-Sectional Heterogeneity

We next explore cross-sectional differences in the propagation of climate-related 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 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 more vulnerable supplier firms.[25]

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

[23]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.

[24]Disaster records often only record major incidents. EM-DAT only records incidents which have caused ten or more associated casualties, affected more than 100 people, lead to the declaration of a state of emergency, or resulted in a call for international assistance.

[25]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, respectively.

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.[26] Table 5 shows the results.[27]

[Insert Table 5 here.]

Consistent with the notion that heat particularly affects firms with high labor intensity, 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. In line with this interpretation, we do not find a significant interaction effect of heat days and supplier asset tangibility. As shown in Table 5b, the effect of flood-related supplier disruptions is concentrated in customer firms with both high capital intensity across suppliers (Column 1) and high labor intensity (Column 2).

Focusing on input substitutability and customer dependence, we find a statistically significant moderating effect of supplier industry competitiveness on the propagation of climate-related supplier shocks for both heat and floods. This finding indicates that customers' ability to switch suppliers and low supplier bargaining power reduce customer exposure to climate-related risks in their supply-chains. 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 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).

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

[27] For ease of readability, the dependent variables in Table 5 are multiplied with 100. The results for customer revenues are shown in Appendix Table A5.

[Insert Table 6 here.]

In line with the idea that climate-related supplier 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 climate-related 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

In this section, we study how firms respond to climate-related shocks to their supply-chains. If such shocks are financially material and become more frequent over time, firms may face incentives to adapt their production networks.[28] However, managing climate change adaptation is a complicated task. In the short- and medium-term, weather outcomes provide a noisy signal of potential changes in the underlying climate distribution. A large literature in finance and economics has proposed Bayesian updating to model how economic agents infer information about changing climate distributions from their own experience (Alevy et al., 2007; Chiang et al., 2011; Deryugina, 2013; Moore, 2017; Kala, 2019; Choi et al., 2020; Kelly et al., 2005). We follow this literature in our main analysis and start from the assumption that firms form expectations about climate-risks from historical information and update their prior going forward based on experienced climate signals.[29]

[28] Note that, for such responses to take place, customers do not necessarily need to be aware of the underlying drivers of supply-chain disruptions and performance effects. While customers may understand their suppliers' climate-risk exposure particularly to salient shocks, merely the occurrence of supply-chain glitches and performance changes may lead customer firms to reevaluate their supplier-relations and extrapolate these signals into the future.

[29] In our main tests in Section 4.1, we do not consider the role of forward-looking projections about climate-risks for firms' expectations and the learning process. We add this perspective in Section 4.4.

4.1 Realized and Expected Climate-Related Shocks

We begin by testing if increases of supplier's experienced exposure to climate-related shocks beyond plausible ex-ante expectations affect the likelihood that the supplier-customer relationship is terminated. In our framework, managers maximize profits and trade off supplier risks – including environmental risks – with other supplier and contract characteristics such as product quality, costs, and delivery times when making decisions about input sourcing.[30] In this setting, customers are aware of supplier locations and the associated exposure to climate-related risks. Initially, the equilibrium choices of supply chain partners are such that profits are maximized at the customer level, and that input costs reflect suppliers' average exposure to shocks.

Hence, if managers understand that weather outcomes are drawn from an underlying climate distribution, transitory climate-related shocks in line with prior expectations should leave supply-chain relationships unaffected. However, shifts in the (perceived) distribution of climate events could render initially optimal supplier choices permanently sub-optimal and lead to supplier terminations.[31]

4.1.1 Empirical Strategy

To examine this question, we construct a measure which indicates that climate-related shocks have increased beyond customers' ex-ante expectations as illustrated in Figure 2. First, in line with the literature (e.g. Kala, 2019; Choi et al., 2020), firms form a prior (i.e. $Expected\ Climate-Related\ Shocks$) based on the historical expected number of climate-related shocks per year at the supplier location *before* the start of any given supplier-customer relationship.[32] Starting in $t = 0$, i.e. the beginning to the supplier relationship, customers then evaluate their experience and update their beliefs about the average annual exposure to climate-related shocks, i.e. $Realized\ Climate - Related\ Shocks$. Our main measure, $\mathbb{1}\left(Realized > Expected\ Climate - Related\ Shocks\right)\ (t)$, takes the value of one in year t if the difference between the realized number of climate-related shocks per year since the beginning of the supplier-customer relationship exceeds the corresponding prior, and zero otherwise.[33] The indicator variable for the deviation of experienced and expected exposure is

[30] We build on the model of adjustment costs under environmental change first introduced by Kelly et al. (2005).

[31] Customers' might infer that there have been changes in the mean or in the variance of climate-related shocks, which might prompt them to seek more robust solutions as in Kala, 2019.

[32] Since firms' time horizon for this benchmark period is unclear, we estimate average shock exposure over different horizons including five, ten, and fifteen year periods.

[33] In additional tests, we use the continuous difference measure $(Realized - Expected\ Climate\ Shocks)\,(t)$.

labelled $\mathbb{1}\left(Realized > Expected\ Climate - Related\ Shocks\right)\ (t)$, and takes a value of one in year t if the difference between the realized number of climate-related shocks per year since the beginning of the supplier-customer relationship exceeds the corresponding prior, and zero otherwise. For alternative tests, we use the difference $(Realized - Expected\ Climate\ Shocks(t)$ between expected and realized values.

To construct our main outcome variable, we use information on the start and end dates of customer-supplier relationships from Factset Revere. In a panel of active customer(c)-supplier(s)-year(t) 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 derived from the long-differences approach introduced by Burke and Emerick (2016), and relies on the fact that short-run climate trends, in contrast to long-run changes, are quasi-randomly assigned across space. The variation in our main measure, constructed as illustrated in Figure 2, is summarized in Figure 6a and 6b. We plot both the difference of *Realized* and *Expected Climate Shocks* (t) as well as the residual variation of this difference after absorbing high dimensional time-varying regional fixed effects. The fixed effects leave the variation largely unaffected, in line with the idea that the underlying trends are quasi-randomly assigned. In economic terms, our identification strategy leverages the idea that managers can incorporate expected levels of climate risk exposure, but not deviations from the expectation into their decision making. Based on this reasoning, we estimate the following linear probability model:

$$\mathbb{1}\left(End\right)_{sct} = \beta \times \mathbb{1}\left(Realized > Expected\ Climate\ Shocks\right)_{st} + \mu_{cs} + \gamma_{n(s)t} + \rho_{c(s)t} + \epsilon_{int} \tag{3}$$

To control for potential confounding effects which may coincidentally correlate with both climate-related 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 $\gamma_{n(s)t}$ to account for industry trends, for example related to trends in make-or-buy choices. Second, we add supplier country-year by customer country-year fixed effects $\rho_{c(s)t}$ to account for changing macroeconomic conditions and changes in trade barriers, such as tariffs or import-related costs. We cluster robust standard errors at the relationship level. To satisfy the exclusion restriction that the observed climate-related shocks and trends affect suppliers only, we exclude all customers-supplier pairs with customers located within a 500 kilometer radius of the affected supplier.[34]

4.1.2 Results

Table 7 reports the estimates obtained from Equation (3). Across all specifications, we find that existing suppliers are more likely to be dropped when the realized exposure to days with high temperatures or flooding exceeds customers' prior expectations. 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.

4.1.3 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 (3) 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, to address concerns that supply-chain relationships in our sample ended because suppliers ceased operations following a climate-related shock instead of being dropped by customers, we

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

exclude supplier firms which were delisted within two years of the relationship end date from the sample. The results, presented in Appendix Table A7a, show that our findings remain similar. Third, 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. Fourth, 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 by the exclusion of these observations.

Fifth, 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 $max\,[1(Realized > Expected\ Climate\ Shocks)]$ for 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. Table A8 shows Cox proportional hazard model estimates of the effect of increases in supplier climate-risk exposure. 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.

4.1.4 Cross-Sectional Heterogeneity

To test the plausibility of the 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 (3) 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-related shock exceedance on supplier termination. Table 8 reports the results.

[Insert Table 8 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. 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 8, 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 supplier-relationships increases and hence modulates customers' reactions to experienced climate-related risks in excess of expectation.

4.2 Learning from Experienced Change

So far, we provide evidence that firms are more likely to terminate existing supplier relationships when climate-related 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 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). Second, we should observe that stronger deviations lead to more pronounced effects (Deryugina, 2013).

[Insert Table 9 here.]

In Table 9a, we first estimate changes in the likelihood of supplier termination as a function of the number of years during which realized climate-related shocks exceed customers' priors.[35] In line with firms following Bayes rule, 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.[36]

Moreover, we test if firms' responses to deviations of realized and expected climate-risk exposure increase with the magnitude of the signal. We estimate Equation (3) using the continuous measure $Realized - Expected\ Climate\ Shocks(t)$ instead of an indicator variable and present results in Panel 9b. Consistent with Bayesian learning, we find that the likelihood of supplier terminations increases with the magnitude of the deviation, measured in heat and flood days.

4.3 Responses to Salient Events

If managers strategically select suppliers and are aware of average climate conditions at supplier locations, transitory shocks in line with ex-ante expectations should leave supply-chain relations unaffected. However, 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.

In our setting, availability bias could influence customers' decisions about replacing suppliers of firms react to recent, salient events. In this case, we would expect the likelihood of supplier termination to increase with recent climate-related shocks. We empirically test this prediction by replacing our measures of climate-risk exceedance in Equation (3) with contemporary climate-related shocks, i.e. *Realized Heat Days* and *Realized Flood Days*, as our main independent variables.

[Insert Table 10 here.]

Our results, presented in Table 10, 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, shown in

[35] 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 $\mathbb{1}\,(Realized > Expected)$.

[36] 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.

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 of differences in coefficient estimates comparing contemporary shocks to climate-risk exceedance are statistically significant across all models and 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 changes in customers' perceptions of climate-change related risks.

4.4 Experienced Heat Days and Temperature Projections

Our previous tests provide evidence that firms form expectations about climate-related risks based on backward-looking historical information. In reality, firms and managers might also consider other signals when updating their beliefs, such as long-term projections about future changes in the local climate. Importantly, perceived short-run changes can diverge substantially from long-term climate projections. In this section, we therefore examine how firms respond when experienced changes differ from future projections.

For simplicity, we first assume that firms still form priors based on historical records of climate-related shocks at supplier locations. To limit the required number of assumption about how climate projections enter firms' expectations and belief updating, we focus on cases where the change in local heat days until mid-century is projected to be close to zero. If climate projections were available to firms in our sample, projections indicating a minimal future change in local climate may attenuate the extent to which firms respond to experienced, short-run changes.

We again implement Equation (3), 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 closer to a business as usual scenario.

[Insert Table 11 here.]

In Table 11, we show the results for these estimations. Panel 11a shows the results when we estimate priors based on 10 year periods before the start of relationships, Panel 11b uses 15 year formation periods. Under a range of 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 do not take forward-looking information into account in a material way, but instead rely primarily on past experience to learn about changes in climate distributions.

We note that this result is also consistent with alternative interpretations. For example, climate projections might not have been available, firms might perceive the uncertainty around climate projections as prohibitively large, or managers might use projections both to form priors and to evaluate experienced climate-related signals in ways which produce indistinguishable responses to short-run changes. While we are unable to differentiate between these explanations, the potential challenges arising from diverging experienced change and projections are worth highlighting: as for example Moore (2017) points out, adaptation will only occur at the speed with which economic agents learn about climate change. If this is based on perceived short-term changes, adaptation may be driven by short-term changes which do not reflect long-term projections, or 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 climate-related 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 climate-related 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.[37]

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 four-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:

$$\mathbb{1}(Exposure\ New < Old)_{sc} = \beta \times \mathbb{1}\left(Realized > Exp.\ Shocks\right)_{st} + \gamma_{nt} + \delta_{ct} + \epsilon_{int} \tag{4}$$

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. $\mathbb{1}(Realized > Exp.\ Shocks)_{st}$ 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}, δ_{ct}) for suppliers and customers. 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 Fig. 1 in Panel 12b. The likelihood

[37] This idea echos the literature on mutual fund selection, which documents large performance differences between hired and fired mutual funds before but not after switches between funds (e.g. Goyal and Wahal, 2008).

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. $\mathbb{1}\left(Realized > Exp.\ Shocks\right) = 1$). This result 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).[38] We find a small, less precisely estimated positive effect of climate-risk exceedance on the difference in heat projections between 'new' and 'old' suppliers. This result is in line with the idea that firms rely less on IPCC climate projections and more on experienced climate shocks (i.e. backward-looking information) when choosing suppliers, matching our previous findings in Section 4.4.

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

[38] 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. Due to data availability, we cannot implement this exercise for flood exposure.

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 climate-related 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 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 climate-related 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 71 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 climate-related shocks propagate to customers through existing supply chain links. Second, we show that firms adapt their supply-chain organizations when climate-related 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 salient, 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 climate-related 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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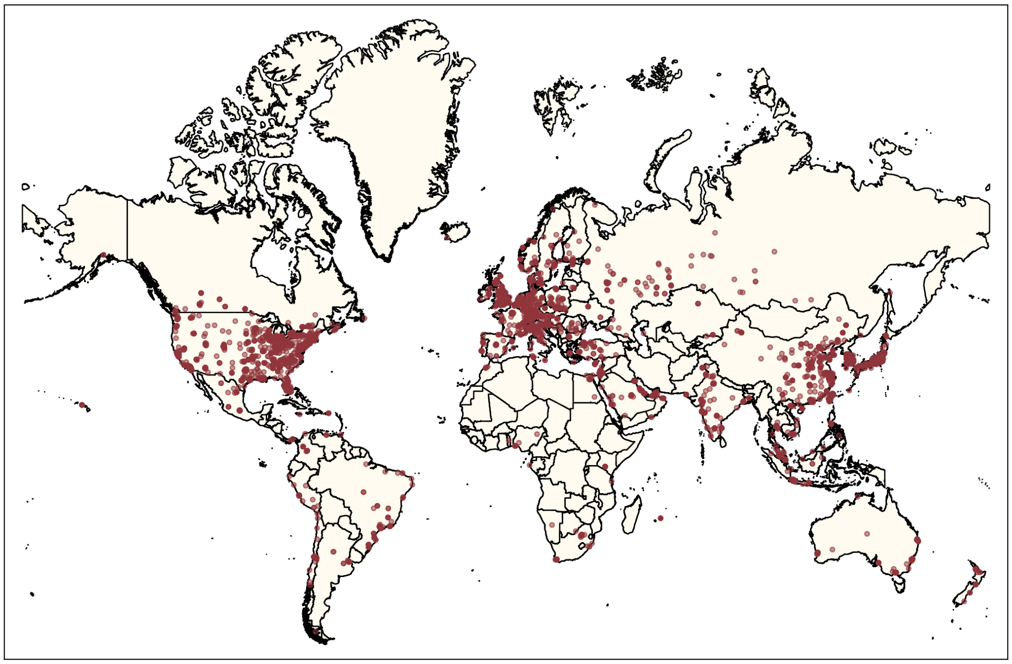
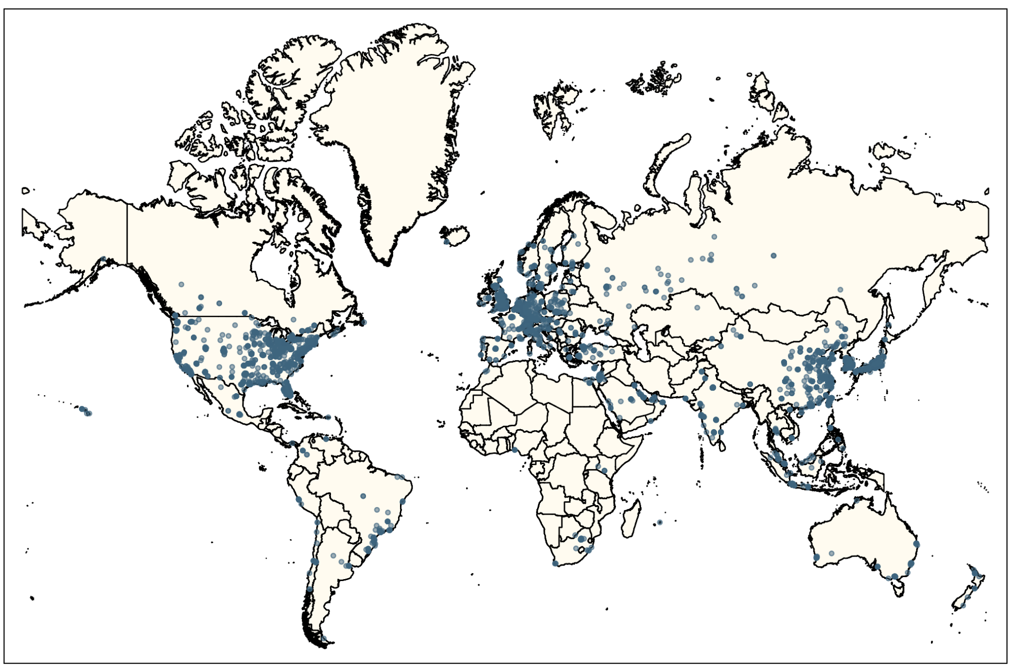
Tables and Figures

Figure 1: Geographic Distribution of Customers and Suppliers



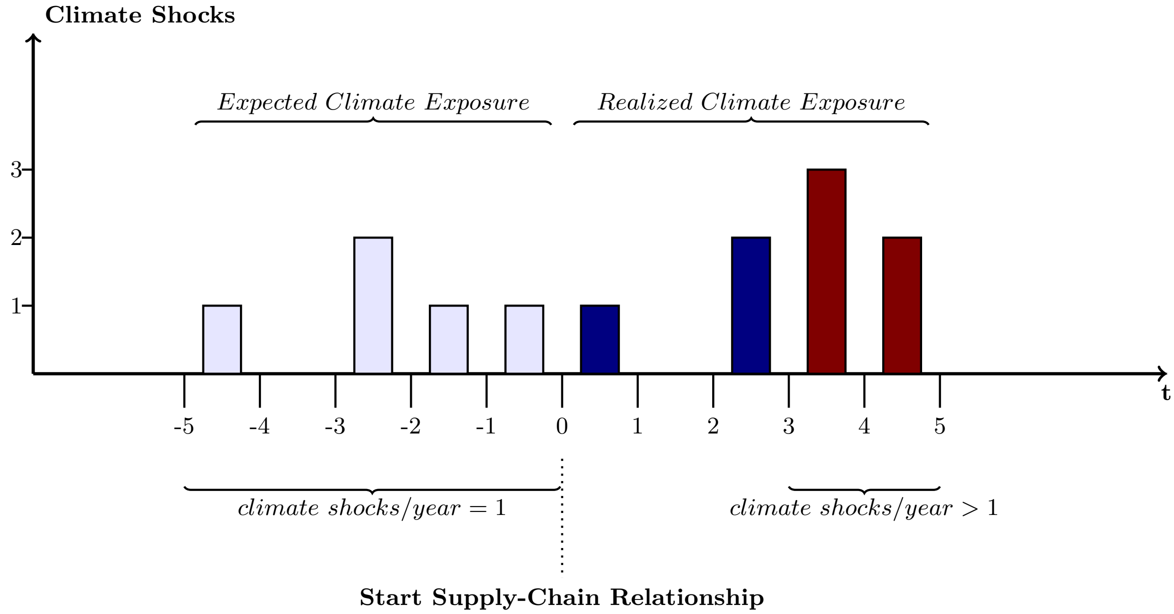
(a) Distribution of Customers



(b) Distribution of Suppliers

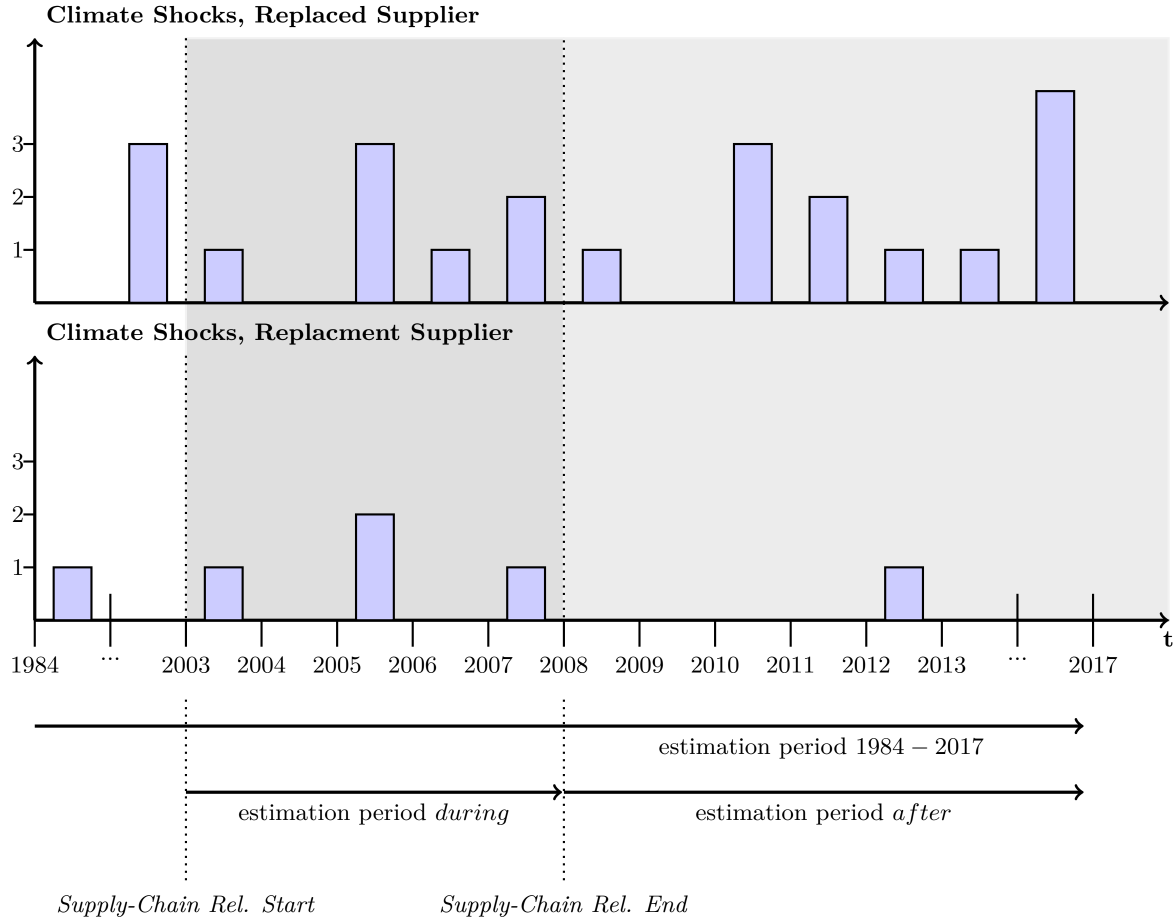
This figure shows the geographical distribution of the customers and suppliers in our sample. Supply-chain relationships and firm locations are obtained from FactSet Revere and FactSet Fundamentals, respectively. The corresponding Table 1 reports the number of customers by geographic regions.

Figure 2: Variable Construction — $\mathbb{1}(\mathit{Realized} > \mathit{Expected\ Climate\ Shocks})\ (t)$



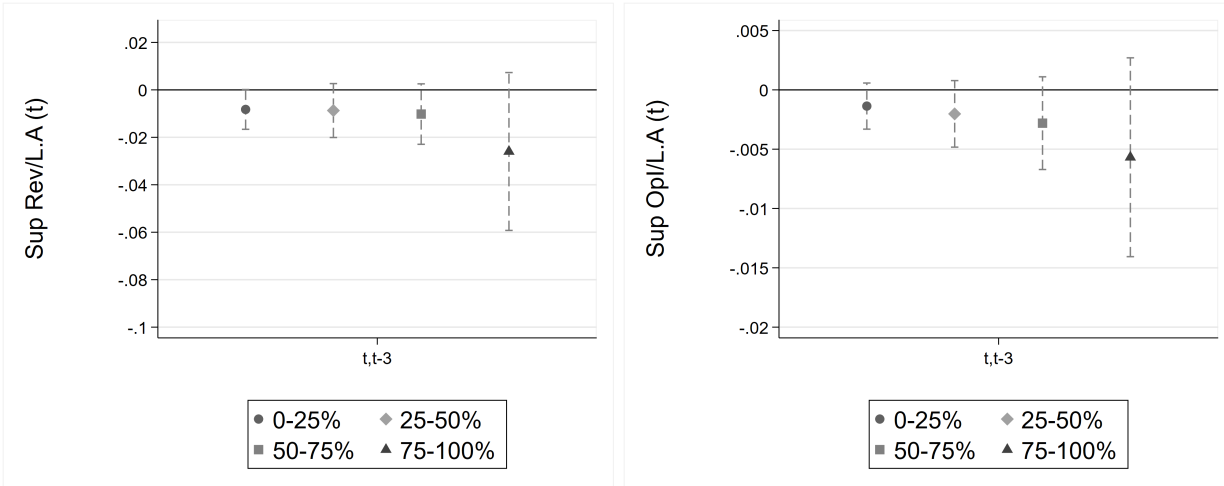
This figure illustrates the construction of $\mathbb{1}\left(\mathit{Realized} > \mathit{Expected\ Climate\ Shocks}\right)\ (t)$, an indicator variable capturing the discrepancy between realized and expected climate risk based on the exposure of a hypothetical supplier to climate shocks over time. It is constructed by first estimating the historical prior as the expected number of climate shocks per year in the supplier location over a benchmark period of five (in robustness tests seven, ten, and fifteen) years *before* the establishment of a given supplier-customer relationship. $\mathbb{1}\left(\mathit{Realized} > \mathit{Expected\ Climate\ Shocks}\right)\ (t)$ then takes the value of one in 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 *(illustrated in red)*, and zero otherwise *(illustrated in blue)*.

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

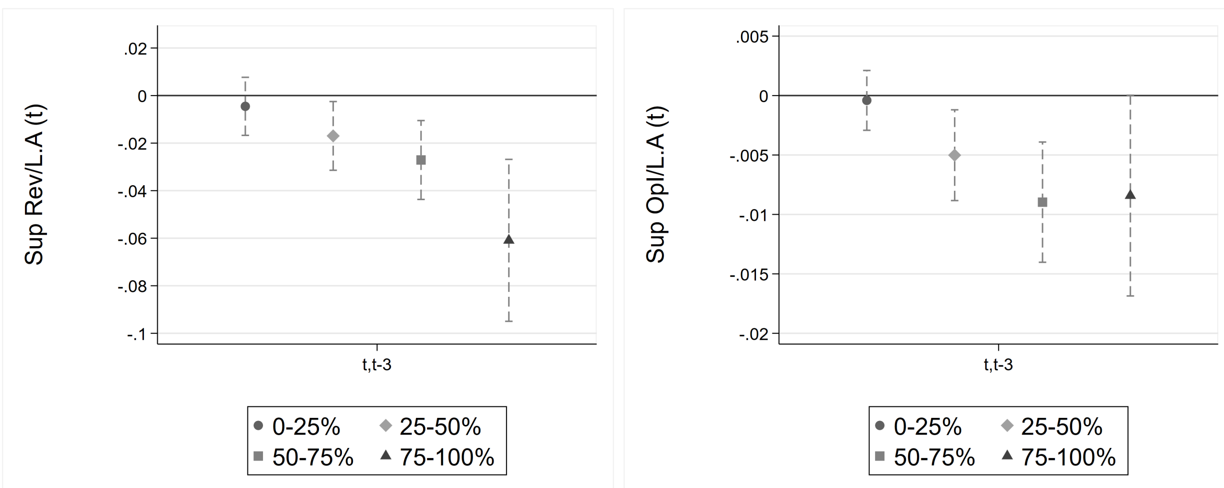


This figure illustrates the construction of the comparison of the climate exposure of replaced and replacement suppliers (Table 12) based on an example of a hypothetical replaced supplier and the replacement. We compare the climate exposure of old and new suppliers based on three time periods. First, we estimate and compare the climate shock 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.

Figure 4: Direct Effects of Climate-Related Shocks By Firm Geographic Concentration



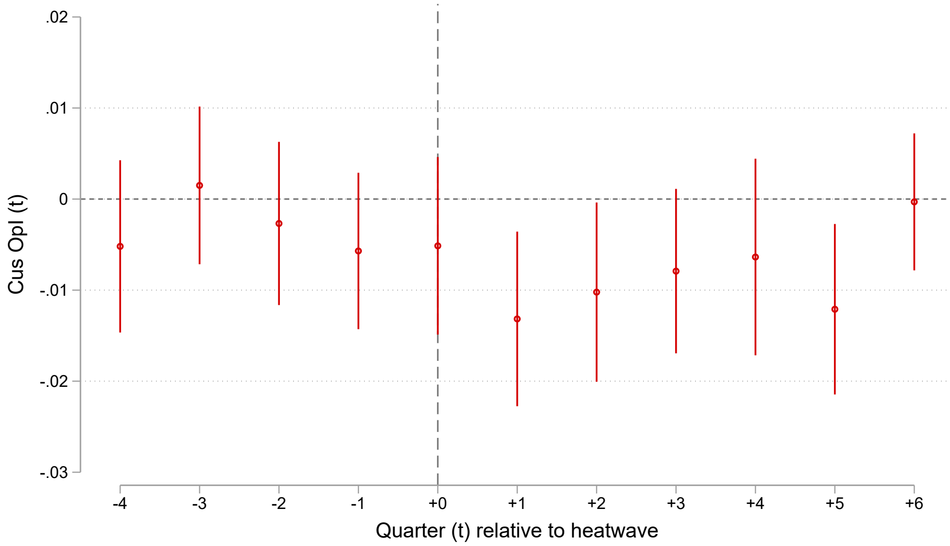
(a) Effect of Heat Days, Supplier Geographic Concentration



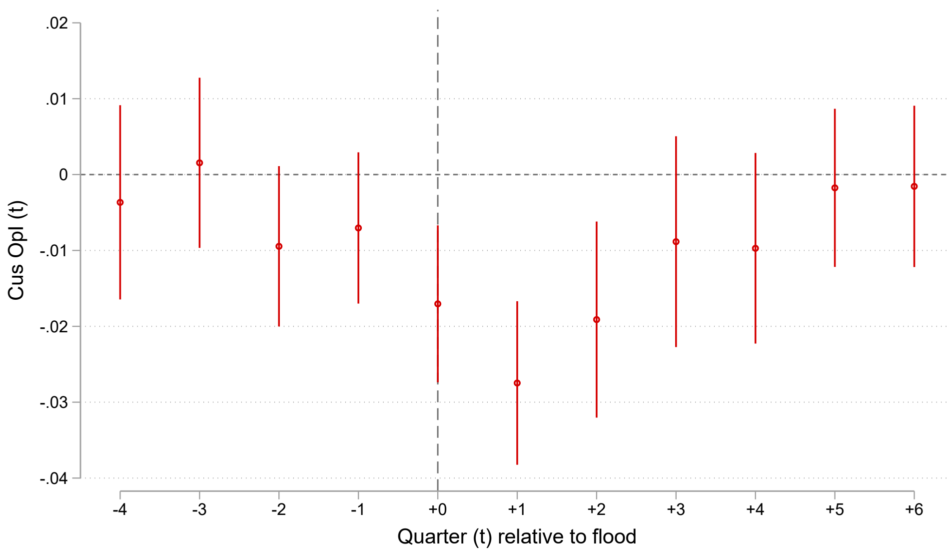
(b) Effect of Flood Days, Supplier Geographic Concentration

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).

Figure 5: Dynamics Plots – Supplier Climate-Related Shocks and Customer Performance



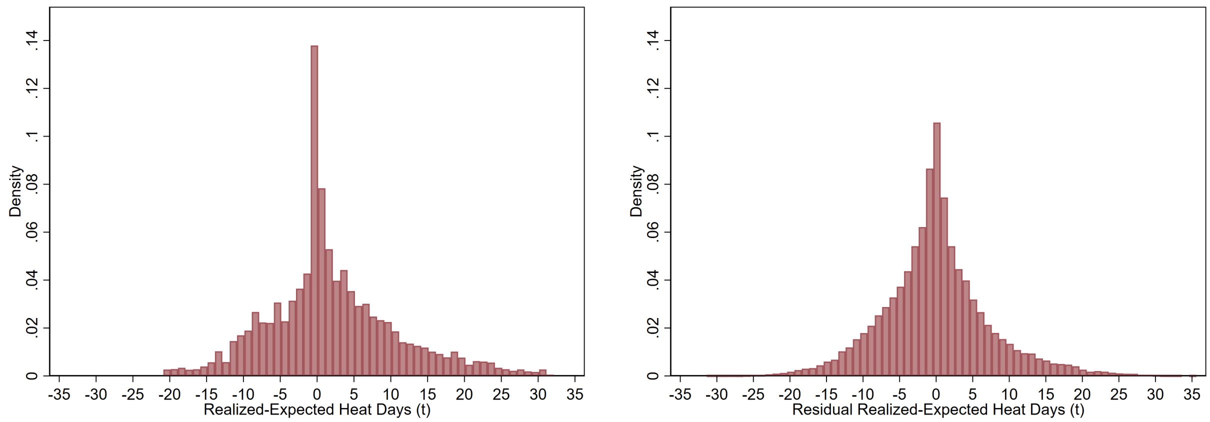
(a) Customer operating income around supplier heatwaves



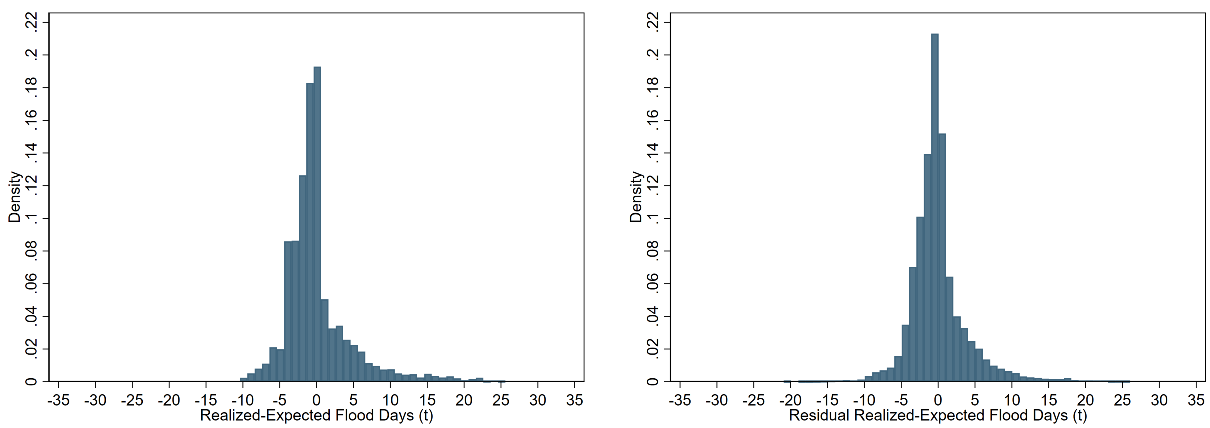
(b) Customer operating income around supplier floods

This figure shows the effect of heatwaves and floods at the supplier firm locations on customer operating income in the 11 quarters around climate-related supplier shocks. 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).

Figure 6: Identifying Variation in Realized vs. Expected Climate-Related Shocks



(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 Climate 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 climate shocks 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.

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), and customer-supplier pairs (Panel C) in our sample. The sample period is 2003 to 2017 and the number of observations refers to unique firm-year-quarters (pair-year-quarters) in Panel A, B, and D (Panel C). Data on market capitalization, book value of assets, revenue, operating income, asset tangibility, inventory, operating margin, accounts payable, 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. "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. The sample excludes observations with missing records on revenue and/or operating income, missing lagged climate exposure records, 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 Climate-Related Shocks

Table 3: Climate-Related Shocks 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 Climate-Related 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 Climate-Related 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 Climate-Related 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 $\times$ Fiscal-Qtr FE	Yes	Yes	Yes	Yes	Yes
Ind $\times$ 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 $\times$ Fiscal-Qtr FE	Yes	Yes	Yes	Yes	Yes
Ind $\times$ 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 $\mathbb{1}\,(\textit{Realized} > \textit{Expected Climate Related Shocks})\,(t)$ 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 climate-related shocks per year since the beginning of the supply-chain relationship exceeds the corresponding expected number of shocks, 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)
$\mathbb{1}\textit{Realized} > \textit{Expected HeatDays}$	0.005**	0.004*	0.009***			
	(0.002)	(0.002)	(0.002)			
$\mathbb{1}\textit{Realized} > \textit{Expected FloodDays}$				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)
$\mathbb{1}\textit{Realized} > \textit{Expected HeatDays}\ (t)$	0.050***	0.061***	0.078***			
	(0.016)	(0.017)	(0.017)			
$\mathbb{1}\textit{Realized} > \textit{Expected FloodDays}\ (t)$				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: Expected vs. Realized Climate Risk – Cross-Section

Notes. This table shows the cross-sectional heterogeneity in the impact of climate-related shock exceedance on supply-chain relationship termination. The measure $\mathbb{1}\,(Realized > Expected\ Climate - Related\ Shocks)\,(t)$ takes the value of one in 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. 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 9: Strength of the Signal – Expected vs. Realized Climate Risk

Notes. This table presents linear probability model estimates on the effect of climate-related shock exceedance, i.e. $\mathbb{1}$ (*Realized* > *Expected Climate Shocks*), on supply-chain relationship termination, taking into account how often realized climate-related shocks have exceeded expectations (Panel 9a) as well as the magnitude of the deviation of realization and expectation (Panel 9b). 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 10: Availability Heuristic and Relationship Termination

Notes. This table presents linear probability model estimates on the effect of transitory climate-related shocks on the likelihood of supply-chain relationship termination. *Realized HeatDays* and *Realized FloodDays* measure the number of heat and flood days at the supplier locations in a given year. ($Realized - Expected\ Climate\ Shocks$) is the continuous difference between the realized and expected number of climate-related shocks 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 11: Experienced Exposure, Projections, and Relationship Termination

Notes. This table presents linear probability model estimates on the effect of $\mathbb{1}$ *Realized* $>$ *Expected Climate* $-$ *Related 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 4^{th} 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

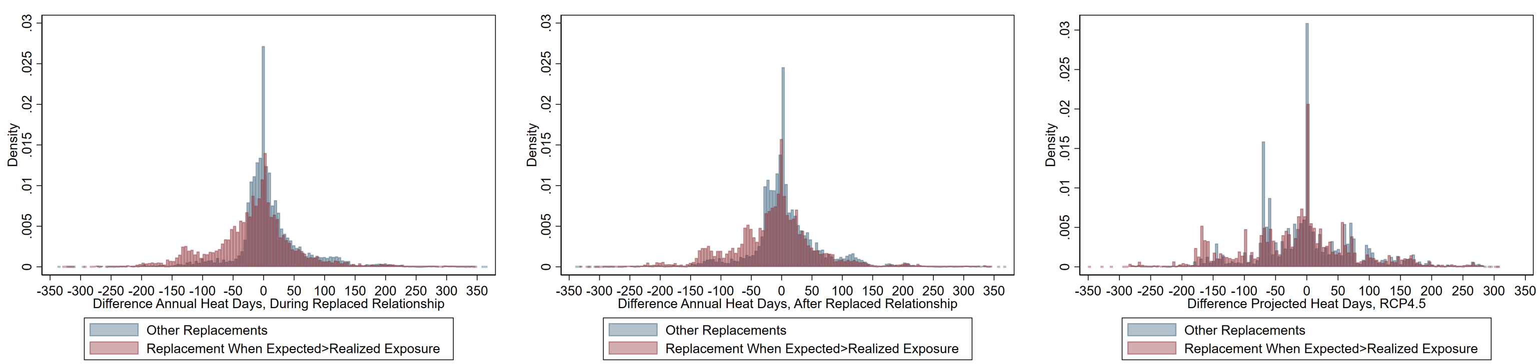
(b) Exceeded Expected Exposure and Projections, prior formed over 15-year benchmark period.

Table 12: Climate Change Risk and Supplier Substitution

Notes. This table shows the effect of climate change 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 climate-related shocks of *new* replacement suppliers is lower than the exposure of *old* replaced suppliers as a function of $\mathbb{1}$ (*Realized* > *Expected Climate Shocks*). The dependent variable takes the value of one if new suppliers are exposed to fewer climate-related shocks 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 climate-related 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

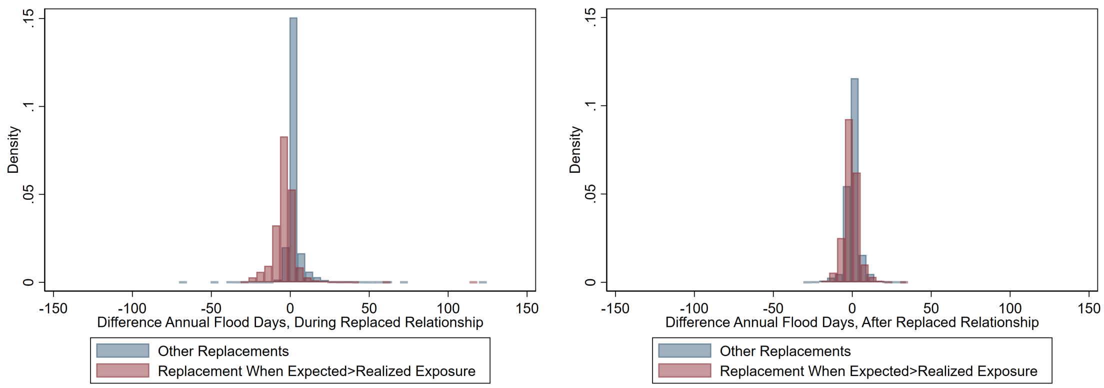
(a) Expected and Actual Decrease in Exposure to Heat



(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

A Appendix

Table A1: Robustness – Climate-Related Shocks and Supplier Firm Performance

Notes. This table shows robustness tests analogous to Table 3 on the impact of climate-related 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 Climate-Related Shocks

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 Climate Shocks

Notes. This table shows OLS regression estimates analogous to Table 4 on the effect of climate shocks at the supplier locations on their customers' revenues over assets (Rev) and operating income over assets (OpI), using indicator variables for climate-related shocks. 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) Climate related 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) Climate related 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 Climate-related shocks over EM-DAT

Notes. This table presents OLS regression estimates on the impact of climate-related 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 a climate-related shocks in the supplier's location in quarter t, in excess of climate-related 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 (0.297)	-0.2049 (0.159)	-1.3050*** (0.295)	-0.5523** (0.233)	-0.5444*** (0.192)	-1.1313*** (0.298)	-0.4261*** (0.131)	-1.1484*** (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 climate-related 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, $\mathbb{1}\,(Realized > Expected\ Climate\ Shocks)\,(t)$, 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 climate-related 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 $\mathbb{1}\,(\textit{Realized} > \textit{Expected Climate Shocks})\,(t)$ 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)
$\mathbb{1}\textit{Realized} > \textit{Expected HeatDays}$	0.004*	0.002	0.007***			
	(0.002)	(0.002)	(0.002)			
$\mathbb{1}\textit{Realized} > \textit{Expected FloodDays}$				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)
$\mathbb{1}\textit{Realized} > \textit{Expected HeatDays}$	0.065***	0.064***	0.068***			
	(0.002)	(0.002)	(0.003)			
$\mathbb{1}\textit{Realized} > \textit{Expected FloodDays}$				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 – Climate-Related Shocks and Relationship Duration

Notes. This table presents Cox proportional hazard model regression estimates on the impact of realized vs. expected climate-related 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 $max\left[\mathbb{1}\left(Realized > Expected\ Climate\ Shocks\right)(t)\right]$ 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 climate-related shocks per year since the beginning of the supply-chain relationship exceeds the corresponding expected number of shocks, 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