Climate Change and Adaptation in Global Supply-Chain Networks*

Nora M.C. Pankratz† Christoph M. Schiller‡

First version: March, 2019
This version: July, 2019

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 and flooding incidents, we first document that the occurrence of climate shocks at affected supplier firms has both a large direct and indirect negative effect on earnings and revenues of suppliers and their customers. Second, we show that customers are 10% to 20% more likely to terminate existing supplier-relationships when realized climate shocks at the supplier firms exceed ex-ante expected climate shocks. Further, customers subsequently switch to suppliers with lower heatwave and flooding exposure. Our results indicate that climate change affects the formation of global production networks.

Keywords: Firm Performance, Climate Change, Climate Adaptation, Supply-Chains.

JEL Codes: Q54; G30; F64; Q51

*We thank Claudia Custodio (discussant) and participants at the 2019 LBS Summer Finance Symposium for many valuable comments and suggestions. Moreover, we thank the Centre for Research on the Epidemiology of Disasters (CRED) for providing data from the Emergency Events Database (EM-DAT). Nora Pankratz thanks the French Social Investment Forum (FIR) and the Principles for Responsible Investment (PRI), and Christoph Schiller thanks the Canadian Securities Institute (CSI) for financial support. All remaining errors are our own.

†School of Business and Economics, Maastricht University. Email: n.pankratz@maastrichtuniversity.nl.
‡W.P. Carey School of Business, Arizona State University. Email: christoph.schiller@asu.edu.

1 Introduction

Climate change is one of the greatest challenges of our time. The average global surface temperature has increased by 0.85° Celsius (1.5° F) since the industrial revolution, leading to more frequent extreme weather events such as heatwaves, forest fires, and catastrophic floods, with dramatic effects for society and economic activity (Carleton and Hsiang, 2016). According to the 2017 U.S. Climate Science Special Report, the cost of extreme climate-related events for the United States alone has exceeded \$1.1 trillion since 1980 (CSSR, 2017).[1] By the end of the century, temperatures are expected to increase even further by 0.9 to 5.4° C (1.6 – 9.7° F) (IPCC, 2013).

While the academic literature in finance and economics has provided broad evidence on the adverse effects of climate change, including corporate earnings (Addoum, Ng, and Ortiz-Bobea, 2019), labor productivity (Graff-Zivin, Hsiang, and Neidell, 2018), stock returns (Kumar, Xin, and Zhang, 2019), and capital structure (Ginglinger and Moreau, 2019), much less is known about how firms and market participants can adapt to climate change. In contrast, managers and investors are increasingly looking for ways to mitigate climate change risks, for example by adapting their operations and investments (Lin, Schmid, and Weisbach, 2018).[2]

In the age of globalization, most firms operate in extensive global production and supply-chain networks. Supply-chains often move through parts of the world that are most vulnerable to climate impacts. As a result, adapting to climate change is a complex task, as firms might be indirectly exposed to climate change risks due to their suppliers and customers.[3] Indeed, Barrot and Sauvagnat (2016) and Seetharam (2018), among others, show that the impact of extreme weather events can propagate through firm-level production networks. Consequently, in a recent survey, over 50% of CEOs mentioned risks posed to their global supply chains by climate change as one of their primary concerns (PWC, 2015).

Hence, the aim of this paper is twofold. First, we investigate if firms are affected by climate change risk due to their global supply-chain network. Specifically, we estimate the firm performance effects of climate change related extreme weather events on supplier firms around the world and the

[1] See for example Dell, Jones, and Olken (2014) and Auffhammer (2018) for a summary of the literature on the economic effects of climate change.

[2] Krueger, Sautner, and Starks (2018) document that institutional investors consider engagement and risk management strategies to address the financial implications of climate change risks for their portfolio firms.

[3] For example, during the 2011 flooding disaster in Thailand, more than 14,500 firms reliant on Thai suppliers experienced business disruptions worldwide (BSR, 2018).

propagation of climate-related performance shocks to their corporate customers. Second, we study how firms adapt their supply-chain organizations in response to climate change risks. In particular, we examine if customers optimize and diversify their supplier network by replacing high-risk with low-risk supplier firms.

We combine detailed global, firm-level supply-chain data from FactSet Revere with geographic location data from FactSet Fundamentals and granular climate data on heatwaves from the European Center for Medium-term Weather Forecasts and floods from the Darthmouth Flood Observatory. Our supply-chain dataset includes 4,289 (4,568) unique supplier (customer) firms, comprising over 200,000 quarterly supplier-customer observations across 51 countries around the world, over the period from 2003 to 2017.[4] We focus on two types of climate change risks – extreme heatwaves and flooding – for the following reasons. First, the literature in physiology and economics has pointed to several direct and indirect channels through which heatwaves 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, Deschenes, Meng, and Zhang, 2018), with sharp declines typically observed at temperatures over 30° C.[5] Given current global carbon emissions, the number of heat days (i.e. days that exceed 100° F) is projected to rise dramatically, from currently 1% of days to more than 15% of days by 2099 (Graff-Zivin and Neidell, 2014), making extreme heatwaves a common and impactful phenomenon in the future. Second, flooding incidents can cause enormous economic damage to the affected region. According to FEMA, the United States suffered more than $260 billion in flood-related damages between 1980 and 2013. As a result of climate change, both inland and coastal floods are expected to become more frequent and severe in the coming years (CSSR, 2017).

While Addoum et al. (2019) and Pankratz (2019) show that exposure to local heatwaves affects the profitability of listed firms in many industries, both the question if climate change related shocks propagate along firm-level links and how customer firms can potentially mitigate such risks are unclear. First, the implications of climate shocks for suppliers and customers might differ. While extreme temperatures and floods might be costly to supplier firms, for example by increasing energy

[4]In contrast to previous research on supply-chains in finance, which has mostly relied on data from Compustat Segment Files, this dataset allows us to study the initiation and termination of customer-supplier relationships. See Section 2 for details.

[5]High temperatures are also associated with higher civil conflict risk (Burke, Hsiang, and Miguel, 2015a) and immigration (Feng, Krueger, and Oppenheimer, 2010), which might indirectly impact firms in the affected areas.

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. In this case, neither heat nor flood related shocks would propagate from suppliers to customers. On the other hand, if heatwaves or floods lead to lower production output, such disruptions could propagate along the supply-chain and affect customer firms, potentially with a delay.

Second, if managers understand the risks of climate change, they plausibly organize operations to absorb climate risks and minimize disruptions due to shocks to their suppliers. Again, we would not expect climate shocks to propagate from suppliers to customer in this case. On the other hand, frictions such as relationship-specific investments or a high degree of input specialization might prevent customer firms from making such adjustments or from switching to alternative suppliers. Further, the risks of climate change have become much more salient over the past decades, as the frequency of extreme weather events and scientific evidence of future risks and public awareness both have increased. If managers are increasingly considering climate change risks when making operational and investment decisions, we would expect that customers become more likely to switch suppliers when observed climate change risks exceed previous expectations.

Our first set of tests focuses on the effect of climate change related weather events on the operating performance of affected supplier firms. Following the climate science literature (Carleton and Hsiang, 2016), we construct a location specific measure of heatwaves for our sample supplier firms based on the daily temperatures over a given quarter in the location of the firm's production facilities. Consistent with Addoum et al. (2019), we document that the occurrence of a heatwave during one of the three previous firm-quarters is associated with a subsequent reduction in revenue (operating income) by 3.9% (9.7%) relative to the sample median. Focusing on flooding incidents, we document a decrease by 3.9% (10.2%) relative to the sample median. These results hold after controlling for firm-fixed effects, firm-specific seasonal trends, industry-specific time trends, as well as a host of firm- and industry characteristics and trends.

Next, we provide evidence that firms are indeed exposed to climate change risks due to their global supply-chain network. Our findings show that climate change related shocks to supplier firms have a negative effect on the performance of their customers. Following the occurrence of a heatwave in a given firm-quarter at a single supplier, customer revenues decrease by 0.2% relative to the sample median. When suppliers are affected by a local flooding incident, customer revenue and operating income are reduced by 1.8% and 2.2%, respectively. Consistent with Barrot and Sauvagnat (2016), these effects hold with a lag of up to four quarters.

We conduct a number of robustness tests. First, we employ counting measures of heatwaves and flood incidents instead of using dummy variables and find similar result. Second, we implement our experiments both at the supplier-customer-quarter observation level as well as in a collapsed sample of customer-quarter-level observations, aggregating across suppliers for each sample customer. The results are similar in both settings. Third, we implement a placebo test by studying time periods in which our supplier-customer pairs were *not yet* or *no longer* in a supply-chain relationship. We find no evidence of climate risk propagation during these placebo periods.

Our main tests focus on the adaptation of supply-chains to climate change risks. We first examine how climate change risk affects the likelihood that customers terminate the relationship with their customers. Assuming that managers trade off potential climate-related risks with other firm characteristics (product quality, costs, delivery times, etc.) when entering a supply-chain relationship, we hypothesize that a customer firm is more likely to terminate an existing supplier-relation when the climate shocks observed over the course of a supply-chain relationship exceed the ex-ante anticipated risks. We therefore construct a measure of *realized vs. expected climate risk* by comparing heatwaves and flood incidents after the establishment of a supply-chain link to the observed climate shocks in the years before as a benchmark.

We document a large, positive effect of realized vs. expected climate risk on supplier termination. Our results show that a supply-chain relationship is 1.0 (3.7) percentage points more likely to be terminated in a given year, if the realized number of heatwaves (floods) exceeds the ex-ante expected number. This effect is economically meaningful given the unconditional expectation that a supply-chain relationship ends in any given year of 15.1% in our sample. The results are robust to using several alternative ways of constructing our climate risk measure, and significant at the 1%-level, controlling for any time-invariant supplier-by-customer characteristics, various time-variant financial supplier and customer characteristics, industry-by-time fixed effects, and country-by-time fixed effects. Importantly, when we solely consider the occurrence of heatwaves and floods throughout the supply-chain relationship (without comparing it to ex-ante expected climate shocks), we find a much smaller, statistically insignificant impact on the likelihood of supply-chain relationship termination. This is consistent with the notion that managers are taking climate risks into consideration when entering a supply-chain relationship.

Last, we examine how firms optimize their supply-chain climate risk by analyzing if customers switch from high climate-risk to low climate-risk suppliers. For this purpose, we consider all instances of ending supply-chain relationships in our sample and match each 'dropped' supplier with the 'replacement' suppliers, i.e. firms with the same 4-digit SIC code which newly became suppliers to the same customer within the next two years. We then compare the realized climate risk of the dropped and replacement suppliers based on the number of heatwaves and flooding incidents over the same time period. We find that replacement suppliers on average have 0.83 fewer heatwaves and 0.03 fewer floods than terminated suppliers, measured over the duration of the relation with the terminated supplier. The result is statically significant at the 1% level (t-statistics of 17.9 and 4.2), and robust to alternative comparison periods and climate risk measures.

Our paper contributes to the literature on the economic effects of climate change along several dimensions. To the best of our knowledge, we present the first evidence of operational adaptation to climate change-risk at the firm level. Our main result shows that managers respond to climate risks resulting from their supply-chain network by switching from high-risk to low-risk suppliers, indicating that climate risks can drive the formation of global firm-level production networks. This finding has important potential implications. As the climate science literature has shown (e.g. Burke, Hsiang, and Miguel, 2015b and Carleton and Hsiang, 2016), developing countries around the world are more severely affected by the outcomes of global climate change than developed countries in North America and Western Europe. However, as particularly the largest corporations traded on international stock exchanges rely on extensive, worldwide production networks, it is important for managers and policymakers to be aware of the extent to which the economic implications of climate change are shared through supply chain links. Moreover, if firms further shift economic activity from 'southern' to 'northern' countries due to heterogeneity in climate change risk, this effect could contribute to widening global inequality and economically weaken the areas most vulnerable to climate change. Lin et al. (2018) also study climate change adaptation, focusing on the investments of electricity generating firms in more flexible power generation technologies.

This paper also provides novel evidence on the implications of climate change for firms and investors. Previous research in the finance literature has studied the direct effects of climate shocks on firm profitability (Zhang et al., 2018; Addoum et al., 2019; Pankratz, 2019), housing prices

(Baldauf, Garlappi, and Yannelis, 2019), 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). Our paper is the first to show that firms can be indirectly exposed to climate shocks due to their global supplier network. This aspect of our findings is most closely related to Barrot and Sauvagnat (2016), Seetharam (2018), and Boehm, Flaaen, and Pandalai-Nayar (2019), who document the propagation of natural disasters along input-output linkages. The fundamental difference between our study and these papers is that we focus on the effects of temperature exposure and flood incidents, allowing us to assess the potential impact of climate change risk propagation along supply-chain links. In contrast, the scientific literature makes no reliable predictions on how natural disasters such as earthquakes and hurricanes will evolve as a result of climate change.

2 Data Sources and Descriptive Statistics

To conduct our empirical analysis, 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 in detail, explain how we link the individual datasets, and provide summary statistics for our main sample. The final sample used for the empirical tests in Sections 3 and 5 varies, as we merge supplier-customer relationship data with different climate change-related databases. For example, in Section 3 we focus on the propagation of climate shocks along existing supply-chain links, while Section 5 explores the determinants of customers switching suppliers. The following summary statistics therefore refer to our main sample used to examine climate shock propagation in Section 3. For this purpose, we retain each supplier- and customer-quarter in our main sample for which a complete record of supply-chain data, financial information, and climate exposure data is available. 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 the recently available FactSet Revere database. Previous research on supply-chains in finance (e.g. Hertzel, Li, Officer, and Rodgers, 2008; Cohen and Frazzini, 2008; Banerjee, Dasgupta, and Kim, 2008) has relied primarily on the SEC's 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 in the context of this paper. First, while the SEC regulation does not apply in other countries, hence limiting existing research mostly to U.S. firms, Factset Revere supply-chain data includes both U.S. and foreign supplier and customer firms. This is important because many of the regions most vulnerable to climate change around the world 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 10-K filings, investor presentations, company websites and press releases, corporate actions, and 10-Q and 8-K filings. This is crucial for our analysis of supply-chain formation and climate change adaptation, as it provides us with precise information on the beginning and end of a given supplier-customer relationship.

In total, our sample includes 4,568 unique customer firms and 4,289 unique supplier firms across 51 different countries, comprising approximately 220,000 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 1 and 2. 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 North America (41%), East Asia and Pacific (30.6%) and Europe or Central Asia (18.4%). The regional distribution of customers is similar to the geographic distribution of the suppliers.

Table 2a (Panel C) presents relationship-level summary statistics for the firms in our sample. As documented, the average supply-chain relationship in the sample lasts 13.83 quarters. Similar to previous research on supply-chains in finance (e.g. Cen, Dasgupta, Elkamhi, and Pungaliya, 2015; Cen, Maydew, Zhang, and Zuo, 2017; Cen, Chen, Hou, and Richardson, 2018), 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 sample customer holds 29 times the assets of the median supplier firm (book value of assets). Second, for firm-pairs where detailed sales data from supplier to customer is available (9.39% of the sample), the average proportion of sales the sample customers represent to their suppliers is 17.87%, while the average proportion of cost-of-goods-sold (COGS) suppliers represent to customers is only 1.82%. 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 Compustat Global.[6] Our main variables of interest for measuring operating firm performance in Section 3 are quarterly revenues and operating income, scaled by asset size. 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. To ensure that international financial records comparable, we convert all variables into U.S. dollars using the WRDS currency conversion tables, and deflate the values using the consumer price index information provided by the International Financial Statistics of the International Monetary Fund.

We further collect data on several additional firm characteristics from FactSet as control variables. These characteristics include firm controls such as the date of the first trade of the firms' shares to construct a proxy for firm age, the price-to-book ratio as well as the debt-to-assets ratio. To remove outliers, we trim 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).

Panels A and B of Table 2a report summary statistics for customer and supplier financial performance and firm characteristics after applying the data filters outlined above. In line with

[6] Compared to our sample of supply-chain relationships from FactSet Revere, we extend the financial performance sample by three years for later placebo tests, see Table 5.

the expectation that suppliers are on average smaller than their customers, the average book value of assets is is 6,354 million USD for customer firms, and 5,097 million USD for suppliers. Customers (Panel A) and suppliers (Panel B) have similar operating performance in our sample. The average quarterly (median) customer *Revenue/Assets* is 23.99% (19.91%) for customers and 21.96% (18.77%) for suppliers. The average quarterly (median) customer *Operating Income/Assets* is 2.47% (2.57%) for customers and 1.92% (2.31%) for suppliers.

2.3 Firm Locations

A crucial requirement for our empirical analysis of the impact of climate shocks on downstream propagation and the formation of supply-chain relationships is identifying the location of our sample firms. In this paper, we obtain information on the location of firms' operations from the FactSet Fundamentals database. Specifically, as our primary measure for firm location we use the addresses (City, Zip Code, Street Name) of firm headquarters as obtained from FactSet Fundamentals.

Of course, firms' plants and establishments are not always located in the same location as firms' headquarters. However, this measurement error is likely to bias our estimates in Sections 3 and 5 against finding any effect of climate shocks on firm performance and supply-chain formation. In addition, we use FactSet Revere information on firms' geographical concentration of assets to determine in which locations firms operate. These records are collected based on firms' public reporting of assets, sales, and income by geographic and product segments. Specifically, publicly listed firms are required to disclose these concentrations for all segments which represent more than 10% of total assets, sales, or income. In our main analysis, we limit our sample to firms with more than 50% of their assets in their home country to ensure that climate shocks affect a substantial part of firms' assets and operations. To match firms with the local information on climate hazards, we geocode the addresses of their headquarters using the Bing Maps API.

We apply two additional location-based data filters to our main sample: First, we remove decentralized firms with $< 50\%$ of assets in their primary geographic segment. Second, we drop all supplier-customer firm-pairs for which the headquarters of the two firms are located within 500km of each other in the analyses of Section 5, to rule out that both firms are affected simultaneously by the same climate shocks. As reported in Panel A and B of Table 2a, both customers and suppliers hold a substantially larger share of their assets in their home country than imposed by our 50% threshold:

the average asset home-country concentration of customers is 79.4%, and the concentration of suppliers' assets is 80.5%.

2.4 Climate Data

In this paper we focus on two types of climate change related shocks – extreme heatwaves and flooding incidents – for the following reasons. First, heatwaves and floods are regionally concentrated events, allowing us to exploit the high granularity of climate data and the resulting geographic variation in climate exposure across our sample firms in our empirical tests. Second, climate science research widely agrees that heatwaves and floods are expected to become significantly more frequent and severe in the coming years (CSSR, 2017), making these climate shocks a particularly important subject of study for assessing the future economic costs of climate change. This is different from other type of natural disasters previously studied in the literature, e.g. earthquakes or hurricanes, as their occurance cannot be unambiguously linked to climate change. Third, 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 shocks possibly affect firms' operating performance and the results propagation effects through different channels. This allows us to further study the way climate shocks affect supply-chain formation by comparing similarities and differences between the effects of heatwaves and flooding incidents.

2.4.1 Heatwaves

First, we construct indicators capturing the occurrence of heatwaves at the firm-quarter-level from daily, location-specific information on maximum temperatures. The global coverage of weather station-based temperature records varies substantially across time and across different regions around the world. The resulting data gaps can cause substantial issues for empirical analysis, as weather station coverage can for example be correlated with other economic characteristics of a given region. To alleviate this concern, we use 're-analysis' temperature data[7] from the European Center for Medium-term Weather Forecasts (ECMWF), which is available at a significantly higher geographical and temporal granularity than the temperature data used in previous research (see

[7]Re-analysis temperatures 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.

e.g. Lin et al., 2018). Specifically, we use the ERA-Interim reanalysis data set with global, daily coverage of a 0.75 × 0.75° latitude-longitude grid. The data is available starting in 1979.[8]

To construct our sample of local heatwave shocks, we begin by matching daily maximum temperatures to customer and supplier firms by based on the closest ERA-interim latitude-longitude grid nodes for the geocoded addresses of our sample firms. Next, we convert the temperatures from Kelvin to °Celsius and identify the start and end dates of heatwaves. Following the heatwave definition of the National Weather Service, we label spells of three or more days with daily maximum temperatures over 30° Celsius by firm location as the occurrence of a heatwave (National Weather Service, 2019)[9]. Additionally, we compute the duration of the heatwaves by location and heatwave, and aggregate the number of heatwave days on the monthly, and later on the firm-quarter level.

Table 2b reports summary statistics on climate shocks affecting the customers and suppliers in our sample. As Panel A (customers) and B (supplier) of Table 2b show, the firms in our sample are regularly exposed to heatwaves, 29.8% of customer-firm-quarters and 36% of supplier-firm-quarters are affected by at least one heatwave in our sample. The average length of the heatwaves (consecutive days over 30° C) is substantial with an average of 23.8 heatwave days per financial quarter for suppliers, conditional on the occurrence of a heatwave, and 24.2 days for customers. On average, suppliers and customers are exposed to similar temperatures, with a sample average temperature of 18.6° Celsius (18.5° Celsius) for the customers (suppliers).

2.4.2 Floods

Second, we obtain data on 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 widely agrees that flooding incidents will also increase significantly in frequency and severity in the future as a direct result of climate change, i.e. due to heavy rainfall, rapid melting of snow and ice, and parched soil (CSSR, 2017). At the same time, flooding can cause significant economic damage, providing us with a second type of

[8] Dee, Uppala, Simmons, Berrisford, Poli, Kobayashi, Andrae, Balmaseda, Balsamo, Bauer, Bechtold, Beljaars, van de Berg, Bidlot, Bormann, Delsol, Dragani, Fuentes, Geer, Haimberger, Healy, Hersbach, Hlm, Isaksen, Kllberg, Koehler, Matricardi, McNally, Monge-Sanz, Morcrette, Park, Peubey, de Rosnay, Tavolato, Thpaut, and Vitart 2011 provide a detailed description of the data set.

[9] Precisely, the National Weather Services defines heatwaves as "three or more consecutive days with the temperature reaching or exceeding 90 degrees *(Fahrenheit)*".

climate shock that potentially affects firms in a different way than heatwaves.

We gather information on surface water levels from the Dartmouth Flood Observatory. To compile this data, the Dartmouth Observatory models the earth surface as a set of highly granular polygons and uses on satellite images and remote sensing sources to identify flooding of inundated ares. In addition, the observatory collects information on floods from news and governmental sources. The dataset includes start and end dates for each flood and detailed geographical information on the inundated areas polygons, from 1984 until today. The dataset further provides additional information on the floods such as the associated damages, size of the affected area, and deaths. We rely on the flood polygons used by the Dartmouth Observatory to spatially match the coordinates of our sample firms to the areas affected by the floods using the software QGIS. 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.

Equivalent to the procedure outlined in Section 2.4.1 for the heatwave records, we compute the number of days for which a firm was exposed to a given flood, and aggregate the count of floods on a monthly basis. Panel A and B of Table 2b illustrate the aggregate flooding summary statistics at the firm-quarter level. On average, suppliers and customers experience floods in 6.0% and 6.1% of all firm-quarters. The average number of 26.7 (30.8) casualties conditional on the occurrence of a flood suggests that we observe flood events with a substantial magnitude.

2.4.3 EM-DAT Disaster Data

For additional robustness tests in Section 3 we also include climate shock 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 datasets in the literature on the economic cost of climate hazards.[10] To compare our heatwave and flood data with the country-level EM-DAT disaster, we first distinguish if the temperature-related EM-DAT events are heatwaves or cold spells. Subsequently, we aggregate flood and heat events on a monthly basis based on the start and end dates, and combine the disaster data with our local records from the ECMWF and the Darthmouth Flood Observatory. Table 2b provides the EM-DAT summary statistics.

We conjecture that our high-granularity heatwave and flood incidents data and the country-level

[10]See for example: Strömberg, 2007; Noy, 2009; Lesk, Rowhani, and Ramankutty, 2016

data from EM-DAT differ along two dimensions. First, using country-level information naturally overstates the extent to which firms have been affected by natural disasters. In that case, the EM-DAT shocks would overstate firms' exposure to both floods and heatwaves. Second, the salience of the two hazard types and the probability that events are registered should differ across data sources. Both heat and flood events are recorded by EM-DAT only if they either 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. While floods are highly visible, the relevance of extreme temperatures and heatwaves can be contingent on the context, and hence more difficult to identify. Therefore, we expect that the disaster data only captures a subset of both floods and heatwaves that we can detect locally, particularly in the case of heatwaves.

In line with this reasoning, the average number of flood-affected firm-quarter observations is significantly higher based on the country-level match compared to the EM-DAT match. For instance, suppliers are physically exposed to floods only 6.1% of the time according to the local data, compared to 49% if we match based on EM-DAT country-level records. The opposite holds for heatwaves. While our local data suggests that heatwaves occur frequently, the disaster statistics yield a much lower affected numbers of firm-quarters - despite the geographic overestimation.

3 Direct Exposure to Climate Shocks

We begin our analysis by studying the direct effects of climate shocks on the supplier firms in our sample. This exercise is important to verify that the shocks we study in this paper indeed have an economically significant effect on firm operating performance. Many of the regions most severely affected by climate change are located outside of the developed countries of North America and Western Europe. Hence, our analysis complements the results in Somanathan, Somanathan, Sudarshan, and Tewari (2015); Zhang et al. (2018); Addoum et al. (2019), as we study the effect of heatwaves on firm earnings and performance in a global setting. Further, by also studying flooding incidents – in addition to local heatwaves – we are able to compare the economic effects of different climate change related risks. In our main analysis we focus on heatwave and flooding data from ECMWF and the Dartmouth Observatory, as the EM-DAT disaster data is less granular for floods and too restrictive for heatwaves, as documented in Section 2.4.3.

One important consideration for our tests is that firms likely adjust to the average climate hazard exposure in production locations. If managers understand climate risks and organize production to maximize profits, they might choose (not) to produce in certain places if adjustment potential is (in)sufficient, or they adjust the production equipment to match the expected climate exposure – contingent on the firm's financial capacity to do so. Hence, it the cross-sectional relationship between climate exposure variables and firm financial performance is likely endogenous.

However, while managers can base their decisions on expected climate exposure, they do not have power over the weather variation over time and the exact timing of climate shocks. Moreover, both floods and heatwaves can only be predicted with precision on short horizons, which are unlikely to allow for substantial adjustment in the production planning. Therefore, the variation in climate shocks over time is an exogenous source of variation and randomly distributed once we condition on fixed firm locations. This allows us to identify the causal impact of floods and heatwaves on firm operating performance.

We isolate the effect of time-series variation in climate shocks for a given firm on firm operating performance by estimating OLS regressions with firm-by-quarter fixed effects. By interacting firm-fixed effects and quarter fixed effects, our model absorbs both any time-invariant firm-level characteristics, as well as firm-specific seasonal effects during the four quarters of the year. This is important because firm operating performance varies seasonally throughout the year, and this seasonal variation might be correlated with the occurrence of climate shocks. Further, we include industry-by-year-by-quarter fixed effects to absorb any industry-specific time trends.

Our two main variables for measuring firm operating performance in the following regression models are sales turnover and profitability. Specifically, we use quarterly revenues and operating income, divided by assets. We specifically focus on these two measures – as opposed to for example earnings – since revenues and operating income are harder to manipulate by firms' strategic accounting - and the incentive to smooth earnings might be particularly high following adverse financial shocks.

In principle, the location-specific variation in flood and heat shocks over time cannot be actively influenced by firm choices. However, as climate shocks could 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 and interact the grouping variables with year-quarter fixed effects in our main specification, following Barrot and Sauvagnat (2016). Specifically, we estimate models of the following form, clustering robust standard errors on the firm level in line with Barrot and Sauvagnat (2016):

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

where y_{iqt} is either $Revenue/Assets$ (Rev/AT) or $Operating\ Income/Assets$ (OpI/AT) of firm i in quarter q of year t, $Climate\ Shocks_{iqt}$ is a dummy variable indicating the occurrence of a heatwave or flood in the location of firm i 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 $\times$ time fixed effects as in Barrot and Sauvagnat (2016). In robustness tests, we also use the count of climate events by financial quarter as an alternative specification. As it is ex-ante unclear if the financial impact of climate shocks manifests immediately or with some delay throughout the financial year, we estimate two different specification of the outline model. First, we limit the climate shock observations to the current financial quarter and second, i.e. we restrict $k = 0$, second we additionally include three lags of three periods, i.e. $k = 3$.

[Insert Table 3 here.]

Table 3 reports the regression results for Equation (1). In Panel A we estimate regressions without climate shock lags, in Panel B we additionally include three lags of climate shock events. The results in both panels indicate that heatwaves and floods adversely impact the bottom line of our supplier firms. However, the results also show that the full financial impact only becomes visible over the course of the financial year. On the one hand, we find a very small contemporaneous impact of heat events on firm operating performance, as both the effect on sales turnover and profitability is statistically indistinguishable from zero in Panel A. At the same time, the occurrence of a flood is associated with an average decrease in $Revenue/Assets$ of 0.19 percentage points, and a decrease in operating income over assets between 0.095 to 0.1 percentage points.

On the other hand, Panel B indicates that the financial impact of heatwaves and floods is in fact much larger than the simple analysis of contemporaneous climate shocks suggests, in line with the findings of Barrot and Sauvagnat (2016). When we include three lags of climate shocks in Equation (1) while holding the sample fixed, we find a material impact of heatwaves on both Rev/AT and OpI/AT between one to three financial firm quarters after the occurrence of a heatwave. The coefficient estimate for the effect of heatwaves on sales turnover in columns (1) and (2) is between -0.25 to -0.26 (statistically significant at the 5 and 10% level), and between -0.09 to -0.12 for operating margin in columns (3) and (4) for the coefficients with a lag of two to three quarters. Floods similarly decrease sales turnover (between -0.25 and -0.29 percentage points, statistically significant on the 5% and 10% level) and profitability (-0.11 to -0.12 percentage points, significant on the 1% level) in the contemporaneous and the previous two financial quarters. Given the average operating margin (OpI/AT) of 2% and sales turnover (Rev/AT) of 22% in our supplier sample, the mean effects are economically meaningful, representing approximately a 1% reduction in sales turnover and a 5.5% reduction in operating income over assets, relative to the sample mean. The documented difference in how quickly financial performance measures reflect the occurrence of climate shocks could have important implications for market participants. If heatwaves are reflected by accounting measures of firm performance with a delay, it becomes more difficult for investors to understand the link between the such temperature events and firm performance. Hence, this delay could help explain the underreaction of investors to firms' exposure to extreme temperatures, documented in the recent literature (Addoum et al., 2019; Pankratz, 2019).

Our results naturally raise questions regarding the economic mechanisms driving the observed effects. In the context of heatwaves, a large literature in economics has focused on the channels through which extreme temperatures can cause aggregate economic losses[11]. With regard to floods, these channels have been studied less explicitly, but the observed net effect could be caused by damages to assets, equipment and infrastructure, as well as production distortions during the floods, e.g. if worker safety is endangered and production thereby constrained throughout the duration of the floods. As the focus of our analysis lies on the direct and indirect performance implications of climate shocks and the adaptation of supply-chain managers, we remain agnostic about the precise mechanics of the directly observable effects in this paper.

We conduct several robustness tests for the direct effects of climate shocks on firm operating performance. First, we estimate the impact of the climate shocks on supplier performance after

[11] Previous research documents that electricity prices increase with heat exposure (Pechan and Eisenack, 2014), while water supply tightens (Mishra and Singh, 2010) and both cognitive and physical worker performance are compromised (Sepannen, Fisk, and Lei, 2006; Xiang, Bi, Pisaniello, and Hansen, 2014).

replacing heatwave and flood dummies with counting variables indicating the number of climate events per financial quarter. The results are reported in Appendix Table A1 and show that the statistical significance and overall pattern remain similar for this alternative specification. Moreover, the statistically strongest effects of heatwaves again appear to occur with a delay of two quarters after the firm was exposed to the heatwaves. Similarly, and in line with our main test in Table 3, contemporaneous floods have a significant immediate as well as a two-quarter delayed impact on sales turnover and operating income. When we use the count of heatwaves and floods per quarter for our estimations, the magnitude of the coefficient estimates is naturally smaller than the aggregate effect for all events in a financial quarter estimated in Table 3.

As our final robustness test on the direct impact of climate shocks, we estimate the impact of heatwave and flooding disasters on supplier performance using the country-level data from EM-DAT. Overall, the results reported in Appendix Table A2 confirm our conjecture from Section 2.4.3: for evaluating the financial impact of climate shocks on the firm level the use of climate data with high geographical granularity is essential. While heatwaves identified as disasters in the EM-DAT database are negatively correlated with supplier performance only in the specifications in columns (1) and (2) and with a delay of one financial quarter, the coefficient estimates are statistically indistinguishable from zero, or even *positive* in all other specifications.

4 Indirect Exposure to Climate Shocks

Based on our result from the previous Section 3, showing that heatwaves and floods significantly decrease supplier operating performance, we next test if climate hazards propagate downstream along supply-chain links. Since particularly the largest corporations traded on international stock exchanges rely on extensive, worldwide production networks, it is important to better understand if even firms which are not located in areas with a high climate risk exposure can indirectly be harmed by increases in the intensity of climate hazards due to their (remote) suppliers.

Analogous to our previous tests, we use sales turnover and profitability, measured by revenue over assets and operating income over assets, as our two main dependent variables for assessing whether climate risk is indeed propagated along supply-chains are. Despite the adverse direct effect on suppliers documented above, the implications of climate shocks for supplier and customer performance might differ. On the one hand, customer firms could be unaffected by shocks to supplying firms if suppliers cannot pass on the incurred costs downstream. At the same time, customers could also include climate factors in their contingency management, enabling them switch suppliers without incurring large costs if a specific supplier is hit by a heatwave or flooding. In both cases, neither heat nor flood related shocks would propagate from suppliers to customer along the supply-chain, and we should not be able to document a significant impact of climate shocks to suppliers on customer financial performance.

On the other hand, environmental shocks such as heatwaves or floods can cause supply-chain glitches and lower production output at the supplier and customer level. These disruptions are particularly likely if the provided inputs have a high level of specificity (Barrot and Sauvagnat, 2016). If climate shocks to suppliers on average cause distortions, we would expect to find a negative relation between customer financial performance and supplier exposure to climate risk.

To test these competing hypotheses, we require two identifying assumptions. As in the previous analysis, it is problematic to study this question in the cross-section, as the exposure of customer firms to climate shocks through suppliers might be endogenous. For instance, if certain industries systematically depend on specific inputs from suppliers clustered in risky areas, climate shocks and customer firm performance might be endogenously correlated. In contrast, it is reasonable to assume that the variation in supplier exposure to climate shocks over time is unrelated to time invariant firm characteristics such as industry associations.[12] Therefore, analogous to our model in Equation (1), all our results in this section are due to within-firm-pair variation over time.

Second, customer firms could experience similar performance effects as their suppliers when they themselves are hit by climate shocks. Therefore, to ensure that our results are not due climate shocks affecting customer firms directly, we exclude all customers-supplier pairs with customers located within a 500 kilometer radius of the affected supplier from our analysis.

Based on these considerations, we estimate two different models. In our first set of tests we estimate pooled OLS regressions of the following form,

$$y_{csqt} = \sum_{t=-3}^{0} \beta_t \times Climate\ Shocks_{csqt} + \mu_{csq} + \gamma_{n(c)t} + \delta_{BS2016} + \epsilon_{csqt} \tag{2}$$

[12] In our later analyses, we find that firms tend to terminate relationships with suppliers that face increases in climate shock exposure compared to historical, expected levels of climate risk. However, the tendency of customers to cut off suppliers that are particularly exposed to climate risk should only bias our effects downward.

where y_{csqt} is either $Revenue/Assets$ or $Operating\ Income/Assets$ of customer c in quarter q of year t, $Climate\ Shocks_{csqt}$ is a dummy variable indicating the occurrence of a heatwave or flood in the location of supplier s in year-quarter qt, μ_{csq} are supplier-customer pair-by-quarter fixed effects, $\gamma_{n(c)qt}$ are customer industry-by-year-by-quarter fixed effects based on 2-digit SIC codes, and δ_{BS2016} are customer firm size, age, and profitability $\times$ year-quarter fixed effects similar to Equation (1). The unit of observation in these test is at the customer-supplier-year-quarter level. By including pair-by-quarter fixed effects ($\gamma_{n(c)qt}$), our model subsumes all time-invariant relationship characteristics (e.g. supplier and customer country characteristics, languages, geographical distance, average input specificity, average relationship strength, and firm fixed effects) as well as relationship-specific seasonal patterns. Our results are therefore obtained from time-series variation in a given firm-pair for the same quarter of the year.

In our second set of tests, we collapse our panel observations at the customer level by aggregating over all suppliers of a given customer, and estimate regressions of the following form,

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

where y_{cqt} again captures customer firm operating performance, and μ_{cq}, $\gamma_{n(c)t}$, and δ_{BS2016} are fixed effects at the customer-by-quarter, industry-by-year-by-quarter, and size/age/ROA $\times$ year-quarter level. $Climate\ Shocks_{cqt}$ is obtained as the maximum of $Climate\ Shocks_{csqt}$ over all suppliers s of customer c in period qt. The unit of observation in these tests as at the customer-year-quarter level.

Based on our findings in Section 3, we include lags of $k = 3$ periods for the climate shocks in both Model (2) and (3). In line with our identifying assumptions that the variation over time in flood and heat shocks on suppliers are exogenous and that the supplier shocks only affect customers through the supply chain link, other characteristics of the customer firms should not be systematically correlated with both the outcome and the flood and heatwave occurrence. Hence, we do not include firm-level controls in our main specification, but again add size, age, and profitability times quarter fixed effects to control for different firm profiles, analogous to Equation 2. In line with Barrot and Sauvagnat (2016), we cluster robust standard errors on the relationship and on the customer firm level in Equations (2) and (3), respectively.

4.1 Climate Shock Propagation – Results

Table 4 reports the results for our first test on customers' sensitivity to supplier climate risk exposure, as detailed in Equation (2). The unit of observation in Panel A is at the supplier-customer-year-quarter level. The first four columns show the impact of supplier heatwaves, columns (5) to (8) report the effect of supplier floods. With regard to heatwaves, we find tentative evidence that the climate shocks on suppliers propagate along the supply chain. Specifically, we find a negative impact (coefficient -0.044) of heatwaves at the supplier locations on customer revenues in column (2), statistically significant at the 10% level. All other coefficient estimates for the propagation effect of heatwaves lagged by one to three quarters are marginally not statistically significant. However, all coefficient estimates carry negative signs, and the difference in the magnitude between the impact of heatwaves on revenues and operating income is in line with the estimations of the direct impact of heat on supplier firms. Hence, while the observed effect is small in our sample, our finding is still economically meaningful, given that the frequency of heatwaves is projected to increase substantially in the future due to ongoing climate change.

In comparison, the shock propagation of floods is unambiguous and both statistically and economically large. According to our estimates, customer revenue over assets decreases between 0.10 to 0.16 percentage points in three quarters after the supplier has initially been exposed to a flood. Moreover, customers' operating income is reduced by 0.02 up to 0.04 percentage points (all effects significant on the 1% level). These magnitudes are economically meaningful even at low climate shock frequencies: Compared to the sample median, the occurrence of a flood at the supplier firm reduces customer revenue and operating income by 1.8% and 2.2%, respectively.

[Insert Table 4 here.]

In Panel B of Table 4, we show the results for the sample collapsed on the customer level, implementing the model in Equation (3). Again, we find evidence that the climate shocks on supplier firms propagate along the supply chain with a tentative, statistically negative impact of heatwaves at the supplier locations on operating income (column (3), coefficient estimate of -0.052, significant at the 5% level). For floods, the results are similar in magnitude to our first set of tests using the full panel. The impact of floods at one of a given customer's supplier firms reduces revenues over assets between -0.15 and -0.16 percentage points (statistically significant at the 10% and 5% level), with a lag of two calendar quarters. Further, floods have a significant negative effect on operating income (coefficient estimates between -0.053 and -0.045 percentage points, significant at the 5% and 10% level), with a lag of one quarter.

Taken together, our results provide evidence that climate change related shocks can propagate downstream along the supply-chain. This finding indicates that climate change could affect even firms in relatively 'climate-safe' parts of the world as supply-chains span the globe. On average, the results also suggest that suppliers can pass some of the cost caused by climate shocks on to customers, or that not all customers in our sample are fully hedged against idiosyncratic shocks to their suppliers through their contingency management. while the evidence on the side of heatwaves is tentative[13], the flood-related effects are pronounced both in a statistical and economic sense. Our results are consistent with Barrot and Sauvagnat (2016), who document that the financial shocks imposed by natural disasters propagate along the supply chain when inputs are specific.

4.2 Climate Shock Propagation – Robustness

We conduct a number of robustness with respect to our findings on the propagation of climate shocks. First, to verify that the effects we observe are indeed attributable to climate shock transmission through supply-chain linkages, we implement a placebo test based on the start and end dates of our sample supply-chain relationships. Specifically, we re-estimate our regressions models specified in Equations (2) and (3) using the same sample of supplier-customer relationships. However, in our placebo tests we use only the periods before and after a given supplier-customer pair was engaged in a supply-chain relationship.

[Insert Table 5 here.]

If the supply-chain data from FactSet Revere correctly identifies the beginning and end of our sample supplier-customer relations, and our results in Section 4.1 are indeed due to the propagation of climate shocks, we should not find a negative effect of supplier climate shocks on customer firm operating performance in the placebo sample. Indeed, as reported in Table 5, we do not find a

[13]Given the marginally insignificant results for the heatwave-based tests, it is important to bear in mind that the empirical setting biases the results downwards. First, if a share of the customers in the sample has a strong contingency management with several alternative suppliers, and second, if managers respond to operational distortions caused by troubled suppliers, and replace suppliers that are particularly exposed, so that affected supply-chain links systematically drop out of the sample.

negative relation between supplier climate shocks and customer firm performance, neither when conducting the tests on the full customer-supplier pair level sample (Panel A), nor on the collapsed sample at the customer level (Panel B).

As an additional robustness test, we estimate the shock propagation based on a count measure of heatwaves and floods instead of an indicator variable. The results are reported in Appendix Table A3. Again, we find weak evidence for a propagation of heatwave-related shocks on the supplier to the customer operating income (column 2, coefficient estimate of -0.015, significant at the 5% level) and strong evidence for the propagation of flood related shocks. Last, we repeat our tests using the country-level climate shock data from EM-DAT, analogously to Section 3. The results are reported in Appendix Table A4. In line with our results focusing on the direct effect of climate shocks, we cannot document a consistent relation between customer performance and the climate disaster measures from EM-DAT.

5 Supply-Chain Adaptation

Our results in the previous sections show that climate-related shocks matter for firm financial performance, both directly and indirectly through supply chain links. Hence, managers have an incentive to monitor the climate-change related risk imposed by their suppliers. In this section, we empirically test if managers indeed take climate-risk considerations into account by adapting their to supply-chain relationships.

5.1 Climate Trends and Supplier Termination

We first test if climate-change risk increases the likelihood that a supplier-customer relationship is terminated. On the one hand, costly climate-related shocks could cause operational issues at a given supplier, making the firm a less attractive supply chain partner going forward. On the other hand, customer and supplier firms often make substantial relationship-specific investments to set up and maintain a supply chain relationship. It is unclear if the adverse financial consequences of climate risk exposure are sufficiently high to result in the termination of an existing customer-supplier relationship.

We use the FactSet Revere information on the start and end dates of customer-supplier relationships to test these hypotheses. To construct the main outcome variable, we generate a panel of firm years in which the customer-supplier relationships are active, and set the dummy variable $\mathbb{1}\,(End)$ to take the value of one in the last year a given supply-chain relationship is reported in FactSet Revere. To avoid mechanical issues in the last year of our sample we drop observations from 2017.

To construct our main variable of interest capturing supplier climate risk exposure, we start with the assumption that managers trade off potential climate-related risks with other firm characteristics such as product quality, costs and delivery times when entering a supply-chain relationship. Under this scenario, a customer firm is generally aware of climate risks associated with a given supplier and continuously weighs the costs and benefits of remaining in the relationship. As long as the costs of leaving a given relationship exceed the costs of staying, the customer will continue the relationship with a supplier. If this assumption holds, realized climate shocks over the course of a supply-chain relationship that fall within the normal, ex-ante anticipated range of events given a supplier's location and climate risk will not substantially influence the likelihood that the supplier is dropped, all else equal. However, if realized climate risks increase beyond the anticipated levels, and in ways that firms are not prepared for or hedged against, it would reduce the economic viability of a supplier-customer relationship and increase the profitability that the relationship ends.

To test this conjecture, we construct the measure $\mathbb{1}\,(Realized > Expected\ Climate\ Shocks)\ (t)$, as illustrated in Figure 3. We first estimate the expected number of climate shocks per year in the supplier location over a benchmark period of five[14] years*before* the establishment of any given supplier-customer relationship. $\mathbb{1}\,(Realized > Expected\ Climate\ Shocks)\ (t)$ 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, and zero otherwise.

In econometric terms, our following test again relies on two identifying assumptions. First, we exploit the fact that climate trends, besides the timing of climate shocks, are to a large extent random over time and cannot be predicted with precision. Hence, managers can incorporate expected levels of climate risk exposure, but not deviations from the expectation into their decision making. Second, to be able to assume that the estimated effect is not caused by the direct impact of changing climate risk on the customer, we again exclude all customers-supplier pairs with customers located

[14]In robustness tests, we use seven, ten, and fifteen years, respectively.

within a 500 kilometer radius of the affected supplier. Based on these assumptions, our measure of realized vs. expected climate risk is orthogonal to other firm decisions, and our corresponding estimate reflects the impact of the change in supplier climate shock exposure. We estimate the following linear probability model,

$$\mathbb{1}\left(End\right)_{sct} = \beta \times \mathbb{1}\left(Realized > Expected\ Climate\ Shocks\right)_{st} + \mu_{cs} + \gamma_{n(s)t} + \rho_{c(s)t} + \epsilon_{int} \quad (4)$$

where $\mathbb{1}\left(End\right)_{sct}$ is an indicator taking the value of one in year t if it is the last year on record of the relation between supplier s and customer c.

To control for potential confounding effects, we estimate the regressions with several dimensions of fixed effects. First, we include relationship fixed-effects μ_{cs} in all specification to account for supplier characteristics that impact the probability of a relationship to end, but do not vary over time. For instance, suppliers could face a fixed probability of termination based on their industry association. Further, we include supplier industry-by-year fixed effects $\gamma_{n(s)t}$ to account for industry trends, for example related to the extent to which customers switch from buying inputs to manufacturing inputs. We also add supplier country-year fixed effects $\rho_{c(s)t}$ to account for changing macroeconomic risks that impact whether customer firms maintain supplier-relationships. In addition, we estimate the model with supplier country-customer-year $\times$ customer country-year fixed effects, to account for changes in international trade dynamics, such as changing barriers or import-related costs. We cluster robust standard errors on the relationship level.

[Insert Table 6 here.]

Table 6 reports the results. Across all specifications, we find a robust, positive impact of high realized vs. expected climate exposure on the likelihood of supply-chain relationship termination. In line with the results on the financial impact of the climate hazards as well as the financial propagation of the shocks in the supply chains, the results suggest that increases in flood exposure increase the probability a supply-chain relationship ends on average by 3.7 percentage points (column 8, coefficient significant at the 1%-level). The impact of heatwave exposure increases is equally strong in terms of its statistical significance but economically smaller at percentage points (column 4, coefficient statistically significant at the 1%-level). The difference in the magnitude between floods and heatwaves is in line with the stronger direct and indirect impact of floods compared to heatwaves documented in Sections 3 and 4. Both the estimate for heatwaves and floods are economically meaningful, given the unconditional expectation of 15.12% that a supply chain relationship ends in any given year in our sample.

To test the robustness of this result, we change the horizon over which we compute the expected number of floods or heatwaves per year. Appendix Table A5 indicates that the results are robust when we extend the period from 5 to 7, 10, or 15 years, as both the estimates for heatwaves and floods remain very similar in magnitude and significance. Moreover, we test whether the results remain stable when we include additional time-variant financial control variables for both the supplier and customer firms. Thereby, we control for changes in the financial health of the firms which could otherwise influence the probability of the continuation of the relationship. As Appendix Table A6 shows, the results again remain very similar both in magnitude and significance when we control for changes in the debt-to-assets ratio, the log price-to-book ratio, and firm size proxied by the natural logarithm of the market value of equity.

5.2 Climate Shocks and Supplier Termination

To validate our assumption that managers take climate risks into account when establishing supply-chain relations, we next replace our measure of realized vs. expected climate risk with a simple measure of realized climate shocks since the beginning of the supplier relationship. If the general level of climate risk exposure is taken into consideration before forming supply chain relationships, climate shocks per se should not be a strong determinant of supplier termination. We again estimate the model in Equation (4), replacing $\mathbb{1}\,(\mathit{Realized} > \mathit{Expected\ Climate\ Shocks})$ with $\mathit{Climate\ Shocks}\ (t)$ of the supplier firm.

[Insert Table 7 here.]

The results, reported in table Table 7 show the sensitivity of supply-chain relationship continuation to realized climate shocks. Depending on the dimension of fixed effects, we find a small, positive impact of heatwave and flood occurrence on the probability that a supply-chain relationship ends for some specifications. However, the economic magnitude of this effect is small: For heatwaves, the probability of termination is increases by 0.16 to 0.17 percentage points (columns 3 and 4, coefficients significant at the 5% level), for floods, there is some evidence of an increase by 0.29 to

0.33 percentage points (columns 5 and 6, coefficients significant at the 1%-level). This effect is an order of magnitude smaller and insignificant compared to the tests based on realized vs. expected climate risk.

Taken together, our results are consistent with the notion that managers are taking climate risks into consideration when entering a supply-chain relation. Also, the results suggest that increases in climate risk exposure can be an important determinant of the probability of the continuation of the relationships. If this effect holds globally, it could have important implications for international development. According to Burke et al., 2015b and Carleton and Hsiang, 2016, developing countries around the world are most severely affected by the outcomes of global climate change. If financial incentives from supply-chain disruptions motivate 'Northern' firms to further shift economic activity from 'Southern' to 'Northern' countries, the effect could contribute to widening global economic inequality.

5.3 Climate Risk Exposure of Old and New Suppliers

To shed further light on the question how firms adapt their supply-chains to climate change, and to examine if climate risks are indeed driving the formation of production networks, we next study if customers switch from high risk to low risk suppliers based on climate exposure. As we showed in the previous section, realized climate shocks in exceedance of previously anticipated levels can increase the likelihood that a given supplier relationship ends. However, it is unclear if managers understand the link between climate risk exposure and financial performance, and hence mitigate these risks by switching to different suppliers with lower climate exposure. Instead, customer managers might simply observe the adverse financial effects of (indirect) climate shocks without considering climate risk as an underlying driver of financial performance effects. Under this scenario, we would not expect to find a difference in climate risk exposure between 'old' suppliers whose supply-chain relationships are terminated and 'new' replacement suppliers.

To test this conjecture, we limit our dataset to supplier-customer links with a known end date, retaining approximately 60,000 observations.[15] Of course, not all supplier-customer relationships in our sample end because of climate risk considerations. However, the noise introduced by this

[15] Note that in contrast to the performance-related tests, in this setting we do not condition on the availability of performance information for customer and supplier firms

measurement error would bias us against finding significant results. For each supplier whose relationship with a customer ends throughout our sample period (i.e. 'old' supplier), we then identify (likely) replacement suppliers who entered a new supply-chain relationship with the same customer within the next two years, as reported in FactSet Revere. We require replacement candidates to have the same four-digit SIC code as the 'old' supplier, and consider only supply-chain relationships recorded by FactSet analysts for the first time in the two years after the 'old' supply-chain relationship ended. After applying these constraints, we identify 100,000 combinations of terminated and replacement suppliers.

Next, we compare the climate hazard exposure of actual supplier firms during the active years of the initial ('old') supply-chain relationship and their respective, likely, replacements. Figure 4 illustrates the construction of the test. First, we compare the number of climate shocks of the actual, replaced supplier to the exposure that a replacement supplier would have had during the time period in which the original relationship was active. Second, we estimate and compare the number of climate shocks that actual and replacement suppliers were exposed to throughout the whole sample period from 1984 to 2017. Third, we compare the time period after which the original supply-chain relationship has ended. In all tests, we keep the observed years between the actual, original, and hypothetical replacement suppliers constant. This requirement is important to ensure that year-specific climate trends do not confound the comparison.

[Insert Table 8 here.]

Table 8 reports the mean differences and t-statistics of the comparison of the exposure of all replaced suppliers and replacement suppliers. We conduct three tests per climate hazard: first, based on the realized shocks throughout the entire sample period, second, based on the duration of the supply-chain relationship, and third, based on the time thereafter until 2017. Focusing on heatwaves, we find that replacement suppliers are on average less exposed during the original, terminated relationship period, experiencing 0.83 fewer heatwaves on average. In the period after the termination and during the time in which the new relationships are active, this difference further increases to 2.0 fewer heatwaves (all differences are significantly different from zero at the 1% level). The same pattern holds with regards to floods. Whereas potential replacement suppliers are slightly less exposed to floods during the original relationship period (difference of -0.031, significant at the 1% level), the difference becomes more pronounced after the termination of the original link (difference of -0.33, significant at the 1% level).

Hence, our results are consistent with the notion that climate risks can drive the formation of supply-chain relations. If suppliers are negatively impacted by climate shocks and the cost of these shocks are shared in supply chains, managers face a financial incentive to manage the extent to which they are indirectly exposed to climate risk. Moreover, we observe that supplier climate risk exposure beyond expected levels increases the probability that customers switch suppliers. In line with the notion that these switches are climate related, managers appear to identify less sensitive supplier firms as alternatives to the original supply-chain partner.

6 Conclusion

In this paper, we combine temporally and spatially granular data on heatwaves and flooding from the European Center for Medium-term Weather Forecasts (ECMWF) and the Darthmouth Flood Observatory with a detailed dataset on global supply chain relationships from FactSet Revere. We obtain a climate-supply-chain database with 4,289 (4,568) suppliers (customers) across 51 countries around the world from 2003 to 2017, and investigate two questions: First, do climate shocks matter financially, and do they propagate along supply chains? And second, if so, how do firms respond to changing climate risk exposure in their supply chain networks?

We present two main insights. First, we test if climate change exposure has direct and indirect firm performance effects due to supply chain networks. We find that the financial performance of suppliers is negatively associated with heatwaves and flooding incidents, and show that the financial consequences of these climate shocks propagate to customers through supply chain links. Second, we study how firms adapt their supply-chain organizations in response to climate change risks. We find that firms are more likely to end relationships with suppliers which experience an unexpectedly high number of climate shocks compared to expectations formed at the beginning of the supply-chain relationship. Moreover, in substituting these suppliers, firms diversify their supplier network and replace high-climate-risk with lower-climate-risk suppliers.

Our results both on climate shock transmission and supply chain adaptation are economically meaningful. For instance, we find that heatwaves and floods are associated with a subsequent reduction of 4% in sales turnover and 10% in profitability at the directly affect firm, relative to the sample median. In terms of the adaptation effects, unexpectedly high numbers of floods and heatwaves increase the probability that customers abandon their suppliers by 4% and 1% compared to the unconditional sample probability of a customer-supplier relationship termination of 15%.

Our finding have two important, potential implications with regard to the impact of climate change on internationally diversified firms, and the impact of the adaptation efforts of these firms on international economic development. First, while developing countries are likely to experience the most pronounced increases in climate shocks, the results on the indirect impact of climate shocks suggest that economic impact of climate change is likely to be – at least partially – shared through economic links in global production networks. Second, if firms in high-climate risk countries are more likely to be substituted by customers in favor of suppliers in less vulnerable locations, the outlined effects could further economically weaken the areas most vulnerable to climate change.

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

References

Addoum, J. M., D. T. Ng, and A. Ortiz-Bobea (2019). Temperature shocks and earning news. *Review of Financial Studies*, Forthcoming.

Auffhammer, M. (2018). Quantifying economic damages from climate change. *Journal of Economic Perspectives 32*(4), 33–52.

Baldauf, M., L. Garlappi, and C. Yannelis (2019). Does climate change affect real estate prices? Only if you believe in it. *Review of Financial Studies*, Forthcoming.

Banerjee, S., S. Dasgupta, and Y. Kim (2008). Buyer–supplier relationships and the stakeholder theory of capital structure. *Journal of Finance 63*(5), 2507–2552.

Bansal, R., D. Kiku, and M. Ochoa (2016). Price of long-run temperature shifts in capital markets. Working Paper 22529, National Bureau of Economic Research.

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

Boehm, C. E., A. Flaaen, and N. Pandalai-Nayar (2019). Input linkages and the transmission of shocks: Firm-level evidence from the 2011 Tōhoku earthquake. *The Review of Economics and Statistics 101*(1), 60–75.

BSR (2018). Climate & Supply Chain – The business case for action. Available at: https://www.bsr.org/reports/BSR_Climate_and_Supply_Chain_Management.pdf.

Burke, M., S. M. Hsiang, and E. Miguel (2015a). Climate and conflict. *Annual Review of Economics 7*(1), 577–617.

Burke, M., S. M. Hsiang, and E. Miguel (2015b). Global non-linear effect of temperature on economic production. *Nature 527*(7577), 235.

Carleton, T. A. and S. M. Hsiang (2016). Social and economic impacts of climate. *Science 353*(6304).

Cen, L., F. Chen, Y. Hou, and G. D. Richardson (2018). Strategic disclosures of litigation loss contingencies when customer-supplier relationships are at risk. *The Accounting Review 93*(2), 137–159.

Cen, L., S. Dasgupta, R. Elkamhi, and R. S. Pungaliya (2015). Reputation and loan contract terms: The role of principal customers. *Review of Finance 20*(2), 501–533.

Cen, L., E. L. Maydew, L. Zhang, and L. Zuo (2017). Customer–supplier relationships and corporate tax avoidance. *Journal of Financial Economics 123*(2), 377–394.

Cohen, L. and A. Frazzini (2008). Economic links and predictable returns. *Journal of Finance 63*(4), 1977–2011.

CRED (2011). EM-DAT: The OFDA/CRED international disaster database. Centre for Research on the Epidemiology of Disasters. Université Catholique de Louvain Brussels, Belgium.

CSSR (2017). Climate science special report. In D. Wuebbles, D. Fahey, K. Hibbard, D. Dokken, B. Stewart, and T. Maycock (Eds.), *Fourth National Climate Assessment, Volume I*. U.S. Global Change Research Program.

Dee, D. P., S. M. Uppala, A. J. Simmons, P. Berrisford, P. Poli, S. Kobayashi, U. Andrae, M. A. Balmaseda, G. Balsamo, P. Bauer, P. Bechtold, A. C. Beljaars, L. van de Berg, J. Bidlot, N. Bormann, C. Delsol, R. Dragani, M. Fuentes, A. J. Geer, L. Haimberger, S. B. Healy, H. Hersbach, E. V. Hlm, L. Isaksen, P. Kllberg, M. Koehler, M. Matricardi, A. P. McNally, B. M. Monge-Sanz, J. Morcrette, B. Park, C. Peubey, P. de Rosnay, C. Tavolato, J. Thpaut, and F. Vitart (2011). The era-interim reanalysis: configuration and performance of the data assimilation system. *Quarterly Journal of the Royal Meteorological Society 137*, 553–597.

Dell, M., B. F. Jones, and B. A. Olken (2014). What do we learn from the weather? The new climate-economy literature. *Journal of Economic Literature 52*(3), 740–98.

Feng, S., A. B. Krueger, and M. Oppenheimer (2010). Linkages among climate change, crop yields, and Mexico–US cross-border migration. *Proceedings of the National Academy of Sciences 107*(32), 14257–14262.

Ginglinger, E. and Q. Moreau (2019). Climate risk and capital structure. Working Paper, Available at SSRN 3327185.

Graff-Zivin, J., S. M. Hsiang, and M. Neidell (2018). Temperature and human capital in the short and long run. *Journal of the Association of Environmental and Resource Economists 5*(1), 77–105.

Graff-Zivin, J. and M. Neidell (2014). Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics 32*(1), 1–26.

Hertzel, M. G., Z. Li, M. S. Officer, and K. J. Rodgers (2008). Inter-firm linkages and the wealth effects of financial distress along the supply chain. *Journal of Financial Economics 87*(2), 374–387.

Hong, H., F. W. Li, and J. Xu (2019). Climate risks and market efficiency. *Journal of Econometrics 208*(1), 265 – 281. Special Issue on Financial Engineering and Risk Management.

IPCC (2013). Summary for policymakers. In T. Stocker, D. Qin, G. Plattner, M. Tignor, S. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex, and P. Midgley (Eds.), *Climate change 2013: the physical science basis, contribution of working group I to the 5th assessment report of the intergovernmental panel on climate change*. Cambridge University Press, Cambridge.

Krueger, P., Z. Sautner, and L. T. Starks (2018). The importance of climate risks for institutional investors. SFI Working Paper.

Kumar, A., W. Xin, and C. Zhang (2019). Climate sensitivity and predictable returns. Working Paper, Available at SSRN 3331872.

Lesk, C., P. Rowhani, and N. Ramankutty (2016). Influence of extreme weather disasters on global crop production. *Nature 529*(7584), 84.

Lin, C., T. Schmid, and M. S. Weisbach (2018). Price risk, production flexibility, and liquidity management: Evidence from electricity generating firms. National Bureau of Economic Research.

Mishra, A. K. and V. P. Singh (2010). A review of drought concepts. *Journal of Hydrology 391*(1-2), 202–216.

National Weather Service (2019). Heat - a weather hazard of summer. Available at: `https://www.weather.gov/btv/heat_awareness`.

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

Pankratz, N. (2019). Climate change, firm performance, and investor surprises. Working Paper, Maastricht University.

Pechan, A. and K. Eisenack (2014). The impact of heat waves on electricity spot markets. *Energy Economics 43*, 63–71.

PWC (2015). CEO pulse on climate change. Available at: `http://download.pwc.com/gx/ceo-pulse/climatechange/index.htm`.

Schlenker, W. and C. A. Taylor (2019). Market expectations about climate change. Working Paper 25554, National Bureau of Economic Research.

Seetharam, I. (2018). The indirect effects of hurricanes: Evidence from firm internal networks. Working Paper.

Sepannen, O., W. Fisk, and Q. H. Lei (2006). Effect of temperature on task performance in office environment. Lawrence Berkeley National Laboratory Working Paper.

Somanathan, E., R. Somanathan, A. Sudarshan, and M. Tewari (2015). The impact of temperature on productivity and labor supply: Evidence from indian manufacturing. Working paper.

Strömberg, D. (2007). Natural disasters, economic development, and humanitarian aid. *Journal of Economic Perspectives 21*(3), 199–222.

Xiang, J., P. Bi, D. Pisaniello, and A. Hansen (2014). Health impacts of workplace heat exposure: an epidemiological review. *Industrial Health 52*(2), 91–101.

Zhang, P., O. Deschenes, K. Meng, and J. Zhang (2018). Temperature effects on productivity and factor reallocation: Evidence from a half million chinese manufacturing plants. *Journal of Environmental Economics and Management 88*, 1–17.

Tables and Figures

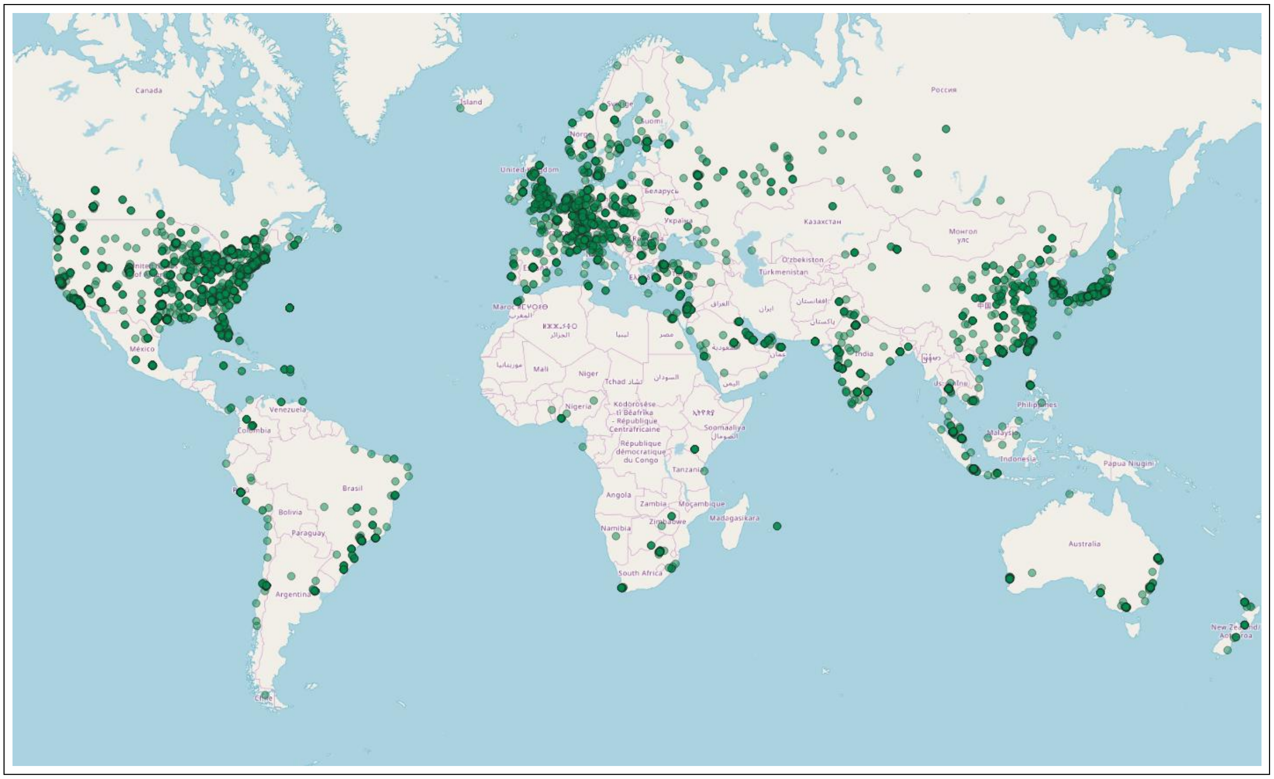

Figure 1: This figure illustrates the geographical distribution of the customers in our sample. Supply-chain relationships and firm locations are obtained from FactSet Revere and FactSet Fundamentals, respectively. The corresponding Table 1 reports the number of customers by regions of the world.

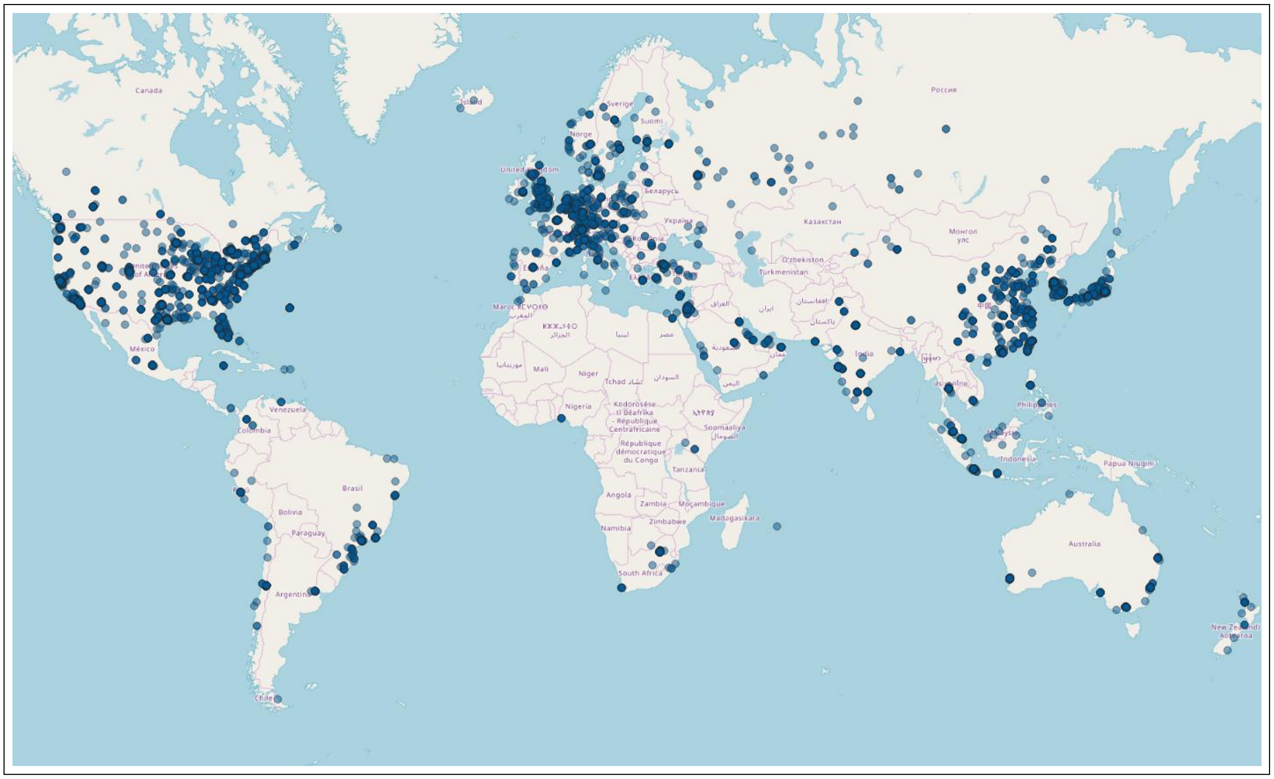

Figure 2: This figure illustrates the geographical distribution of the suppliers in our sample. Supply-chain relationships and firm locations are obtained from FactSet Revere and FactSet Fundamentals, respectively. The corresponding Table 1 reports the number of customers by regions of the world.

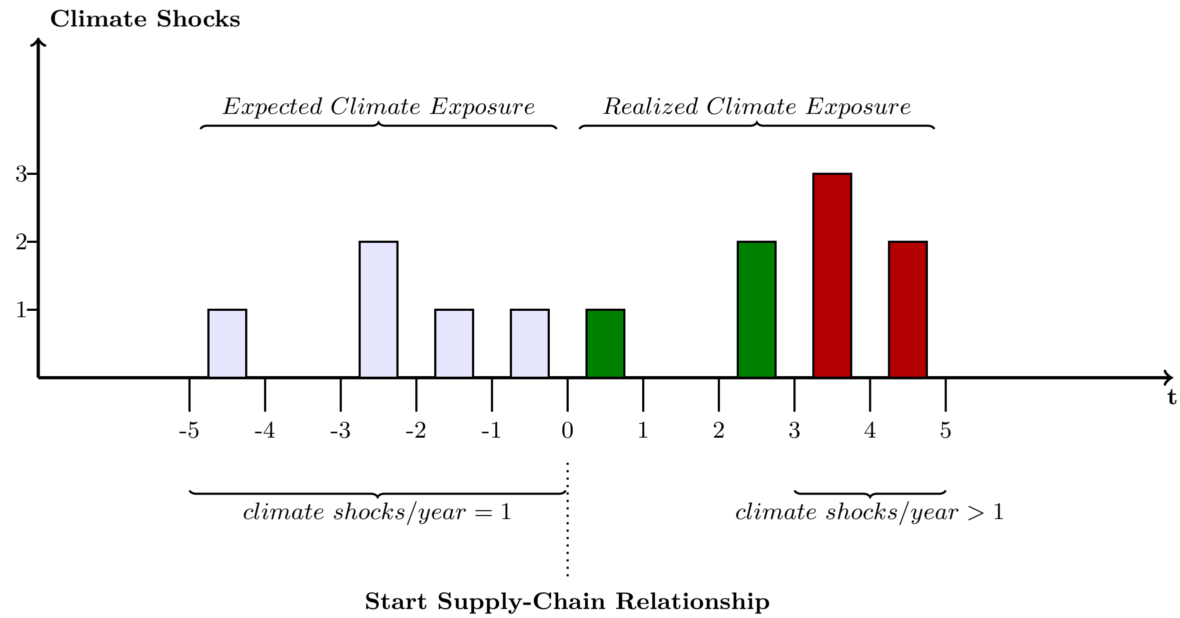

Figure 3: This figure illustrates the construction of $\mathbb{1}\,(\textit{Realized} > \textit{Expected Climate Shocks})\ (t)$, an indicator variable capturing the discrepancy between realized and expected climate risk based on the exposure of a hypothetical supplier to climate shocks over time. It is constructed by first estimating the 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 a given supplier-customer relationship. $\mathbb{1}\,(\textit{Realized} > \textit{Expected Climate Shocks})\ (t)$ 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 green)*.

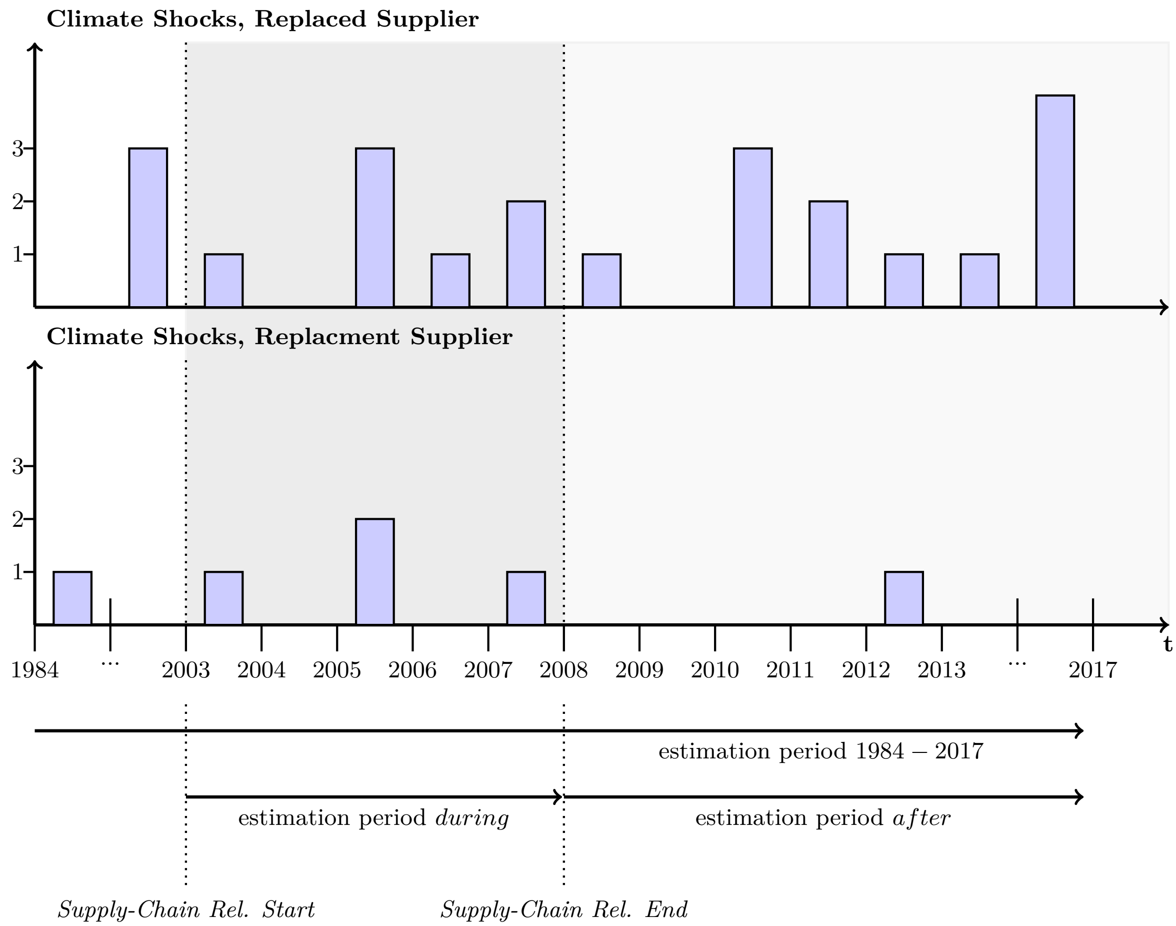

Figure 4: This figure illustrates the construction of the comparison of the climate exposure of replaced and replacement suppliers, based on an example of a hypothetical replaced supplier and the replacement. We compare the climate exposure of old and new suppliers based on three time periods. First, we compute the exposure to climate shocks for actual and replacement suppliers throughout the whole sample period from 1984 to 2017. Second, we estimate and compare the climate shock exposure of the replaced and replacement supplier based on the years (*illustrated in dark grey*) during which the initial supply-chain relationship was active. Third, we compare the exposure of both suppliers during the years (*illustrated in light grey*) after the initial supplier has been replaced.

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 their 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 2000 to 2017. We drop firms that operate in the financial industry (one-digit SIC code of 6). The number of observations refers to firms.

Customers

SIC Code	No.	%
1	460	10.1
2	863	18.9
3	1,147	25.1
4	721	15.8
5	646	14.1
7	518	11.3
8	195	4.3
9	18	0.4
Total	4,568	100.0

Suppliers

SIC Code	No.	%
1	482	11.2
2	803	18.7
3	1,226	28.6
4	637	14.9
5	313	7.3
7	606	14.1
8	212	4.9
9	10	0.2
Total	4,289	100.0

Customers

Region	No.	%
East Asia & Pacific	1,397	30.6
Europe & Central Asia	838	18.4
Latin America & Caribbean	183	4.0
Middle East & North Africa	135	3.0
North America	1,852	40.6
South Asia	99	2.2
Sub-Saharan Africa	54	1.2
Total	4,558	100.0

Suppliers

Region	No.	%
East Asia & Pacific	1,457	34.0
Europe & Central Asia	775	18.1
Latin America & Caribbean	135	3.2
Middle East & North Africa	96	2.2
North America	1,756	41.0
South Asia	27	0.6
Sub-Saharan Africa	36	0.8
Total	4,282	100.0

Table 2a: Summary Statistics – Firm and Relationship Characteristics

Notes. This table presents summary statistics of the financial performance of the customer firms (Panel A) and supplier firms (Panel B) in our sample, as well as the characteristics of the customer-supplier pairs (Panel C). The sample period is 2000 to 2017 and the number of observations refers to firm-quarters (pair year) in Panel A and B (Panel C). The percentage of assets, price-book ratio, and debt-asset ratio are obtained from Factset, and total assets, revenues and operating income over total assets are from Compustat Global and Compustat North America. The sample excludes firms with less than 50% of their assets in their home country, 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 (one-digit SIC code of 6).

Panel A: Customers

Variables	N	Mean	SD	p25	p50	p75
Pct. Assets Home Country	93,076.000	88.825	12,374.838	77.018	95.888	100.000
Price-Book Ratio	77,938.000	4.386	69.987	1.245	1.991	3.318
Debt-Assets Ratio	81,532.000	25.921	58.712	7.998	23.106	37.155
Total Assets mUSD	93,076.000	6,353.646	22,195.190	381.761	1,296.504	4,250.391
Revenue/Assets (Quarter)	93,076.000	23.988	17.143	11.630	19.914	32.019
Op. Income/Assets (Quarter)	93,076.000	2.474	2.941	1.214	2.565	3.959

Panel B: Suppliers

Variables	N	Mean	SD	p25	p50	p75
Pct. Assets Home Country	86,615.000	88.338	17.919	78.192	96.616	100.000
Price-Book Ratio	72,695.000	3.749	20.676	1.258	2.025	3.368
Debt-Assets Ratio	75,939.000	23.447	24.425	4.898	20.115	35.377
Total Assets mUSD	86,615.000	5,096.686	21,595.702	194.664	690.095	2,612.214
Revenue/Assets (Quarter)	86,615.000	21.958	15.482	10.871	18.769	29.542
Op. Income/Assets (Quarter)	86,615.000	1.932	3.653	0.781	2.310	3.758

Panel C: Customer-Supplier Pairs

Variables	N	Mean	SD	p25	p50	p75
Suppl. Sales/Total Suppl. Sales	2,439	17.873	17.363	8.667	13.000	20.400
Suppl. Sales/Cust. Cost Goods Sold	1,848	1.815	5.085	0.058	0.274	1.171
Customer/Supplier Assets	25,954	342.489	1,036.583	4.908	29.036	172.786
Customer/Supplier Sales	25,954	1.336	1.437	0.542	0.902	1.522
Customer/Supplier Op. Income	25,954	1.022	1.584	0.429	0.917	1.566
Distance Customer-Supplier (km)	25,954	4,043.456	3,894.813	699.792	2,593.262	6,904.968
Customer-Supplier Active (Quarters)	25,954	13.828	10.612	8.000	12.000	16.000

Table 2b: Summary Statistics – Climate Exposure

Notes. This Table presents summary statistics of the climate exposure measures of the customers (Panel A) and suppliers (Panel B) in our sample. The sample period is 2000 to 2017 and the number of observations refers to firm-quarters. We apply similar data filters as in Table 2a. The variables *heatwave days*, *flood days*, and *flood deaths* are constructed conditional on the respective occurrence of a heatwave of flood incident, lowering the respective number of observations. Heatwave occurrence and characteristics are constructed using daily temperature data from the ERA-Interim database of the European Center for Medium-term Weather Forecasts, flood-related variables are obtained from the Darthmouth Flood Observatory, and EM-DAT indicators are from the Emergency Events Database (EM-DAT) provided by the Centre for Research on the Epidemiology of Disasters (CRED).

Panel A: Customers

Variables	N	Mean	SD	p25	p50	p75
Heatwave in Financial Quarter	93,076.000	0.301	0.459	0.000	0.000	1.000
Number Heatwaves in Financial Quarter	93,076.000	0.534	0.918	0.000	0.000	1.000
Heatwave Days	28,041.000	23.881	26.243	7.000	16.000	32.000
Average Temperature	93,076.000	18.843	8.920	11.468	20.379	26.426
Flood in Financial Quarter	93,076.000	0.062	0.241	0.000	0.000	0.000
Number Floods in Financial Quarter	93,076.000	0.082	0.347	0.000	0.000	0.000
Flood Deaths	5,774.000	29.338	147.970	0.000	4.000	18.000
EM-DAT Flood	93,076.000	0.503	0.500	0.000	1.000	1.000
EM-DAT Heatwave	93,076.000	0.054	0.226	0.000	0.000	0.000

Panel B: Suppliers

Variables	N	Mean	SD	p25	p50	p75
Heatwave in Financial Quarter	86,615.000	0.373	0.484	0.000	0.000	1.000
Number Heatwaves in Financial Quarter	86,615.000	0.676	0.996	0.000	0.000	1.000
Heatwave Days	32,315.000	24.499	25.613	7.000	17.000	33.000
Average Temperature	86,615.000	18.723	8.797	11.370	20.204	26.177
Flood in Financial Quarter	86,615.000	0.063	0.243	0.000	0.000	0.000
Number Floods in Financial Quarter	86,615.000	0.084	0.351	0.000	0.000	0.000
Flood Deaths	5,476.000	33.801	166.491	1.000	5.000	22.000
EM-DAT Flood	86,615.000	0.511	0.500	0.000	1.000	1.000
EM-DAT Heatwave	86,615.000	0.055	0.228	0.000	0.000	0.000

Table 3: Climate Shocks and Supplier Firm Performance

Notes. This Table presents OLS regression estimates on the impact of climate shocks in the location of the sample supplier firms on their revenues (Rev) and operating income (OpI), both scaled by assets. *Heatwave* (t) and *Flood* (t) are dummy variables indicating the occurrence of a climate shock in quarter t, respectively. Panel A shows the results for contemporaneous climate shocks observed during financial quarter t, Panel B includes three additional climate lags. The number of observations refers to supplier firm-quarters, and the sample period is 2000 to 2017. We apply similar data filters as in Table 2a. All regressions include firm-by-quarter fixed effects to control for time invariant firm characteristics and firm-specific seasonal effects, and industry-by-year-by-quarter fixed effects. Columns (2), (4), (6), and (8) 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 on the firm level. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Panel A

	Dependent Variable:							
	Sup Rev (t)		Sup OpI (t)		Sup Rev (t)		Sup OpI (t)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Heatwave (t)	0.03166	0.02241	-0.01930	-0.01513				
	(0.1065)	(0.1071)	(0.0360)	(0.0363)				
Flood (t)					-0.18854*	-0.15404	-0.09460***	-0.09774***
					(0.1112)	(0.1111)	(0.0361)	(0.0364)
Observations	86,615	86,615	86,615	86,615	86,615	86,615	86,615	86,615
R-squared	0.887	0.889	0.740	0.741	0.887	0.889	0.740	0.741
Firm-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind-Year-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BS2016 FE	No	Yes	No	Yes	No	Yes	No	Yes

Panel B

	Dependent Variable:							
	Sup Rev (t)		Sup OpI (t)		Sup Rev (t)		Sup OpI (t)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Heatwave (t)	-0.05987	-0.06485	-0.04328	-0.03768				
	(0.1253)	(0.1252)	(0.0393)	(0.0398)				
Heatwave (t-1)	-0.26467**	-0.26323**	-0.01000	-0.00882				
	(0.1316)	(0.1298)	(0.0428)	(0.0431)				
Heatwave (t-2)	-0.26348**	-0.23965*	-0.13313***	-0.12375***				
	(0.1326)	(0.1311)	(0.0402)	(0.0405)				
Heatwave (t-3)	-0.25308**	-0.23141*	-0.10326***	-0.09929**				
	(0.1201)	(0.1186)	(0.0388)	(0.0391)				
Flood (t)					-0.26743**	-0.22553*	-0.11412***	-0.11614***
					(0.1288)	(0.1286)	(0.0403)	(0.0406)
Flood (t-1)					-0.25238**	-0.21675*	-0.02420	-0.02420
					(0.1237)	(0.1238)	(0.0416)	(0.0419)
Flood (t-2)					-0.29058**	-0.28779**	-0.12465***	-0.11980***
					(0.1266)	(0.1280)	(0.0414)	(0.0413)
Flood (t-3)					-0.07022	-0.04943	0.00359	0.00740
					(0.1188)	(0.1197)	(0.0376)	(0.0374)
Observations	86,615	86,615	86,615	86,615	86,615	86,615	86,615	86,615
R-squared	0.887	0.889	0.740	0.741	0.887	0.889	0.740	0.741
Firm-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind-Year-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BS2016 FE	No	Yes	No	Yes	No	Yes	No	Yes

Table 4: Downstream Propagation of Climate Shocks

Notes. This table presents OLS regression estimates on the impact of climate shocks at the supplier location on revenues over assets (Rev) and operating income over assets (OpI) of their respective customers. In Panel A the unit of observation is at the supplier-customer pair-quarter level. In Panel B we collapse the data at the customer level by aggregating across suppliers. The climate shock dummy variables take the value of one if at least one supplier has been affected by a heatwave or a flood, respectively. Hence, the number of observations in Panel B refers to customer firm-quarters. The sample period in both panels is from 2003 to 2017. *Sup Heatwave* (t) and *Sup Flood* (t) are dummy variables indicating the occurrence of a climate shock at the location of the supplier firm. We apply similar data filters as in Table 3. All regressions include relationship-by-quarter fixed effects (Panel A) and customer-by-quarter fixed effects (Panel B), respectively, as well as year-by-quarter fixed effects. Columns (2), (4), (6), and (8) additionally include terciles of size, age, and ROA interacted with year-by-quarter fixed effects (BS2016 FE) as in Table 3. Standard errors are clustered on the customer-supplier relationship level. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Supplier-Customer Pair-Level

	Dependent Variable:							
	Cus Rev (t)		Cus OpI (t)		Cus Rev (t)		Cus OpI (t)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sup Heatwave (t)	0.02786	0.02672	-0.01790	-0.01912				
	(0.0470)	(0.0465)	(0.0137)	(0.0132)				
Sup Heatwave (t-1)	-0.01464	-0.01745	-0.00962	-0.00987				
	(0.0221)	(0.0213)	(0.0068)	(0.0066)				
Sup Heatwave (t-2)	-0.03825	-0.04398*	-0.00806	-0.00803				
	(0.0245)	(0.0238)	(0.0074)	(0.0071)				
Sup Heatwave (t-3)	-0.02819	-0.02662	-0.00956	-0.00805				
	(0.0258)	(0.0251)	(0.0072)	(0.0070)				
Sup Flood (t)					-0.08335	-0.06364	-0.01944	-0.01096
					(0.0569)	(0.0544)	(0.0161)	(0.0154)
Sup Flood (t-1)					-0.11191***	-0.09930**	-0.03034**	-0.02220*
					(0.0418)	(0.0411)	(0.0122)	(0.0117)
Sup Flood (t-2)					-0.11857***	-0.12130***	-0.03792***	-0.03555***
					(0.0416)	(0.0406)	(0.0120)	(0.0115)
Sup Flood (t-3)					-0.15530***	-0.14299***	-0.03110***	-0.02366**
					(0.0430)	(0.0418)	(0.0120)	(0.0117)
Observations	214,302	214,302	214,302	214,302	214,302	214,302	214,302	214,302
R-squared	0.948	0.951	0.807	0.820	0.948	0.951	0.807	0.820
Relationship-by-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BS2016 FE	No	Yes	No	Yes	No	Yes	No	Yes

Panel B: Customer Firm-Level

	Dependent Variable:							
	Cus Rev (t)		Cus OpI (t)		Cus Rev (t)		Cus OpI (t)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sup Heatwave (t)	-0.04554	-0.02099	-0.03659	-0.02541				
	(0.1113)	(0.1114)	(0.0294)	(0.0290)				
Sup Heatwave (t-1)	-0.12701	-0.10292	-0.05150**	-0.03996				
	(0.0836)	(0.0838)	(0.0258)	(0.0259)				
Sup Heatwave (t-2)	-0.05269	-0.06724	0.00114	0.00398				
	(0.0748)	(0.0747)	(0.0258)	(0.0258)				
Sup Heatwave (t-3)	-0.05443	-0.04173	-0.00864	-0.00528				
	(0.0784)	(0.0785)	(0.0251)	(0.0251)				
Sup Flood (t)					0.02105	0.03538	0.00680	0.02062
					(0.0892)	(0.0889)	(0.0250)	(0.0255)
Sup Flood (t-1)					-0.10328	-0.09463	-0.05304**	-0.04528*
					(0.0818)	(0.0816)	(0.0248)	(0.0247)
Sup Flood (t-2)					-0.15035*	-0.16157**	-0.03007	-0.03828
					(0.0786)	(0.0781)	(0.0243)	(0.0240)
Sup Flood (t-3)					-0.07456	-0.08922	0.00754	0.00636
					(0.0857)	(0.0874)	(0.0258)	(0.0255)
Observations	44,566	44,565	44,566	44,565	44,566	44,565	44,566	44,565
R-squared	0.888	0.891	0.671	0.679	0.888	0.891	0.671	0.679
Firm-by-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BS2016 FE	No	Yes	No	Yes	No	Yes	No	Yes

Table 5: Downstream Propagation – Placebo Tests

Notes. This table presents the results of placebo tests on the impact of climate shocks at the supplier location on customer revenues over assets (Rev) and operating income over assets (OpI). We construct the placebo sample by restricting the observations to *real* customer-supplier pairs during periods in which the relationship was *not yet* or *no longer* active. We apply similar data filters as in Table 4. *Heatwave* (*t*) and *Flood* (*t*) are dummies indicating the occurrence of a climate shock in period *t*. In Panel A, the number of observations refers to supplier-customer pair-quarters. In Panel B, we collapse the data in a similar way as in Panel B of Table 4. The sample period in both panels is from 2003 to 2017. All regressions include relationship-by-quarter fixed effects (Panel A) and customer-by-quarter fixed effects (Panel B), respectively, as well as year-by-quarter fixed effects. Columns (2), (4), (6), and (8) 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-supplier relationship level. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Supplier-Customer Pair Level

	Dependent Variable:							
	Cus Rev (t)		Cus OpI (t)		Cus Rev (t)		Cus OpI (t)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sup Heatwave (t)	-0.02492	-0.02748	-0.01388	-0.00968				
	(0.0395)	(0.0383)	(0.0105)	(0.0099)				
Sup Heatwave (t-1)	0.02350	0.01697	0.00199	0.00006				
	(0.0200)	(0.0196)	(0.0055)	(0.0054)				
Sup Heatwave (t-2)	0.03437*	0.02456	0.00914*	0.00623				
	(0.0189)	(0.0185)	(0.0054)	(0.0053)				
Sup Heatwave (t-3)	0.01116	0.00337	0.00062	-0.00202				
	(0.0204)	(0.0199)	(0.0053)	(0.0052)				
Sup Flood (t)					0.07029*	0.05970	0.01540	0.01676
					(0.0383)	(0.0375)	(0.0111)	(0.0105)
Sup Flood (t-1)					-0.00240	-0.01806	0.01524*	0.01616*
					(0.0315)	(0.0306)	(0.0087)	(0.0083)
Sup Flood (t-2)					0.01146	0.01105	0.01409*	0.01733**
					(0.0317)	(0.0307)	(0.0085)	(0.0081)
Sup Flood (t-3)					0.01051	0.00328	0.00825	0.00849
					(0.0311)	(0.0304)	(0.0084)	(0.0082)
Observations	542,962	542,961	542,962	542,961	542,962	542,961	542,962	542,961
R-squared	0.887	0.891	0.685	0.703	0.887	0.891	0.685	0.703
Relationship-by-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BS2016 FE	No	Yes	No	Yes	No	Yes	No	Yes

Panel B: Customer Firm Level

	Dependent Variable:							
	Cus Rev (t)		Cus OpI (t)		Cus Rev (t)		Cus OpI (t)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sup Heatwave (t)	-0.11981	-0.11738	-0.02767	-0.02955				
	(0.0882)	(0.0878)	(0.0267)	(0.0265)				
Sup Heatwave (t-1)	0.15363**	0.16255**	0.00044	-0.00175				
	(0.0743)	(0.0745)	(0.0234)	(0.0234)				
Sup Heatwave (t-2)	0.01662	0.03214	0.01570	0.01661				
	(0.0727)	(0.0729)	(0.0226)	(0.0229)				
Sup Heatwave (t-3)	-0.02077	-0.00569	0.04261**	0.04308**				
	(0.0739)	(0.0741)	(0.0216)	(0.0215)				
Sup Flood (t)				0.10892	0.08744	0.01090	0.00010	
					(0.0740)	(0.0747)	(0.0217)	(0.0217)
Sup Flood (t-1)					0.13973*	0.12288	0.06497***	0.06359***
					(0.0784)	(0.0782)	(0.0203)	(0.0202)
Sup Flood (t-2)					0.00940	0.00138	0.03121	0.02713
					(0.0733)	(0.0731)	(0.0219)	(0.0219)
Sup Flood (t-3)					0.08090	0.07144	0.02089	0.01358
					(0.0718)	(0.0718)	(0.0211)	(0.0212)
Observations	77,342	77,339	77,342	77,339	77,342	77,339	77,342	77,339
R-squared	0.839	0.842	0.587	0.596	0.839	0.842	0.587	0.596
Firm-by-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BS2016 FE	No	Yes	No	Yes	No	Yes	No	Yes

Table 6: Expected vs. Realized Climate Risk and Relationship Termination

Notes. This table presents linear probability model estimates on the impact of realized vs. expected supplier-firm climate shocks on the likelihood of supply-chain relationship termination. Panel A reports the results for heatwaves, Panel B reports the results for flooding incidents. The unit of observation in all regressions 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. The regressions include only pair-years in which the relationship was active. Our main variable of interest is the indicator variable $\mathbb{1}\,(\textit{Realized} > \textit{Expected Climate Shocks})\,(t)$, capturing the deviation of realized from expected supplier climate. It is constructed by first estimating the expected number of climate shocks per year in the supplier location over a benchmark period of five years *before* the establishment a given supplier-customer relationship. $\mathbb{1}\,(\textit{Realized} > \textit{Expected Climate Shocks})\,(t)$ 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, and zero otherwise. We exclude customers headquartered within a 500 kilometer radius of the supplier and apply similar data filters as in Table 4. The regressions include relationship fixed effects, 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.

Panel A: Heatwaves

	Dependent Variable: Last Relationship Year (0/1)			
	(1)	(2)	(3)	(4)
$\mathbb{1}\,(\textit{Realized} > \textit{Expected Heatwaves})\,(t)$	0.02320***	0.02309***	0.01422***	0.01045***
	(0.0022)	(0.0023)	(0.0023)	(0.0023)
Observations	299,718	298,053	297,998	294,330
R-squared	0.353	0.378	0.413	0.415
Relationship FE	Yes	Yes	Yes	Yes
Yr FE	Yes	Yes	Yes	Yes
Sup-Industry-by-Yr FE	No	Yes	Yes	No
Sup-Country-by-Yr FE	No	No	Yes	No
Sup-Country-by-Cus-Country-by-Yr FE	No	No	No	Yes

Panel B: Flooding Incidents

	Dependent Variable: Last Relationship Year (0/1)			
	(1)	(2)	(3)	(4)
$\mathbb{1}\,(\textit{Realized} > \textit{Expected Floods})\,(t)$	0.04707***	0.04770***	0.03982***	0.03681***
	(0.0021)	(0.0022)	(0.0022)	(0.0022)
Observations	299,718	298,053	297,998	294,330
R-squared	0.354	0.379	0.413	0.416
Relationship FE	Yes	Yes	Yes	Yes
Yr FE	Yes	Yes	Yes	Yes
Sup-Industry-by-Yr FE	No	Yes	Yes	No
Sup-Country-by-Yr FE	No	No	Yes	No
Sup-Country-by-Cus-Country-by-Yr FE	No	No	No	Yes

Table 7: Robustness – Realized Climate Risk and Relationship Termination

Notes. This table presents linear probability model estimates on the of realized supplier-firm climate shocks on the likelihood of supply-chain relationship termination. Panel A reports the results for heatwaves, Panel B reports the results for flooding incidents. *Heatwave* (t) and *Flood* (t) are dummy variables indicating the occurrence of a climate shock in the location of the supplier firm in year t, respectively. The unit of observation is at the supplier-customer-year level. We include only active supply-chain relationship years. The dependent variable takes the value of one if a given supplier-customer relationship ends after the current year t, and zero otherwise. Similar to Table 6, we exclude all customers located within 500 kilometers of their supplier and apply similar data filters as in Table 6. The regressions include relationship fixed effects, 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.

Panel A: Heatwaves

	Dependent Variable: Last Relationship Year (0/1)			
	(1)	(2)	(3)	(4)
Heatwave (t)	0.00118	0.00104	0.00171**	0.00160**
	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Observations	299,718	298,053	297,998	294,330
R-squared	0.353	0.378	0.413	0.415
Relationship FE	Yes	Yes	Yes	Yes
Yr FE	Yes	Yes	Yes	Yes
Sup-Industry-by-Yr FE	No	Yes	Yes	No
Sup-Country-by-Yr FE	No	No	Yes	No
Sup-Country-by-Cus-Country-by-Yr FE	No	No	No	Yes

Panel B: Flood Incidents

	Dependent Variable: Last Relationship Year (0/1)			
	(1)	(2)	(3)	(4)
Flood (t)	0.00285***	0.00331***	0.00106	0.00010
	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Observations	299,718	298,053	297,998	294,330
R-squared	0.353	0.378	0.413	0.415
Relationship FE	Yes	Yes	Yes	Yes
Yr FE	Yes	Yes	Yes	Yes
Sup-Industry-by-Yr FE	No	Yes	Yes	No
Sup-Country-by-Yr FE	No	No	Yes	No
Sup-Country-by-Cus-Country-by-Yr FE	No	No	No	Yes

Table 8: Climate Change Risk and Supplier Substitution

Notes. This table reports the difference in climate change exposure between terminated suppliers and their subsequent replacements. To construct the sample for this table, we match each supplier firm for which the supplier-customer relationship is terminated during the sample period ("old suppliers") (as reported in Table 6) with their replacements ("new suppliers"). Replacement suppliers are identified as those firms with identical 4-digit SIC codes as the "old suppliers", which enter a new supply-chain relationship with a given customer within two years of the previous supply-chain relationship termination. Panel A shows the comparison for heatwave exposure, Panel B shows the results for flood exposure. The first line in each panel compares the number of climate shocks over the period from 1984 to 2017, the second line compares the exposure during the period in which the "old" supply-chain relationship was active, and the third line refers to the time period after the "old" relationship is abandoned. t-statistics are reported in brackets. *, ** and *** indicate statistical significance at the 5%, 1% and 0.1% level, respectively.

Panel A: Heatwaves

	(1) New vs. Old	
Heatwaves 1984-2017	-5.239***	[-17.569]
Heatwaves during Terminated Supply Chain Relationship	-0.829***	[-17.993]
Heatwaves after Termination of the Original Supply Chain Relationship	-2.065***	[-22.606]
Observations	100,172	

Panel B: Flood Incidents

	(1) New vs. Old	
Floods 1984-2017	-0.000	[-0.008]
Floods During Terminated Supply Chain Relationship	-0.031***	[-4.182]
Floods After Termination of the Original Supply Chain Relationship	-0.333***	[-23.340]
Observations	100,172	

A Appendix

Table A1: Robustness – Climate Shocks and Supplier Firm Performance

Notes. This table presents OLS regression estimates on the impact of climate shocks in the location of the sample supplier firms on their revenues (Rev) and operating income (OpI), both scaled by assets. *Heatwaves* (t) and *Floods* (t) are continuous variables measuring the total number (count) of climate shocks in the supplier's location in quarter t. Panel A shows the results for contemporaneous climate shocks observed during financial quarter t, Panel B includes three additional climate lags. The number of observations refers to supplier firm-quarters, and the sample period is 2000 to 2017. We apply similar data filters as in Table 2a. All regressions include firm-by-quarter fixed effects to control for time invariant firm characteristics and firm-specific seasonal effects, and industry-by-year-by-quarter fixed effects. Columns (2), (4), (6), and (8) 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 on the firm level. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Dependent Variable:							
	Sup Rev (t)		Sup OpI (t)		Sup Rev (t)		Sup OpI (t)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Heatwaves	-0.00036	0.00942	0.00884	0.00969				
	(0.0621)	(0.0624)	(0.0190)	(0.0192)				
Heatwaves (t-1)	-0.09555	-0.09363	-0.00385	-0.00613				
	(0.0696)	(0.0686)	(0.0209)	(0.0211)				
Heatwaves (t-2)	-0.14765**	-0.14069**	-0.06833***	-0.06902***				
	(0.0715)	(0.0709)	(0.0207)	(0.0208)				
Heatwaves (t-3)	-0.20294***	-0.18615***	-0.05274**	-0.05239**				
	(0.0660)	(0.0659)	(0.0206)	(0.0207)				
Floods					-0.22041**	-0.19408**	-0.09581***	-0.09614***
					(0.0885)	(0.0887)	(0.0283)	(0.0287)
Floods (t-1)					-0.17513*	-0.15295*	-0.02764	-0.02481
					(0.0924)	(0.0922)	(0.0286)	(0.0288)
Floods (t-2)					-0.18122**	-0.18212**	-0.07107**	-0.06623**
					(0.0912)	(0.0923)	(0.0297)	(0.0296)
Floods (t-3)					-0.06639	-0.05708	-0.01064	-0.00673
					(0.0853)	(0.0860)	(0.0272)	(0.0271)
Observations	86,615	86,615	86,615	86,615	86,615	86,615	86,615	86,615
R-squared	0.887	0.889	0.740	0.741	0.887	0.889	0.740	0.741
Firm-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind-Year-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BS2016 FE	No	Yes	No	Yes	No	Yes	No	Yes

Table A2: Robustness – EM-DAT Climate Shocks and Supplier Performance

Notes. This table presents OLS regression estimates on the impact of climate shocks in the location of the sample supplier firms on supplier firm revenues (Rev) and operating income (OpI), both scaled by assets. $EM - DAT\ Heatwave\ (t)$ and $EM - DAT\ Flood(t)$ are dummy variables indicating the occurrence of a climate shock in the supplier's location in quarter t based on the EM-DAT international disaster database. The number of observations refers to supplier firm-quarters, and the sample period is 2003 to 2017. We apply similar data filters as in Table 2a. All regressions include firm-by-quarter fixed effects to control for time invariant firm characteristics and firm-specific seasonal effects, and industry-by-year-by-quarter fixed effects. Columns (2), (4), (6), and (8) 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 on the firm level. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Dependent Variable:							
	Sup Rev (t)		Sup OpI (t)		Sup Rev (t)		Sup OpI (t)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EM-DAT Heatwave (t)	-0.05013	-0.22382	0.04729	0.02408				
	(0.1862)	(0.1977)	(0.0556)	(0.0669)				
EM-DAT Heatwave (t-1)	-0.34675**	-0.38940**	-0.12494***	-0.15618***				
	(0.1511)	(0.1602)	(0.0483)	(0.0560)				
EM-DAT Heatwave (t-2)	0.07203	-0.01361	0.07404	0.07325				
	(0.1546)	(0.1579)	(0.0559)	(0.0603)				
EM-DAT Heatwave (t-3)	0.16453	0.02850	0.07788	0.06295				
	(0.1547)	(0.1603)	(0.0569)	(0.0601)				
EM-DAT Flood (t)					-0.03392	-0.00332	0.00581	0.00484
					(0.0755)	(0.0797)	(0.0268)	(0.0285)
EM-DAT Flood (t-1)					-0.04415	0.02797	0.06244**	0.06291*
					(0.0822)	(0.0836)	(0.0303)	(0.0323)
EM-DAT Flood (t-2)					-0.03657	0.01128	0.04908	0.05400*
					(0.0759)	(0.0787)	(0.0300)	(0.0319)
EM-DAT Flood (t-3)					-0.07892	-0.02729	0.02255	0.02113
					(0.0703)	(0.0725)	(0.0264)	(0.0286)
Observations	86,615	86,615	86,615	86,615	86,615	86,615	86,615	86,615
R-squared	0.887	0.889	0.740	0.741	0.887	0.889	0.740	0.741
Firm-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind-Yr-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BS2016 FE	No	Yes	No	Yes	No	Yes	No	Yes

Table A3: Robustness – Downstream Propagation of Climate Shocks

Notes. This table presents OLS regression estimates on the impact of climate shocks at the supplier location on revenues over assets (Rev) and operating income over assets (OpI) of their respective customers. The unit of observation is at the supplier-customer pair-quarter level and the sample period is from 2003 to 2017. *Sup Heatwaves* (t) and *Sup Floods* (t) are continuous variables measuring the total number (count) of climate shocks in the supplier's location in quarter t. 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. Columns (2), (4), (6), and (8) 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-supplier relationship level. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Dependent Variable:							
	Cus Rev (t)		Cus OpI (t)		Cus Rev (t)		Cus OpI (t)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sup Heatwaves (t)	0.02938	0.03503	-0.01539**	-0.01081				
	(0.0257)	(0.0250)	(0.0072)	(0.0069)				
Sup Heatwaves (t-1)	0.00610	0.00773	-0.00487	-0.00314				
	(0.0120)	(0.0117)	(0.0033)	(0.0031)				
Sup Heatwaves (t-2)	0.00525	0.00278	-0.00061	-0.00052				
	(0.0123)	(0.0119)	(0.0035)	(0.0034)				
Sup Heatwaves (t-3)	0.00787	0.01075	-0.00344	-0.00183				
	(0.0129)	(0.0126)	(0.0033)	(0.0032)				
Sup Floods (t)					-0.11948***	-0.10698**	-0.03053**	-0.02331**
					(0.0451)	(0.0424)	(0.0123)	(0.0115)
Sup Floods (t-1)					-0.13504***	-0.13094***	-0.03392***	-0.02911***
					(0.0323)	(0.0315)	(0.0094)	(0.0088)
Sup Floods (t-2)					-0.15698***	-0.15939***	-0.03760***	-0.03565***
					(0.0318)	(0.0307)	(0.0083)	(0.0079)
Sup Floods (t-3)					-0.15580***	-0.14692***	-0.02846***	-0.02304***
					(0.0321)	(0.0315)	(0.0083)	(0.0080)
Observations	214,302	214,302	214,302	214,302	214,302	214,302	214,302	214,302
R-squared	0.948	0.951	0.807	0.820	0.948	0.951	0.807	0.820
Relationship-by-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yr-by-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BS2016 FE	No	Yes	No	Yes	No	Yes	No	Yes

Table A4: Robustness – Downstream Propagation of EM-DAT Climate Shocks

Notes. This table presents OLS regression estimates on the impact of climate shocks at the supplier location on revenues over assets (Rev) and operating income over assets (OpI) of their respective customers. The unit of observation is at the supplier-customer pair-quarter level and the sample period is from 2003 to 2017. $EM - DAT\ Heatwave\ (t)$ and $EM - DAT\ Flood\ (t)$ are dummy variables indicating the occurrence of a climate shock in the supplier's location in quarter t based on the EM-DAT international disaster database. 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. Columns (2), (4), (6), and (8) 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-supplier relationship level. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Dependent Variable:							
	Cus Rev (t)		Cus OpI (t)		Cus Rev (t)		Cus OpI (t)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EM-DAT Heatwave (t)	-0.07784	-0.09911	0.04383*	0.04897**				
	(0.0831)	(0.0820)	(0.0264)	(0.0245)				
EM-DAT Heatwave (t-1)	0.08667*	0.06417	0.00409	0.00762				
	(0.0497)	(0.0486)	(0.0155)	(0.0149)				
EM-DAT Heatwave (t-2)	-0.11003**	-0.10010**	-0.01911	-0.01421				
	(0.0502)	(0.0499)	(0.0153)	(0.0148)				
EM-DAT Heatwave (t-3)	-0.04647	-0.04014	0.01404	0.01114				
	(0.0521)	(0.0516)	(0.0168)	(0.0163)				
EM-DAT Flood (t)					0.06421	0.04346	0.02854**	0.02195**
					(0.0408)	(0.0406)	(0.0117)	(0.0112)
EM-DAT Flood (t-1)					0.02745	0.01803	-0.00236	-0.00463
					(0.0225)	(0.0222)	(0.0070)	(0.0068)
EM-DAT Flood (t-2)					0.01866	0.01528	0.01159*	0.01082
					(0.0235)	(0.0228)	(0.0068)	(0.0066)
EM-DAT Flood (t-3)					0.04297*	0.05178**	-0.00326	-0.00228
					(0.0227)	(0.0229)	(0.0067)	(0.0063)
Observations	214,302	214,302	214,302	214,302	214,302	214,302	214,302	214,302
R-squared	0.948	0.951	0.807	0.820	0.948	0.951	0.807	0.820
Relationship-by-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BS2016 FE	No	Yes	No	Yes	No	Yes	No	Yes

Table A5: Robustness – Expected vs. Realized Climate Risk

Notes. This table presents linear probability model estimates on the impact of realized vs. expected supplier-firm climate shocks on the likelihood of supply-chain relationship termination. The sample and variables are constructed similarly as in Table 6. In Panels A, B, and C we use benchmark periods of seven, ten, and fifteen years before the establishment of a supply-chain relationship to construct our main variables of interest, $\mathbb{1}\,(\textit{Realized} > \textit{Expected Climate Shocks})\,(t)$, as illustrated in Figure 3. We apply similar data filters as in Table 6. The regressions include relationship fixed effects, 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.

Panel A: 7-year benchmark period

	Dependent Variable: Last Relationship Year (0/1)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}\,(\textit{Realized} > \textit{Expected Heatwaves})\,(t)$	0.01340***	0.01259***	0.00744***	0.00564***				
	(0.0021)	(0.0021)	(0.0022)	(0.0022)				
$\mathbb{1}\,(\textit{Realized} > \textit{Expected Floods})\,(t)$					0.07069***	0.07149***	0.06483***	0.06027***
					(0.0022)	(0.0022)	(0.0023)	(0.0023)
Observations	299,718	298,053	297,998	294,330	299,718	298,053	297,998	294,330
R-squared	0.353	0.378	0.413	0.415	0.356	0.381	0.415	0.417
Relationship FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sup-Industry-by-Yr FE	No	Yes	Yes	No	No	Yes	Yes	No
Sup-Country-by-Yr FE	No	Yes	Yes	No	No	Yes	Yes	No
Sup-Country-by-Cus-Country-by-Yr FE	No	No	No	Yes	No	No	No	Yes

Panel B: 10-year benchmark period

	Dependent Variable: Last Relationship Year (0/1)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}\,(\textit{Realized} > \textit{Expected Heatwaves})\,(t)$	0.01452***	0.01203***	0.00671***	0.00662***				
	(0.0021)	(0.0021)	(0.0021)	(0.0021)				
$\mathbb{1}\,(\textit{Realized} > \textit{Expected Floods})\,(t)$					0.07492***	0.07381***	0.07195***	0.06895***
					(0.0022)	(0.0022)	(0.0023)	(0.0023)
Observations	299,718	298,053	297,998	294,330	299,718	298,053	297,998	294,330
R-squared	0.353	0.378	0.413	0.415	0.356	0.381	0.415	0.417
Relationship FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sup-Industry-by-Yr FE	No	Yes	Yes	No	No	Yes	Yes	No
Sup-Country-by-Yr FE	No	Yes	Yes	No	No	Yes	Yes	No
Sup-Country-by-Cus-Country-by-Yr FE	No	No	No	Yes	No	No	No	Yes

Panel C: 15-year benchmark period

	Dependent Variable: Last Relationship Year (0/1)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}\,(\textit{Realized} > \textit{Expected Heatwaves})\,(t)$	0.01984***	0.01691***	0.01286***	0.01414***				
	(0.0021)	(0.0021)	(0.0022)	(0.0022)				
$\mathbb{1}\,(\textit{Realized} > \textit{Expected Floods})\,(t)$					0.06034***	0.05982***	0.05815***	0.05595***
					(0.0022)	(0.0022)	(0.0023)	(0.0023)
Observations	299,718	298,053	297,998	294,330	299,718	298,053	297,998	294,330
R-squared	0.353	0.378	0.413	0.415	0.355	0.380	0.414	0.416
Relationship FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sup-Industry-by-Yr FE	No	Yes	Yes	No	No	Yes	Yes	No
Sup-Country-by-Yr FE	No	Yes	Yes	No	No	Yes	Yes	No
Sup-Country-by-Cus-Country-by-Yr FE	No	No	No	Yes	No	No	No	Yes

Table A6: Robustness – Expected vs. Realized Climate Risk with Control Variables

Notes. This table presents linear probability model estimates on the impact of realized vs. expected supplier-firm climate shocks on the likelihood of supply-chain relationship termination, controlling for supplier and customer firm characteristics. The sample and variables are constructed similarly as in Table 6. In Panels A, B, and C we use benchmark periods of seven, ten, 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 3. We apply similar data filters as in Table 6. The regressions include relationship fixed effects, 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.

Panel A: 7-year benchmark period

	Dependent Variable: Last Relationship Year (0/1)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}\,(Realized > Expected\ Heatwaves)\,(t)$	0.01306***	0.01154***	0.00614*	0.00612*				
	(0.0032)	(0.0033)	(0.0034)	(0.0034)				
$\mathbb{1}\,(Realized > Expected\ Floods)\,(t)$					0.06411***	0.06738***	0.06050***	0.05226***
					(0.0035)	(0.0035)	(0.0036)	(0.0036)
Debt-Assets Ratio Supplier	-0.00035**	-0.00056***	-0.00004	0.00017	-0.00035**	-0.00055***	-0.00005	0.00016
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Debt-Assets Ratio Customer	0.00014	0.00004	0.00001	0.00037*	0.00012	0.00002	-0.00001	0.00035*
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Price-Book Ratio Customer	-0.02256***	-0.01471***	-0.01023***	-0.01515***	-0.02205***	-0.01425***	-0.00990***	-0.01517***
	(0.0034)	(0.0034)	(0.0033)	(0.0035)	(0.0034)	(0.0034)	(0.0033)	(0.0035)
Price-Book Ratio Supplier	-0.00089	0.00790**	0.00863***	0.00066	-0.00089	0.00783**	0.00882***	0.00080
	(0.0032)	(0.0033)	(0.0033)	(0.0032)	(0.0032)	(0.0033)	(0.0032)	(0.0032)
Ln(MV Equity) Supplier	-0.02108***	-0.02462***	-0.01757***	-0.01110***	-0.02106***	-0.02457***	-0.01739***	-0.01097***
	(0.0028)	(0.0029)	(0.0029)	(0.0029)	(0.0028)	(0.0029)	(0.0029)	(0.0029)
Ln(MV Equity) Customer	-0.00093	-0.00032	0.00018	-0.00039	-0.00106	-0.00043	0.00008	-0.00051
	(0.0017)	(0.0016)	(0.0016)	(0.0017)	(0.0017)	(0.0016)	(0.0016)	(0.0017)
Observations	137,239	137,171	137,099	133,519	137,239	137,171	137,099	133,519
R-squared	0.373	0.400	0.435	0.439	0.375	0.403	0.436	0.440
Relationship FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SupIndustry-Yr FE	No	No	Yes	No	No	No	Yes	No
SupCountry-Yr FE	No	No	Yes	No	No	No	Yes	No
SupCountry-CusCountry-Yr FE	No	No	No	Yes	No	No	No	Yes

Panel B: 10-year benchmark period

	Dependent Variable: Last Relationship Year (0/1)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}\,(Realized > Expected\ Heatwaves)\,(t)$	0.01727***	0.01362***	0.00728**	0.00907***				
	(0.0032)	(0.0032)	(0.0033)	(0.0033)				
$\mathbb{1}\,(Realized > Expected\ Floods)\,(t)$					0.06559***	0.06581***	0.06344***	0.05770***
					(0.0035)	(0.0035)	(0.0037)	(0.0037)
Debt-Assets Ratio Supplier	-0.00034**	-0.00055***	-0.00004	0.00017	-0.00035**	-0.00056***	-0.00005	0.00016
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Debt-Assets Ratio Customer	0.00014	0.00005	0.00001	0.00037*	0.00011	0.00001	-0.00001	0.00034*
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Price-Book Ratio Customer	-0.02254***	-0.01470***	-0.01022***	-0.01514***	-0.02211***	-0.01438***	-0.01001***	-0.01527***
	(0.0034)	(0.0034)	(0.0033)	(0.0035)	(0.0034)	(0.0034)	(0.0033)	(0.0035)
Price-Book Ratio Supplier	-0.00078	0.00796**	0.00866***	0.00069	-0.00082	0.00800**	0.00896***	0.00095
	(0.0032)	(0.0033)	(0.0033)	(0.0032)	(0.0032)	(0.0033)	(0.0032)	(0.0032)
Ln(MV Equity) Supplier	-0.02105***	-0.02456***	-0.01754***	-0.01112***	-0.02068***	-0.02420***	-0.01710***	-0.01070***
	(0.0028)	(0.0029)	(0.0029)	(0.0029)	(0.0028)	(0.0029)	(0.0029)	(0.0029)
Ln(MV Equity) Customer	-0.00093	-0.00032	0.00018	-0.00038	-0.00114	-0.00051	-0.00000	-0.00059
	(0.0017)	(0.0016)	(0.0016)	(0.0017)	(0.0017)	(0.0016)	(0.0016)	(0.0017)
Observations	137,239	137,171	137,099	133,519	137,239	137,171	137,099	133,519
R-squared	0.373	0.400	0.435	0.439	0.375	0.402	0.436	0.440
Relationship FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SupIndustry-Yr FE	No	No	Yes	No	No	No	Yes	No
SupCountry-Yr FE	No	No	Yes	No	No	No	Yes	No
SupCountry-CusCountry-Yr FE	No	No	No	Yes	No	No	No	Yes