How Does Climate Change Affect Firm Sales? Identifying Supply Effects*

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Abstract

We estimate the supply side effect of climate change on firm sales by exploiting variation in local temperature across suppliers of the same client. We find that suppliers experiencing a 1°C increase in average daily temperature decrease their sales by 2%. In addition, extreme hot and cold weather events lead to larger drops in sales. The effect is more pronounced among suppliers in manufacturing and heat-sensitive industries, which is consistent with lower labor productivity and labor supply when temperatures are higher. Financially constrained suppliers are more affected due to their lack of financial flexibility to adapt to changes in temperatures.

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1. Introduction

It is widely accepted among climate scientists that the global mean temperature is likely to increase by 2°C relative to the pre-industrial average by the mid-21st century unless greenhouse gas emissions decline to net zero (Intergovernmental Panel on Climate Change (IPCC) (2021)). What is the impact of these changes in temperature in the real economy? Several studies document the detrimental effects of climate change and weather conditions in the agricultural sector (e.g., Mendelsohn, Nordhaus, and Shaw (1994), Schlenker, Hanemann, and Fisher (2005)). The economic consequences of changes in temperature on other industries, which are less directly impacted by the weather, are not well understood and previous evidence is inconclusive. While several studies show the negative effects of climate change on total factor productivity and labor supply (e.g., Graff-Zivin and Neidell (2014)), there is mixed evidence that these effects translate to firm performance (e.g., Addoum, Ng, and Ortiz-Bobea (2020)).

In this paper, we estimate the supply-side effects of changes in temperature on firm sales. Identifying the supply side effects is challenging as weather shocks can simultaneously affect the ability of firms to supply products and services as well as demand for such products and services. We address this challenge by exploiting production networks, which allows us to control for changes in firm-specific demand. Specifically, we use supplier-client pair sales to estimate the differential impact of changes in temperature across suppliers selling to the same client in the same year. Our estimation includes client-by-time fixed effects as well as observable supplier characteristics and industry fixed effects to absorb unobserved heterogeneity at the supplier level. Our identification strategy follows the Khwaja and Mian (2008) approach to identify credit supply effects.

Our baseline results show that increases in temperature lead to reductions in firm sales. A 1°C increase in the average daily temperature in supplier counties is associated with a negative and statistically significant drop in sales of 2% when compared to the other suppliers of the same client. This effect is also economically significant. Given our identification strategy, this estimated difference in sales can be attributed to supply side factors, such as changes in labor supply, productivity, or operating costs, which can lead to lower output.

We also investigate the effect of extreme weather events. These events are potentially more disruptive, and firms may have less time to adapt. We find that extreme heat events, and especially extreme cold events, have a stronger effect on supplier sales at -8% and -36%, respectively. However, we do not find that weather shocks lead to termination of supply chain relationships.

Our main identifying assumption is that differences in sales growth between treatment and control groups would have followed parallel trends in the absence of the treatment (i.e., the treatment amounts to the supplier being exposed to a change in the average temperature). We find no evidence of pre-existing differential trends in sales growth across different suppliers. Our identification strategy also requires that local changes in temperature should be exogenous to the suppliers' activity. While it is unequivocal that the economic activity of certain firms and industries – particularly in CO_2-intensive sectors – have an impact on climate (IPCC (2021)), such an impact is at the global level, rather than at the firm level.

Next, we investigate three channels through which changes in temperature can affect firm supply. The first channel is labor productivity and labor supply. We use industry classifications to identify labor intensive firms. Our results are mostly driven by manufacturing firms and heat-sensitive suppliers. This is consistent with a higher temperature lowering labor productivity due to workers' absence or harder working conditions, which is consistent with the findings in Graff-Zivin and Neidell (2014).

The second channel is financial constraints. Financially constrained firms may not be able to adapt to changes due to their lack of financial flexibility and inability to raise additional capital to absorb the increased costs associated with changes in temperature. In contrast, unconstrained firms may invest in strategies that mitigate the negative effects of climate change (e.g., Fried (2019), Gourio and Fries (2020)). Our proxies of financial constraints are the ratio of long-term debt maturing next year to total long-term debt, credit rating, firm size, and number of business segments. We find that the effect of changes in temperature on financially constrained firms is 1.5

to 2 times larger than our baseline estimates. Our results suggest that financially constrained firms have limited financial resources to overcome weather shocks without affecting production. An alternative interpretation of these results is that larger firms and diversified firms have more operational flexibility. These firms can use their internal networks to reallocate resources across their business and geographic segments to respond and adapt to changes in temperature. This interpretation is consistent with Giroud and Mueller (2019), who find that the propagation of economic shocks through firm internal networks is stronger for financially constrained firms.

The third channel is switching costs. Barrot and Sauvagnat (2016) show that switching costs between trade partners due to input specificity are substantial and can explain the propagation of shocks in production networks. We use industries that sell standardized goods and whether a firm applies for patents as proxies for input specificity and switching costs. Patent counts capture the importance of relationship-specific investments and restrictions on finding alternative sources. Intangible assets are associated with more specific and differentiated inputs. We find that the reduction in sales is more pronounced for suppliers that are easier to substitute, i.e., sell a standardized good or have no patents. These findings are consistent with the idea that the supplier-specific economic costs of weather shocks are larger when switching costs are lower. In addition, we find that that the drop in sales is larger for suppliers located further away from their clients. Distant suppliers are less likely to be part of a local production network. Therefore, their clients are more likely to have a transactional relationship with them and their switching costs will likely be lower.

This paper contributes to the literature on the costs of climate change on the real economic activity. Early cross-sectional studies show that countries with higher mean temperature exhibit lower levels and growth in per capita income (Gallup, Sachs, and Mellinger (1999), Dell, Jones, and Olken (2009)). More recent set of studies show a similar negative effect of higher temperatures on output using exogenous variation in location-specific temperature (Dell, Jones, and Olken (2012), Hsiang (2010)). Temperature extremes have also been shown to affect sales and labor productivity. Specifically, Graff-Zivin and Neidell (2014) show that extremely hot temperatures reduce hours worked across several heat-sensitive industries. Moreover, Jones and Olken (2010), Hsiang (2010), and Dell, Jones, and Olken (2012) find that temperature shocks negatively affect light manufacturing exports and reduce output in the industrial and service sectors. Addoum, Ng, and Ortiz-Bobea (2020) find that the effect of the average temperature on firm performance is insignificant using establishment-level and firm-level data in the United States. Pankratz and Schiller (2019) find that heat waves and flooding at supplier locations lead to a reduction in operating performance of suppliers and their customers in global supply chains.[1] Thus, previous research has found mixed results on the *overall effects* of climate change on firm performance.

To the best of our knowledge, we are the first to identify the *supply effects* of climate change on firm sales by controlling for firm-specific demand. This is important because the demand effects of changes in temperature on firm sales can be ambiguous and heterogeneous across regions and industries. Benmir, Jaccard, and Vermandel (2021) propose a model in which environmental externalities raise households' willingness to consume goods. There is also evidence that climate change and associated phenomena including pollution increases the consumption of electricity and other goods such as air conditioning, air purifiers and medicine (e.g., Abel et al. (2018), Dechênes, Greenstone, and Shapiro (2017), and Ito and Zhang (2020)). Our results show that the effects of temperature changes on the supply side are sizable, and shed light on the apparent puzzle that temperature affects productivity but not firm performance. We also identify the channels that drive our effects. Our results suggest that the decline in sales can be due to lower labor productivity and labor supply, lack of financial resources to adapt the productive processes, and to clients' ability to switch to other non-disrupted suppliers.

[1] Chen, Huynh, and Zhang (2018), Zhang et al. (2018), and Colmer et al. (2019) show that that higher local temperature lowers total factor productivity, value-added, and employment in manufacturing using establishment-level or firm-level data in other countries.

2. Data and Methodology

2.1 Sample and variables

Our sample consists of supplier-client pairs with headquarters in the United States. To obtain these data, we rely on regulations SFAS numbers 14 and 131, which require that publicly listed firms in the United States disclose, on a yearly basis, the identity of clients and the sales to clients whose purchases represent more than 10% of total sales.[2] We collect this information from the Compustat Segment files for the period 2000-2015. From these files we unambiguously identify the suppliers (using the GVKEY unique code from Compustat), and obtain the text names for their most important clients. Using text-searching algorithms complemented with manual searches, we match the reported client names to the Compustat database to obtain information about clients such as financials, location, and industry. As we restrict the searches to publicly traded firms in Compustat, we are unable to identify clients that are private firms, governments, or firms based outside of the United States. We exclude suppliers that are financial firms (SIC codes 6000-6999) or public administration (SIC codes 9100-9729).

We obtain temperature and precipitation data from the PRISM Climate Group (2019). PRISM gathers climate observations from weather stations in continental United States and uses sophisticated climate modelling techniques to interpolate weather data at each 4 km × 4 km grid (Daly and Byrant (2013)). The interpolation method takes elevation, slope orientation, wind direction, rain shadows, terrain complexity, proximity to coastlines and location of temperature inversions, and cold air pools into account. This results in a balanced panel of weather data for continental United States.

In extensions to our main estimates, we focus on extreme weather events. We obtain extreme weather events data from the National Oceanic and Atmospheric Administration (NOAA) Storm

[2] The reporting regulations imply that we cannot identify clients that buy small amounts or aggregate clients While our sample of clients and suppliers is not exhaustive, this arguably does not compromise our estimations, which rely on comparing the differential impact of temperature across different suppliers to the same firm. In addition, the restriction that the client is important for all suppliers makes the suppliers more comparable.

Events Database (NOAA (2019)). This database records the occurrence of significant weather events that have enough intensity to cause loss of life, injuries, significant property damage, and/or disruption to commerce (NOAA (2019)).

We map the weather grids in PRISM and extreme weather event locations to counties in the U.S. Census Bureau files. We compute average daily weather variables at the county level for each year and the annual number of extreme weather events by event type at the county level for each year. Figure 1 plots the change in average daily temperature per county and year over the sample period.

Finally, we match the weather variables in each county to the firms in Compustat using the county location of the firms' main headquarters and the firm's fiscal year end. Since a firm's production plants and sales locations are not always located in the same county as their headquarters, our proxy of the exposure to temperature is prone to measurement error. As supplier-client pair data is not available at the plant or establishment level, we face a trade-off between obtaining a more precise measure of temperature and the possibility to control for demand-side effects. We favor the latter, since measurement error is expected to lead to an attenuation bias, while not controlling for demand effects could lead to a bias of ambiguous sign.

2.2 Summary statistics

Panel A of Table 1 contains a year-by-year description of our sample. Our sample consists of 12,439 supplier-client-year observations for 1,856 unique suppliers and 419 unique clients over the period 2000-2015, with about 780 observations per year on average. Sales to clients in our sample account, on average, for 31.3% of the total sales of sample firms. Panel A also shows that the coefficient of our variable of interest is estimated using the variation in the change in temperature of more than five suppliers per client. The last two columns show that there is also a large degree of time-series variation in the average temperatures in the counties where firms are located, with the change in average daily temperature in the counties where firms are headquartered ranging from -1.4°C to 0.91°C.

Panels B and C show that the average daily temperature and average daily precipitation in headquarters counties for both client firms and supplier firms are similar. The annual increase in average daily temperature is higher than -0.54°C for 75% of the counties in our sample, and the standard deviation of the change in average temperature is 0.85°C.

Panels B and C of Table 1 also contain descriptive statistics for the firms in our pair-level sample. Panel B presents summary statistics for supplier firms. Panel C presents summary statistics for client firms. Client firms are larger than supplier firms in terms of total assets. This is due to regulation SFAS 14, which only requires to disclose of the names of clients that account for at least 10% of the suppliers' total sales. Client firms are more levered, hold less cash, have more tangible assets, and have a lower Tobin's Q than supplier firms. Table IA.1 in the Internet Appendix contains descriptive statistics of the Compustat firm-level sample that we use in some robustness tests.

2.3 Methodology

Our main objective is to examine whether changes in local temperature affect firms' sales. To investigate this hypothesis, we estimate the following regression equation:

$$\Delta \ln(Sales)_{ijt} = \beta_1 \Delta\, Temp_{it} + \beta_2 Prcp_{it} + \gamma X_{it-1} + \delta_{jt} + \varepsilon_{ijt}, \quad (1)$$

The dependent variable measures the annual growth rate in supplier i's sales to client j between years t-1 and t.[3] The main independent variable, $\Delta\, Temp_{it}$, is the change in average daily temperature in degrees Celsius in the county where supplier i is headquartered from year t-1 to year t. Following the climate economics literature, we include the average daily precipitation in inches in the county where supplier i is headquartered from year t-1 to year t ($Prcp_{it}$) (Auffhammer et al. (2013); Dell, Jones and Olken (2014)). In all specifications, we add a set of lagged supplier characteristics, X_{it-1}, which include firm size (*Assets*), ratio of the market value

[3] We require non-missing sales data in two consecutive years to calculate the change in sales for each client-supplier pair.

of assets to book value of assets (*Tobin's Q*), ratio of cash to assets (*Cash*), ratio of total debt to market value of assets (*Leverage*) and ratio of net property, plant and equipment to total assets (*Tangibility*).

Importantly, our client-supplier data allows us to include client-by-year fixed effects, δ_{jt}, in the regressions. Therefore, identification comes from the variation in the change in temperature across the suppliers of a given client in the same year. As derived formally by Khwaja and Mian (2008) in the context of shocks to the banking system, client-by-year fixed effects absorb all unobserved heterogeneity at the client level in a given year; thus, they allow us to compare the changes in business transactions across suppliers selling to the same firm. For this reason, our results are unlikely to be driven by changes in firm-specific demand.[4] The estimated difference in sales can therefore be plausibly attributed to supply-side factors, such as changes in labor supply or productivity of suppliers or an increase in operating costs, both of which can lead to lower output. In addition, weather shocks can affect the quality of products or services, or delay deliveries to clients. [5] In more stringent specifications, we include (supplier) industry fixed effects, δ_s, to control for time-invariant differences across industries, and industry-by-year fixed effects, δ_{st}, to control for time-varying differences across industries.

The main coefficient of interest is β_1, which estimates the effect of changes in temperature on supplier-client sales. A negative β_1 would indicate that suppliers that observe increases in average daily temperature in their county of location reduce their sales by larger amounts than otherwise similar suppliers selling to the same client. In our baseline regressions, we cluster the standard errors at the supplier county level as it corresponds to the variation we explore in the main explanatory variable ($\Delta\, Temp_{it}$). Table A.1 in the Appendix provides variable definitions and data sources.

[4] Client-year fixed effects account for changes in demand stemming for example from changes in temperature in the client county, independently of whether the client is located in the same or a different location as the supplier.
[5] Clients could decide to reduce their purchases from suppliers with a weather shock due for example to increased production costs leading to higher prices, or anticipation of disruptions in the input delivery. The resulting drop in output is nevertheless supply-driven, as it is triggered by supply-side changes in the weather.

2.4 Identifying assumptions

The main identifying assumption in our estimates is that local changes in temperature are exogenous to the suppliers' business transactions or sales. While it is true that collectively, the business transactions among certain firms and industries – particularly in CO_2-intensive sectors – has a major impact on climate, such an impact is at a global level, and often the areas that are most affected are those with lower levels of industrialization and economic activity. Therefore, it is difficult to argue that an individual firms' business transactions affect the local temperature.

Another assumption is that the response of sales for a firm's products or services would have been the same for firms absent the weather shocks (i.e., the treatment corresponds to the supplier being exposed to a change in the average temperature). We address this issue in Section 3.2.

Our identification strategy exploits the variation in changes in temperatures across suppliers of the same client each year using client-by-time fixed effects. Paravisini, Rappoport, and Schnabl (2020) argue that an additional identifying assumption of empirical strategies following Khwaja and Mian (2008) is that changes in a firms' credit demand are equally spread across all the banks lending to the firm. In our case, this implies that changes in clients' purchases are equally spread across all suppliers, which is more plausible when suppliers are from the same industry. For this reason, our specifications include industry-by-time fixed effects to restrict the variation of interest to suppliers within the same industry and time period.

3. Results

3.1 Baseline estimates

Table 2 presents the estimates of the regression in equation (1). In all columns, we estimate the effect of changes in temperature on changes in supplier-client sales. We do not control for precipitation in columns (1)-(3), but we do in columns (4)-(6). We estimate the regressions using three different sets of fixed effects: client-by-year fixed effects in columns (1) and (4); supplier industry fixed effects and client-by-year fixed effects in columns (2) and (5); and supplier industry-by-year and client-by-year fixed effects in columns (3) and (6).

The results show that the temperature variable ($\Delta Temp$) coefficient is negative and statistically significant in all specifications. Precipitation does not significantly affect the estimates. Our estimates indicate that a 1°C yearly increase in the average daily temperature in the supplier county leads to a 1.2% to 1.9% reduction in sales. A 1°C increase in temperature is not uncommon at the local (county) level as the standard deviation of the annual change in average temperature corresponds to 0.85°C over our sample period.

As mentioned before, the inclusion of client-by-year fixed effects in all our specifications absorb all observed and unobserved heterogeneity at the client level in a given year, including potential changes in the client's demand for inputs, which might be correlated with the changes in temperature. By controlling for demand effects, our results reconcile previous findings in the literature showing negative effects of temperature on firm productivity (Graff-Zivin and Neidell (2014), Jones and Olken (2010), Hsiang (2010), Dell, Jones, and Olken (2012)) but no overall effects on firm-level or establishment-level sales or productivity (Addoum, Ng and Ortiz-Bobea (2020)) We further address this issue in Section 5.

3.2 Placebo tests

Our identification strategy assumes that the response of sales for a firm's products or services would have been the same for firms absent the weather shocks (i.e., the treatment corresponds to the supplier being exposed to a change in the average temperature). To evaluate this assumption, we perform regressions using leads and lags of the dependent variable, $\Delta\log(Sales)$. We conduct these placebo tests using the specification in column (4) of Table 2. We estimate the coefficient of the change in temperature in regressions in which we fix the weather shock at time 0, and vary the dependent variable over a period between -2 and +2 years.

Table 3 reports the estimates and Figure 2 shows the coefficients of the change in temperature and the 95% confidence intervals. The coefficient at time 0 is -0.014, corresponding to the estimate in column (4) of Table 2. The coefficients for year t-2, t-1, t+1 and t+2 are not statistically significant. Thus, there is no evidence of pre-existing differential trends between treatment and control groups.

3.3 Extreme weather events

We next examine whether extreme weather events affect firms' business transactions. In columns (1)-(3) of Table 4, we test whether excessive heat in supplier counties affects sales. The variable of interest is *Heat Events*, which measures the number of extreme heat events that takes place in the county where a supplier is located. The incidence of extreme heat events is rare in our sample. Table 1 shows that the average number of heat events in our sample is 0.0053, i.e., approximately one in 200 observations is hit by one such event during our sample period. We find that the coefficient of *Heat Events* is negative and significant. The effect of extreme heat events is also economically significant. An extreme heat event is associated with a further 6.2% to 8.0% reduction in sales, relative to firms with no such event.

In columns (4)-(6) of Table 4, we test whether extreme cold events in supplier counties affect sales. The variable of interest is *Cold Events*, the number of extreme cold events that takes place in the county where a supplier is located. The incidence of such events is low in our sample, with an average value of 0.0007, or slightly less than one in 1000 observations. We find that the *Cold Events* variable coefficient is negative and significant. The extreme cold events have an even more meaningful effect on sales than the extreme heat events. Firms hit an extreme cold event suffer an additional reduction in their sales of 31% to 36%. These results suggest that extreme cold events, even if less often, can have a more disruptive effect on the firm's business activity.

4. How Does Temperature Impact Firm Sales?

Our baseline specifications control for observed and unobserved, time-variant and time-invariant, demand-side factors, allowing us to plausibly attribute the estimated difference in sales to supply-side factors. These factors might include reductions in output due to lower labor supply or productivity (i.e., absenteeism, working conditions, workforce health and safety) or higher operating costs (e.g., energy or investment costs for air conditioning, equipment cooling or heating systems, higher transportation costs). In addition, weather shocks can affect the quality or the price of products or services, or delay deliveries to clients, leading to lower purchases by clients who prefer to buy their inputs from undisrupted suppliers that do not compromise on quality. In this section, we exploit the heterogeneity in our data to analyze the channels through which changes in the temperature might affect firm supply, and which firm characteristics can mitigate or amplify the effect of weather shocks on firm sales.

4.1 Labor supply and productivity channel

We first explore whether the mechanism behind the negative effects on firm sales documented in the baseline results might be due to lower labor supply and productivity (Graff-Zivin and Neidell (2014), Chen, Huynh, and Zhang (2019), and Zhang et al. (2018)). If this is the case, we expect that our baseline results are primarily driven by firms whose output is most sensitive to the weather conditions. We consider three measures to test for this mechanism: (1) whether a firm belongs to heat-sensitive industries; (2) whether a firm is operating in manufacturing; and (3) the ratio of the number of employees to assets as a proxy for labor intensity.

If temperature primarily affects economic performance via a productivity channel, firms in the manufacturing industries are likely to be driving the results. Colmer et al. (2019) find that higher local temperature lowers the value-added and employment in French manufacturing firms. Using plant-level data, Chen, Huynh, and Zhang (2019) document that higher local temperature lowers total factor productivity. Panel A of Table 5 reports the subsample results split by whether a firm is in manufacturing industries. Columns (1)-(3) present the results for firms in manufacturing industries. The coefficient of $\Delta Temp$ is -2.2%, and is statistically significant across specifications. Columns (4)-(6) present the results for firms in other industries. The coefficient of $\Delta Temp$ is positive but not statistically different from zero.

Firms in industries with predominantly outdoor activities or manufacturing processes are expected to be more sensitive to heat. Following Graff-Zivin and Neidell (2014), we identify firms operating in heat sensitive industries as firms operating in agriculture, forestry, fishing, and hunting (SIC 100-999); mining (SIC 1000-1499); construction (SIC 1500-1799); manufacturing industries (SIC 2000-3999); and transportation and utilities (SIC 4000-4999). Panel B of Table 5 reports the subsample results split by whether a firm is in heat-sensitive industries or not. Columns (1)-(3) present the results for firms in heat-sensitive industries. The coefficient of $\Delta Temp$ ranges from -2.0% to -2.3%, and is statistically significant across specifications. Columns (4)-(6) present the results for firms not in heat-sensitive industries. The coefficient of $\Delta Temp$ is not statistically significant.

Firms with higher labor intensity are expected to be more sensitive to heat. Panel C of Table 5 reports the subsample results split by whether a firm is above or below the median of the ratio of the number of employees to assets. Columns (1)-(3) present the results for firms with high labor intensity. The coefficient of $\Delta Temp$ is negative for all the specifications and statistically significant at -2.2% in column (3). Columns (4)-(6) present the results for firms with low labor intensity. The coefficient of $\Delta Temp$ is statistically insignificant across these specifications.

4.2 Financial constraints channel

Disruptions to firms' production processes might be particularly severe if suppliers cannot effectively adapt to the changing climate conditions, for example by hiring more workers to reduce the drop in productivity, reallocating resources across their different business segments, or promptly investing in the necessary equipment to resume (or boost) production. Firms might be more flexible to adapt to changing weather conditions if they are financially unconstrained and thus are able to tap capital markets relatively easily. Large firms might also adapt to changes in the temperature more easily than small firms due to economies of scale and economies of scope. Likewise, conglomerates might also adapt to changes in the environment more easily than single-segment firms as they might more easily increase the production in unaffected plants or reallocate resources across different business segments to compensate for the reduction in activities in affected plants/segments.

To measure the ability of firms to adapt to changes in the temperature, we consider the following five measures of financial constraints: (1) whether a firm is rated or non-rated; (2) ratio of long-term debt maturing within one year to total long-term debt; (3) total assets; (4) number of employees; and (5) whether a firm is a single-segment firm or a conglomerate.

Table 6 reports the results. Panel A presents the subsample results split by whether a firm is rated by a credit rating agency. Firms with a credit rating have access to public debt markets and therefore are less financially constrained. Columns (1)-(3) present the results for firms with a credit rating. The coefficient of Δ*Temp* ranges from 2.4% to 2.7%, and is positive and statistically significant in two specifications. Columns (4)-(6) present the results for firms without a credit rating. The coefficient of Δ*Temp* ranges from -2.4% to -3.1%, and is statistically significant across all specifications. The magnitude is more pronounced than the baseline estimates in Table 2. We conclude that unrated firms are more negatively affected by the increase in temperature.

Panel B presents the subsample results split by the ratio of long-term debt maturing within one year to total long-term debt. A high ratio indicates that the firm is more financially constrained as it needs to repay a high fraction of its long-term debt within one year. Since debt contracts are written a number of years prior to the realization of the shocks, the maturity structure is pre-determined (Almeida et al., 2012). We split the sample into high and low ratio of long-term debt maturing within one year according to the median value of its distribution. Columns (1)-(3) presents the results for firms with a lower ratio of debt maturing. The coefficient of Δ*Temp* is not statistically different from zero. Columns (4)-(6) presents the results for firm with a higher ratio of debt maturing. The coefficient of Δ*Temp* ranges from -3.8% to -4.2%, and is statistically significant across specifications. The magnitude is more pronounced than the baseline estimates in Table 2 as in Panel A. In addition, we find that firms with more debt due next year are more affected by the change in temperature.

Firm size can proxy for financial constraints as well as operational flexibility. Larger firms have less financial constraints and more operational flexibility than smaller firms. Panel C of Table 6 presents the subsample results split by total assets. We split the sample into high and low total assets according to the median value of its distribution. Columns (1)-(3) present the results for firms with total assets above the median of the distribution. The coefficient of Δ*Temp* is not statistically different from zero. Columns (4)-(6) present the results for firms with total assets below the median. The coefficient of $\Delta Temp$ ranges from -3.0% to -4.2%, and is statistically significant across all specifications. We find similar results when we split the sample by the number of employees in Panel D. In this case, the coefficient of $\Delta Temp$ for the small firms ranges from -2.5% to -3.0%, and is statistically significant in two out of three specifications. Thus, we conclude that the negative effects on firm sales of increases in temperature are driven by smaller firms, which are more likely to have less financial and operational flexibility to adapt to weather shocks.

The number of business segments can also proxy for financial constraints and operational flexibility. Conglomerates (i.e., multi-segment firms) have more operational flexibility and less financial constraints than smaller firms due to internal capital markets. Panel E presents the subsample results split by whether a firm is single segment or multi segment. Columns (1)-(3) present the results for multi-segment firms. The coefficient of $\Delta Temp$ is not statistically significant. Columns (4)-(6) present the results for single-segment firms. The coefficient of $\Delta Temp$ ranges from -1.7% to -2.1%, and is statistically significant across all specifications. We conclude that the negative effects of increases in temperature are driven by single-segment firms, which are more likely to be financially and operationally constrained.

Overall, we find that the negative effects of climate change are driven by firms with more financial constraints and less operational flexibility as these firms can have more difficulties (or can take more time) to adapt to changes in temperature. These results highlight the role of financial constraints in adaptation to climate change and climate policies (Bartram, Hou and Kim (2021)).

4.3 Interaction between labor productivity and financial constraints

Next, we examine whether the labor productivity channel and financial constraints/adaptability channels interact. Building on the previous results, we expect changes in local temperature to be more disruptive for labor intensive firms that are less able to adapt. To examine this idea, we split supplier firms in our sample into four groups according to their exposure to heat and their capability to adapt. We use the industry (manufacturing or non-manufacturing) to proxy for heat exposure, and the same proxies (credit rating, proportion of long-term debt maturing, total assets, number of employees and business segments) for financial constraints/adaptability as in Table 6.

Table 7 reports the results. We report the specification with client-by-time and supplier industry-by-time fixed effects for each of the four interaction groups. In all cases except for the number of employees, the coefficient of $\Delta Temp$ is negative and statistically significant only in Column (3), the subsample consisting of manufacturing firms that are more financially constrained or have lower operating flexibility. In Panel D, the coefficient of $\Delta Temp$ is negative and only marginally insignificant at 10% level in Column (3). The full set of results are contained in Table IA.2 of the Internet Appendix, and the results using the heat sensitive industry classification for heat exposure are reported in Table IA.3. Together, the results in this interaction analysis suggest that the negative effects on sales of higher temperature are concentrated among manufacturing firms that are more financially constrained or have lower operational flexibility.

4.4 Switching costs channel

In this subsection, we study whether input specificity and relationship capital mitigate the negative effects of higher local temperature on cash flows. If a supplier sells a specific product or service, the client's switching costs are likely to be higher (Barrot and Sauvagnat (2016)). In addition, input specificity should be correlated with higher relationship capital between a supplier and client. Relationship capital should help to mitigate disruptions, firms with stronger client-supplier relationship are expected to be less affected by higher local temperature.

Suppliers selling more standardized goods are likely to have weaker client-supplier relationship, since clients can easily substitute away from a disrupted supplier. Note that we cannot identify whether observed changes in sales at the client-supplier pair level are supplier- or client-originated, though these are triggered by the weather events at the supplier level. It may be that supplier is indeed disrupted and therefore cannot supply the goods, or it may be the case that clients, observing the shock and anticipating possible disruption decide to reduce their purchases from the supplier and possibly switch to a different one.

We consider three measures for input specificity and the strength of client-supplier relationship: (1) whether a firm is in an industry that sells standardized goods; (2) whether a firm has patents;

(3) the geographical distance between client and supplier.

We identify industries that are more likely to sell standardized products or, in other words, industries with lower costs of switching to other suppliers following Giannetti, Burkart, and Ellingsen (2011). Panel A of Table 8 reports the subsample results split by whether a firm operates in industries that sell standardized goods or not. Columns (1)-(3) present the results for firms in industries that sell non-standardized goods. The coefficient of Δ*Temp* is not statistically significant. Columns (4)-(6) present the results for firms in industries that sell standardized goods. The coefficient of Δ*Temp* ranges is -3.6%, and is statistically significant at the 10% level in all specifications.

An alternative measure of input specificity and relationship capital is given by patents. Panel B of Table 8 reports the subsample results split by the whether a firm filed for patents or not. Columns (1)-(3) present the results for firms that file for patents. The coefficient of Δ*Temp* ranges from -0.7% to -1.2%, but is not statistically significant. Columns (4)-(6) present the results for firms with no patents. The coefficient of Δ*Temp* ranges from -1.4% to -1.9%, and statistically significant at the 10% level in column (6).

Supplier-client pairs that are closer to each other geographically are likely to have a stronger relationship. Panel C of Table 8 reports the subsample results split by the geographical distance between corporate headquarters of a client-supplier pair. We split the sample into high and distance according to the median value of its distribution. Columns (1)-(3) present the results for client-supplier pairs that are more closely located. The coefficient of Δ*Temp* is not statistically significant. Columns (4)-(6) present the results for client-supplier pairs that are farther apart. The coefficient of Δ*Temp* ranges from -2.9% to -3.1%, and is statistically significant across specifications.

In short, the evidence suggests that the negative effects on sales due to the increase in temperature are more pronounced for suppliers that are easier to substitute (i.e., sell a standardized good, have no patents, or are more distant) and thus switching costs are lower.

4.5 Extensive margin

Our baseline results in Table 2 are estimated under the assumption that clients and suppliers maintain their relationship during two consecutive years; otherwise these transactions would not be observed in the data. Therefore, our baseline results are on the intensive margin. We also estimate an extensive margin regression based on equation (1) but replacing the dependent variable with a dummy that takes a value of one if we observe transactions in year t–1 but not in year t, suggesting a termination of the relationship or a significant reduction in transactions between the client and the supplier. A positive and statistically significant coefficient on $\Delta Temp$ indicates that suppliers exposed to increases in temperature suffer a significant decrease in sales, such that sales to the client fall below the 10% reporting threshold and eventually to zero. Table 9 presents the results of a linear probability model. We find that the coefficients are not statistically significant in any of the specifications, suggesting that changes in temperature do not lead to termination of supply chain relationships.

Our results in Table 9 contrast with those of Pankratz and Schiller (2019), who find that heatwaves and natural disasters (floods) can disrupt the global supply chain at the extensive margin. Our findings show that within the United States, changes in temperature are not as likely to have such a disruptive effect. This may be explained by the fact that our sample is a domestic supply-chain network, rather than a global one, and client and suppliers may have stronger business relationships, and lower information asymmetries due to their geographical proximity. This may also be explained by our weather events being less severe than the ones studied by Pankratz and Schiller (2019), and for this reason causing less disruption.

5. Robustness

In this section, we show several robustness checks of our primary findings. The Internet Appendix shows these results.

Table IA.4 reports the results for the subsample in which the sum of reported sales represents at least 24% of total sales, which corresponds to our median coverage of supplier sales. In this test, we address the potential concern that the effects on firm sales are driven by suppliers in which the coverage of inter-firm trade is poor. The magnitudes of the coefficients of the change in temperature are similar at about -1.6% to -2.2%.

Table IA.5 reports the results with squared weather variables. In this test, we address the potential concern that the impact of weather shocks on firm sales is non-linear. The coefficients of the square of change in temperature and the square of precipitation are not statistically different from zero. The magnitudes of the coefficients of the change in temperature are similar at about -1.2% to -1.8%.

Table IA.6 reports the results with the change in precipitation as a control variable. In this test, we address the potential concern that instead of the level of precipitation, we should instead control for the change in precipitation. The coefficients of the change in precipitation are not statistically different from zero. The magnitudes of the coefficients of the change in temperature are similar to those in Table 2 at about -1.3% to -1.8%.

Table IA.7 reports the results with standard errors clustered at the state level. In this test, we address the potential concern that weather variables are spatially correlated at a broader scale (Hsiang (2016)). The coefficients of the change in temperature remain statistically significant across all specifications. Table IA.8 reports the results using zip code level weather variables. In this test, we address the potential concern that county-level weather variables are not sufficiently precise. The coefficients of the change in zip code level temperature are similar to those in Table 2 at about -1.2% to -1.8%.

Table IA.9 reports the results with industry fixed effects at the three-digit SIC code level. In this test, we address the potential concern that industry fixed effects at the two-digit SIC code level are too coarse. The magnitudes of the coefficients of the change in temperature are similar to those in Table 2 at about -1.2% to -1.8%.

Table IA.10 reports the results of extreme weather effects on the extensive margin. Columns (1)-(3) show that the coefficients of *Heat Events* on the relationship termination dummy variable is positive, but only significant in one specification. Columns (4)-(6) show that the coefficients of

Cold Events on the termination dummy variable are positive but statistically insignificant. The effects on the extensive margin seem to be insignificant for both the average temperature and extreme weather events.

Table IA.11 reports the estimates of firm-level regression of sales, productivity, and profitability. We draw our sample of U.S. firms from the Compustat Industrial Annual database. The sample period ranges from 2000 to 2015. We exclude financial firms (SIC codes 6000-6999) or public administration (SIC codes 9100-9729). The dependent variables are the change in the log of sales, change in the ratio of sales to the number of employees, ratio of EBIT to assets (return on assets), and ratio of net income to assets. The main explanatory variable is the change in average local temperature. Table IA.12 also report estimates of reports the estimates of firm-level regression of sales, productivity, and profitability using levels. The main explanatory variable is the average local temperature and the regressions include firm fixed effects. In the firm-level tests, we are not able to include client-by-year fixed effects and therefore we are not controlling for firm-specific demand.

We find that local average temperature does not significantly affect aggregated firm-level sales, productivity, and profitability. These results are consistent with those in Addoum, Ng, and Ortiz-Bobea (2020) who find no evidence that temperature affects sales, productivity, and profitability using establishment-level or firm-level data. Our results suggest that failing to account for changes in demand for the firms' products leads us to find no effects of the increase in temperature on firm performance, which is consistent with the results in Addoum, Ng, and Ortiz-Bobea (2020). This highlights the importance of controlling for firm-specific demand to understand the supply-side effects of climate change on firm performance.

6. Conclusion

This paper studies the supply side effects of changes in local temperature exploiting production networks. We compare sales of intermediate goods across suppliers that trade with the same client but are exposed to different temperature shocks, which allow us to distinguish supply-side effects from demand-side effects.

We show that changes in local temperature can have sizable effects on firm sales at the intensive margin controlling for firm-specific demand. A 1°C increase in average daily temperature in supplier counties leads to a negative and significant effect on firm sales of 2%. We also show that firms exposed to extreme hot and cold weather events suffer larger reductions in sales.

We examine the channels by which changes in local temperature affect firm sales. First, the reduction in sales in response to increases in local temperature is primarily driven by firms operating in heat-sensitive industries, manufacturing industries, and labor-intensive firms, suggesting that lower labor supply and productivity are driving these effects. Second, we find that financially unconstrained firms are better able to deal with the adverse effects of increased local temperature and therefore face lower reductions in sales, suggesting that financial constraints play an important role in the ability of firms adapting to climate change. Finally, input specificity and relationship capital are important drivers of the impact of temperature on supplier sales. We find that suppliers experience a lower reduction in sales when clients have higher switching costs.

Overall, our results suggest that climate change can have important effects on real economic activity. Policy makers should consider supply-side effects when they design policies to address climate change challenges.

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Table 1: Summary Statistics - Client-Supplier Pair Sample

Panel A presents the number of observations (supplier-client pairs), number of suppliers, number of clients, average number of suppliers per client, average fraction of total sales of the supplier, average temperature at supplier firms' headquarter counties and client firms' headquarter counties included in the sample per year. Panels B and C present mean, median, 25th percentile, 75th percentile, standard deviation, and number of observations for each supplier and client variable. The sample consists of yearly observations of Compustat firms in the 2000-2015 period. Variable definitions are in Table A.1 in the Appendix.

Panel A: Sample by Year

Year	Observations	Unique Suppliers	Unique Clients	Average Number of Suppliers per Client	Average Supplier Sales Coverage	Average Change in Temperature in Supplier Counties	Average Change in Temperature in Client Counties
2000	535	387	108	4.9537	0.3051	-0.6297	-0.5455
2001	807	552	152	5.3092	0.3206	0.4742	0.3255
2002	857	564	176	4.8693	0.3267	0.0165	-0.0054
2003	915	620	170	5.3824	0.3041	-0.5647	-0.6638
2004	896	596	172	5.2093	0.3087	0.2399	0.3559
2005	844	565	166	5.0843	0.3205	0.2973	0.2997
2006	899	593	169	5.3195	0.3082	0.4675	0.4955
2007	859	592	164	5.2378	0.3003	-0.4050	-0.4966
2008	800	565	151	5.2980	0.3007	-0.4545	-0.2122
2009	770	545	154	5.0000	0.3016	-0.1492	-0.2086
2010	747	522	143	5.2238	0.3094	0.5358	0.6431
2011	721	490	143	5.0420	0.3183	0.1185	-0.0354
2012	707	470	133	5.3158	0.3174	0.8309	0.8567
2013	713	465	138	5.1667	0.3212	-1.4147	-1.4008
2014	715	455	146	4.8973	0.3277	-0.2711	-0.2102
2015	654	428	134	4.8806	0.3209	0.9052	0.8825
Total	12,439	1,856	419	5.1422	0.3128	0.0018	0.0058

Table 1: Continued

Panel B: Suppliers

Variable	Mean	25th Percentile	Median	75th Percentile	Standard Deviation	Observations
Δlog(Sales)	0.0159	-0.1641	0.0363	0.2253	0.5081	12,439
Temp	13.7013	10.2014	13.2761	16.5212	4.2085	12,439
ΔTemp	-0.0013	-0.5383	0.0364	0.5313	0.8520	12,439
Prcp	2.5856	1.6308	2.7168	3.4307	1.1783	12,439
Cold Events	0.0007	0	0	0	0.0269	12,439
Heat Events	0.0053	0	0	0	0.1261	12,439
Tobin's Q	2.2007	1.1006	1.5232	2.3639	2.7290	12,439
Cash	0.1623	0.0339	0.1065	0.2335	0.1718	12,439
Log(Assets)	5.7910	4.4207	5.7189	7.1434	1.9850	12,439
Tangibility	0.2229	0.0647	0.1488	0.3022	0.2187	12,439
Leverage	0.1991	0.0024	0.1096	0.3125	0.2383	12,439

Panel C: Clients

Variable	Mean	25th Percentile	Median	75th Percentile	Standard Deviation	Observations
Δlog(Sales)	0.0159	-0.1641	0.0363	0.2253	0.5081	12,439
Temp	13.5199	10.6018	12.9288	15.7605	3.8481	7,718
ΔTemp	-0.0083	-0.5093	0.0212	0.5290	0.8485	7,718
Prcp	2.7238	1.9107	2.8200	3.4682	1.1309	7,718
Cold Events	0.0005	0	0	0	0.0228	7,718
Heat Events	0.0056	0	0	0	0.0744	7,718
Tobin's Q	1.8209	1.1427	1.5144	1.9989	1.1871	7,556
Cash	0.0718	0.0274	0.0530	0.0977	0.0636	9,588
Log(Assets)	10.5486	9.5921	10.5606	11.6768	1.4233	9,792
Tangibility	0.2630	0.0869	0.1885	0.4331	0.2110	7,681
Leverage	0.2492	0.1052	0.1740	0.3129	0.2219	9,491

Table 2: Client-Supplier Sales Growth Regressions

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable Δlog(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. Δ*Temp* is the change in average daily temperature in degree Celsius in the county of the corporate headquarters for supplier *i* from year *t*-1 to year *t. Prcp* is the average daily precipitation in millimeters in the county of the corporate headquarters for supplier *i* in between years *t*-1 and *t*. *Tobin's Q* is the ratio of the market value of assets to book value of assets. *Cash* is the ratio of cash and equivalents to total assets. *Assets* is total assets. *Tangibility* is the ratio of net property, plant and equipment to total assets. *Leverage* is the ratio of total debt to the market value of assets. All financial variables are for the supplier and lagged one period. Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. Industry fixed effects are defined by two-digit SIC code. Robust *p*-values clustered at the supplier county level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
ΔTemp	-0.012*	-0.013*	-0.017**	-0.014*	-0.014*	-0.019**
	(0.085)	(0.072)	(0.023)	(0.069)	(0.052)	(0.015)
Prcp				-0.007	-0.008	-0.009
				(0.236)	(0.166)	(0.124)
Tobin's Q	0.013***	0.013***	0.014***	0.013***	0.013***	0.014***
	(0.002)	(0.001)	(0.000)	(0.002)	(0.001)	(0.000)
Cash	-0.082	-0.076	-0.072	-0.084	-0.078	-0.075
	(0.137)	(0.180)	(0.221)	(0.127)	(0.166)	(0.201)
Log(Assets)	0.014***	0.013***	0.013***	0.014***	0.013***	0.013***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Tangibility	-0.014	-0.045	-0.044	-0.014	-0.045	-0.044
	(0.673)	(0.308)	(0.326)	(0.675)	(0.313)	(0.328)
Leverage	-0.053**	-0.051**	-0.047*	-0.052**	-0.050**	-0.046*
	(0.018)	(0.031)	(0.072)	(0.023)	(0.035)	(0.079)
Observations	12,439	12,439	12,439	12,439	12,439	12,439
R-squared	0.298	0.302	0.333	0.298	0.302	0.334
Client-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No
Industry-Year FE	No	No	Yes	No	No	Yes

Table 3: Placebo Regressions

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variables are lags and leads of Δlog(*Sales*), the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. Δ*Temp* is the change in average daily temperature in degree Celsius in the county of the corporate headquarters for supplier *i* from year *t*-1 to year *t*. *Prcp* is the average daily precipitation in millimeters in the county of the corporate headquarters for supplier *i* between years *t*-1 and *t*. *Tobin's Q* is the ratio of the market value of assets to book value of assets. *Cash* is the ratio of cash and equivalents to total assets. *Assets* is total assets. *Tangibility* is the ratio of net property, plant and equipment to total assets. *Leverage* is the ratio of total debt to the market value of assets. Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. Industry fixed effects are defined by two-digit SIC code. Robust *p*-values clustered at the supplier county level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Year *t*-2	Year *t*-1	Year *t*	Year *t*+1	Year *t*+2
	(1)	(2)	(3)	(4)	(5)
ΔTemp	-0.013	-0.001	-0.014*	0.003	0.015
	(0.217)	(0.949)	(0.069)	(0.770)	(0.100)
Prcp	-0.004	-0.009	-0.007	-0.001	0.015**
	(0.597)	(0.126)	(0.236)	(0.860)	(0.019)
Tobin's Q	0.007	0.010**	0.013***	0.010***	0.006*
	(0.257)	(0.020)	(0.002)	(0.005)	(0.085)
Cash/Assets	-0.043	0.002	-0.084	0.008	-0.028
	(0.477)	(0.980)	(0.127)	(0.891)	(0.657)
Log(Assets)	0.006*	0.010***	0.014***	0.012***	0.014**
	(0.093)	(0.007)	(0.000)	(0.002)	(0.014)
Tangibility	-0.051	-0.024	-0.014	-0.005	-0.002
	(0.254)	(0.542)	(0.675)	(0.899)	(0.967)
Leverage	-0.012	-0.048*	-0.052**	-0.034	-0.055*
	(0.740)	(0.054)	(0.023)	(0.177)	(0.054)
Observations	5,794	8,340	12,439	8,340	5,794
R-squared	0.347	0.321	0.298	0.329	0.326
Client-Year FE	Yes	Yes	Yes	Yes	Yes

Table 4: Extreme Weather Events

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable Δlog(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. *Cold Events* is the number of cold events recorded in the county of corporate headquarters between years *t*-1 and *t*. *Heat Events* is the number of heat events recorded in the county of corporate headquarters between years *t*-1 and *t*. *Temp* is the average daily temperature in degree Celsius in the county of the corporate headquarters for supplier *i* between years *t*-1 and *t*. *Prcp* is the average daily precipitation in millimeters in the county of the corporate headquarters for supplier *i* between years *t*-1 and *t*. *Tobin's Q* is the ratio of the market value of assets to book value of assets. *Cash* is the ratio of cash and equivalents to total assets. *Assets* is total assets. *Tangibility* is the ratio of net property, plant and equipment to total assets. *Leverage* is the ratio of total debt to the market value of assets. All financial variables are for the supplier and lagged one period. Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. Industry fixed effects are defined by two-digit SIC code. Robust *p*-values clustered at the supplier county level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Heat Events	-0.062**	-0.064**	-0.080**			
	(0.024)	(0.020)	(0.024)			
Cold Events				-0.313***	-0.333***	-0.357***
				(0.006)	(0.004)	(0.003)
Temp	-0.016	-0.015	-0.020*	-0.016	-0.016	-0.021*
	(0.156)	(0.168)	(0.078)	(0.146)	(0.157)	(0.071)
Prcp	0.007	0.006	0.007	0.006	0.006	0.007
	(0.620)	(0.650)	(0.617)	(0.631)	(0.661)	(0.632)
Tobin's Q	0.013***	0.013***	0.015***	0.013***	0.013***	0.015***
	(0.002)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
Cash	-0.091	-0.085	-0.081	-0.092	-0.085	-0.082
	(0.102)	(0.145)	(0.185)	(0.101)	(0.142)	(0.181)
Log(Assets)	0.016***	0.014***	0.015***	0.016***	0.014***	0.015***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tangibility	-0.056	-0.081	-0.080	-0.056	-0.082	-0.081
	(0.193)	(0.143)	(0.153)	(0.188)	(0.142)	(0.151)
Leverage	-0.039	-0.040	-0.039	-0.039	-0.039	-0.039
	(0.106)	(0.127)	(0.180)	(0.107)	(0.130)	(0.183)
Observations	12,413	12,413	12,412	12,413	12,413	12,412
R-squared	0.323	0.327	0.358	0.323	0.327	0.358
Client-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No
Industry-Year FE	No	No	Yes	No	No	Yes

Table 5: Labor Supply and Productivity

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable Δlog(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. Δ*Temp* is the change in average daily temperature in degree Celsius in the county of the corporate headquarters for supplier *i* from year *t*-1 to year *t. Prcp* is the average daily precipitation in millimeters in the county of the corporate headquarters for supplier *i* in between years *t*-1 and *t*. Manufacturing industries are defined as industries with SIC codes between 2000 and 3999. Heat sensitive industries are defined as in Graff-Zivin and Neidell (2014). The high and low labor intensity groups consist of those firms that are above and below the median of the ratio of number of employees to assets. All financial variables are for the supplier and lagged one period. Regressions include the same control variables as in Table 2 (coefficients not shown). Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. Robust *p*-values clustered at the supplier county level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Manufacturing Industries

	Manufacturing Industries			Non-Manufacturing Industries		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔTemp	-0.022**	-0.022**	-0.022**	0.023	0.024	0.011
	(0.015)	(0.013)	(0.025)	(0.239)	(0.223)	(0.635)
Prcp	-0.010	-0.009	-0.010	-0.014	-0.020*	-0.024**
	(0.158)	(0.226)	(0.180)	(0.179)	(0.079)	(0.020)
Observations	8,567	8,567	8,557	3,053	3,053	3,031
R-squared	0.304	0.306	0.319	0.368	0.377	0.447
Client-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No
Industry-Year FE	No	No	Yes	No	No	Yes

Panel B: Heat Sensitive Industries

	Heat Sensitive Industries			Non-Heat Sensitive Industries		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔTemp	-0.020**	-0.021**	-0.023**	0.035	0.034	0.034
	(0.015)	(0.010)	(0.011)	(0.111)	(0.124)	(0.141)
Prcp	-0.010*	-0.011*	-0.013**	0.002	-0.004	-0.008
	(0.096)	(0.083)	(0.043)	(0.855)	(0.790)	(0.575)
Observations	10,224	10,224	10,218	1,432	1,432	1,416
R-squared	0.315	0.318	0.342	0.380	0.387	0.449
Client-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No
Industry-Year FE	No	No	Yes	No	No	Yes

Table 5: Continued

Panel C: Labor Intensity

	High Labor Intensity			Low Labor Intensity		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔTemp	-0.015	-0.014	-0.022**	-0.010	-0.010	-0.007
	(0.177)	(0.188)	(0.047)	(0.486)	(0.487)	(0.659)
Prcp	0.010	0.009	0.007	-0.018**	-0.019**	-0.019*
	(0.145)	(0.193)	(0.311)	(0.046)	(0.043)	(0.062)
Observations	5,530	5,528	5,452	5,539	5,535	5,432
R-squared	0.355	0.365	0.419	0.333	0.339	0.381
Client-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No
Industry-Year FE	No	No	Yes	No	No	Yes

Table 6: Financial Constraints

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable Δlog(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. Δ*Temp* is the change in average daily temperature in degree Celsius in the county of the corporate headquarters for supplier *i* from year *t*-1 to year *t. Prcp* is the average daily precipitation in millimeters in the county of the corporate headquarters for supplier *i* in between years *t*-1 and *t*. The rated and unrated groups consist of those firms with a credit rating and without a credit rating (Panel A). The high and low long-term debt maturing groups consist of those firms that are above and below the median of the ratio of long-term debt maturing within one year to total long-term debt (Panel B). The high and low assets groups consist of those firms that are above and below the median (Panel C).. The high and low number of employees groups consist of those firms that are above and below the median (Panel D). The multi- and single-segment groups consist of those firms with one business segment and more than one business segment (Panel E). All financial variables are for the supplier and lagged one period. Regressions include the same control variables as in Table 2 (coefficients not shown). Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. Industry fixed effects are defined by two-digit SIC code. Robust *p*-values clustered at the supplier county level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Credit Rating

	Rated			Unrated		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔTemp	0.027**	0.026**	0.024	-0.024**	-0.024**	-0.031***
	(0.028)	(0.038)	(0.109)	(0.017)	(0.016)	(0.003)
Prcp	0.001	0.001	-0.004	-0.007	-0.008	-0.010
	(0.933)	(0.917)	(0.657)	(0.373)	(0.285)	(0.185)
Observations	2,776	2,776	2,651	8,775	8,773	8,676
R-squared	0.403	0.420	0.488	0.311	0.315	0.347
Client-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No
Industry-Year FE	No	No	Yes	No	No	Yes

Panel B: Long-Term Debt Maturing

	Low Long-Term Debt Maturing			High Long-Term Debt Maturing		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔTemp	0.008	0.006	0.005	-0.042***	-0.042***	-0.038**
	(0.523)	(0.633)	(0.751)	(0.007)	(0.008)	(0.015)
Prcp	-0.017**	-0.019**	-0.021**	0.014	0.012	0.016
	(0.039)	(0.028)	(0.016)	(0.175)	(0.245)	(0.143)
Observations	4,026	4,025	3,892	3,975	3,975	3,842
R-squared	0.367	0.378	0.438	0.363	0.373	0.430
Client-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No
Industry-Year FE	No	No	Yes	No	No	Yes

Table 6: Continued

Panel C: Assets

	High Assets			Low Assets		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔTemp	0.004	0.004	0.001	-0.030**	-0.030**	-0.042***
	(0.657)	(0.720)	(0.900)	(0.030)	(0.023)	(0.006)
Prcp	-0.006	-0.008	-0.010	-0.011	-0.014	-0.020**
	(0.383)	(0.269)	(0.145)	(0.189)	(0.155)	(0.049)
Observations	5,614	5,612	5,528	5,656	5,655	5,529
R-squared	0.377	0.385	0.436	0.341	0.349	0.386
Client-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No
Industry-Year FE	No	No	Yes	No	No	Yes

Panel D: Number of Employees

	High Number of Employees			Low Number of Employees		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔTemp	0.001	0.001	-0.004	-0.025	-0.027*	-0.030*
	(0.889)	(0.877)	(0.688)	(0.132)	(0.097)	(0.094)
Prcp	0.002	0.002	0.001	-0.021**	-0.022**	-0.027***
	(0.680)	(0.764)	(0.827)	(0.028)	(0.034)	(0.009)
Observations	5,469	5,469	5,386	5,497	5,494	5,369
R-squared	0.360	0.368	0.437	0.341	0.351	0.385
Client-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No
Industry-Year FE	No	No	Yes	No	No	Yes

Panel E: Number of Business Segments

	Multi Segment			Single Segment		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔTemp	-0.001	-0.003	-0.003	-0.017**	-0.018**	-0.021**
	(0.954)	(0.890)	(0.873)	(0.043)	(0.039)	(0.020)
Prcp	0.006	0.005	0.014	-0.010	-0.012*	-0.015*
	(0.594)	(0.671)	(0.303)	(0.155)	(0.080)	(0.051)
Observations	2,207	2,207	2,060	9,123	9,121	9,034
R-squared	0.375	0.391	0.490	0.315	0.320	0.356
Client-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No
Industry-Year FE	No	No	Yes	No	No	Yes

Table 7: Labor Productivity and Financial Constraints

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable Δlog(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. Δ *Temp* is the change in average daily temperature in degree Celsius in the county of the corporate headquarters for supplier *i* from year *t*-1 to year *t*. The rated and unrated groups consist of those firms with a credit rating and without a credit rating (Panel A). The high and low long-term debt maturing groups consist of those firms that are above and below the median of the ratio of long-term debt maturing within one year to total long-term debt (Panel B). The high and low assets groups consist of those firms that are above and below the median (Panel C). The high and low number of employees groups consist of those firms that are above and below the median (Panel D). The multi- and single-segment groups consist of those firms with one business segment and more than one business segment (Panel E). Manufacturing industries are defined as industries with SIC codes between 2000 and 3999. All financial variables are for the supplier and lagged one period. Regressions include the same control variables as in Table 2 (coefficients not shown). Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. Industry fixed effects are defined by 2-digit SIC code. Robust *p*-values clustered at the supplier county level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Credit Rating

	Rated		Unrated	
	Manufacturing	Non-Manufacturing	Manufacturing	Non-Manufacturing
	(1)	(2)	(3)	(4)
ΔTemp	0.011	0.087***	-0.035**	0.006
	(0.507)	(0.009)	(0.011)	(0.833)
Observations	1,957	545	5,926	2,008
R-squared	0.448	0.560	0.339	0.469
Client-Year FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes

Panel B: Long-Term Debt Maturing

	Low Long-Term Debt Maturing		High Long-Term Debt Maturing	
	Manufacturing	Non-Manufacturing	Manufacturing	Non-Manufacturing
	(1)	(2)	(3)	(4)
ΔTemp	0.003	0.031	-0.045***	0.041
	(0.879)	(0.363)	(0.006)	(0.440)
Observations	2,593	976	2,836	627
R-squared	0.421	0.488	0.423	0.584
Client-Year FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes

Table 7: Continued

Panel C: Assets

	High Assets		Low Assets	
	Manufacturing	Non- Manufacturing	Manufacturing	Non- Manufacturing
	(1)	(2)	(3)	(4)
ΔTemp	0.004	0.010	-0.060***	0.020
	(0.742)	(0.618)	(0.004)	(0.639)
Observations	3,881	1,297	3,779	1,155
R-squared	0.406	0.502	0.387	0.526
Client-Year FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes

Panel D: Number of Employees

	High Number of Employees		Low Number of Employees	
	Manufacturing	Non- Manufacturing	Manufacturing	Non- Manufacturing
	(1)	(2)	(3)	(4)
ΔTemp	-0.002	-0.030	-0.037	0.030
	(0.819)	(0.220)	(0.132)	(0.534)
Observations	3,910	1,107	3,634	1,155
R-squared	0.417	0.515	0.367	0.526
Client-Year FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes

Panel E: Number of Business Segments

	Multi Segment		Single Segment	
	Manufacturing	Non- Manufacturing	Manufacturing	Non- Manufacturing
	(1)	(2)	(3)	(4)
ΔTemp	0.013	0.024	-0.028**	0.013
	(0.499)	(0.812)	(0.020)	(0.590)
Observations	1,594	230	6,053	2,209
R-squared	0.446	0.680	0.336	0.465
Client-Year FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes

Table 8: Switching Costs

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable Δlog(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. Δ*Temp* is the change in average daily temperature in degree Celsius in the county of the corporate headquarters for supplier *i* from year *t*-1 to year *t. Prcp* is the average daily precipitation in millimeters in the county of the corporate headquarters for supplier *i* in between years *t*-1 and *t*. Standardized goods are defined as in Giannetti, Burkart and Ellingsen (2011) (Panel A). Firms with patents are firms with at least one patent filed (Panel B). The high and low distance between supplier and client groups consist of those firms that are above and below the median (Panel C). All financial variables are for the supplier and lagged one period. Regressions include the same control variables as in Table 2 (coefficients not shown). Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. Industry fixed effects are defined by two-digit SIC code. Robust *p*-values clustered at the supplier county level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Standardized Goods

	Non-Standardized Goods			Standardized Goods		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔTemp	-0.011	-0.011	-0.017*	-0.036*	-0.036*	-0.036*
	(0.276)	(0.264)	(0.092)	(0.083)	(0.078)	(0.099)
Prcp	0.004	0.003	0.003	-0.035***	-0.034***	-0.035***
	(0.510)	(0.595)	(0.667)	(0.001)	(0.002)	(0.002)
Observations	7,247	7,247	7,232	3,120	3,120	3,103
R-squared	0.313	0.317	0.348	0.278	0.280	0.288
Client-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No
Industry-Year FE	No	No	Yes	No	No	Yes

Panel B: Patents

	Positive Patents			Zero Patents		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔTemp	-0.007	-0.008	-0.012	-0.014	-0.014	-0.019*
	(0.687)	(0.653)	(0.464)	(0.152)	(0.134)	(0.064)
Prcp	0.011	0.012	0.011	-0.013*	-0.014**	-0.019***
	(0.344)	(0.362)	(0.415)	(0.054)	(0.032)	(0.010)
Observations	2,593	2,586	2,537	9,043	9,043	9,007
R-squared	0.371	0.380	0.412	0.308	0.312	0.355
Client-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No
Industry-Year FE	No	No	Yes	No	No	Yes

Table 8: Continued

Panel C: Distance

	Low Distance			High Distance		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔTemp	0.017	0.019	0.024	-0.029*	-0.029*	-0.031*
	(0.222)	(0.181)	(0.193)	(0.084)	(0.080)	(0.085)
Prcp	-0.015	-0.014	-0.020	0.011	0.015*	0.016**
	(0.294)	(0.332)	(0.217)	(0.183)	(0.065)	(0.040)
Observations	3,488	3,488	3,341	3,470	3,465	3,315
R-squared	0.337	0.346	0.425	0.358	0.367	0.419
Client-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No
Industry-Year FE	No	No	Yes	No	No	Yes

Table 9: Extensive Margin

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable is a dummy variable that takes a value of one if the client-supplier relationship disappears from the sample between years *t-1* and *t*, and zero otherwise. Δ*Temp* is the change in average daily temperature in degree Celsius in the county of the corporate headquarters for supplier *i* from year *t*-1 to year *t*. *Prcp* is the average daily precipitation in millimeters in the county of the corporate headquarters for supplier *i* in between years *t*-1 and *t*. *Tobin's Q* is the ratio of the market value of assets to book value of assets. *Cash* is the ratio of cash and equivalents to total assets. *Assets* is total assets. *Tangibility* is the ratio of net property, plant and equipment to total assets. *Leverage* is the ratio of total debt to the market value of assets. All financial variables are for the supplier and lagged one period. Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. Industry fixed effects are defined by two-digit SIC code. Robust *p*-values clustered at the supplier county level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
ΔTemp	-0.004	-0.004	-0.004	-0.005	-0.005	-0.006
	(0.241)	(0.227)	(0.220)	(0.177)	(0.114)	(0.115)
Prcp				-0.005	-0.007	-0.008
				(0.538)	(0.307)	(0.292)
Tobin's Q	0.004**	0.003**	0.003*	0.004**	0.003**	0.003*
	(0.017)	(0.039)	(0.054)	(0.020)	(0.043)	(0.060)
Cash	-0.016	-0.019	-0.012	-0.017	-0.022	-0.015
	(0.669)	(0.598)	(0.748)	(0.626)	(0.543)	(0.686)
Log(Assets)	-0.021***	-0.017***	-0.016***	-0.021***	-0.017***	-0.016***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Tangibility	-0.050	-0.041	-0.040	-0.050	-0.042	-0.041
	(0.329)	(0.521)	(0.550)	(0.325)	(0.513)	(0.540)
Leverage	0.068**	0.049*	0.060**	0.068**	0.049*	0.060**
	(0.026)	(0.077)	(0.043)	(0.024)	(0.076)	(0.042)
Observations	23,193	23,193	23,193	23,193	23,193	23,193
R-squared	0.427	0.440	0.455	0.427	0.440	0.455
Client-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No
Industry-Year FE	No	No	Yes	No	No	Yes

Figure 1: Changes in Temperature

This figure plots the change in average daily temperature at the county level. Temperature variables are averaged by calendar year from 2000 to 2015.

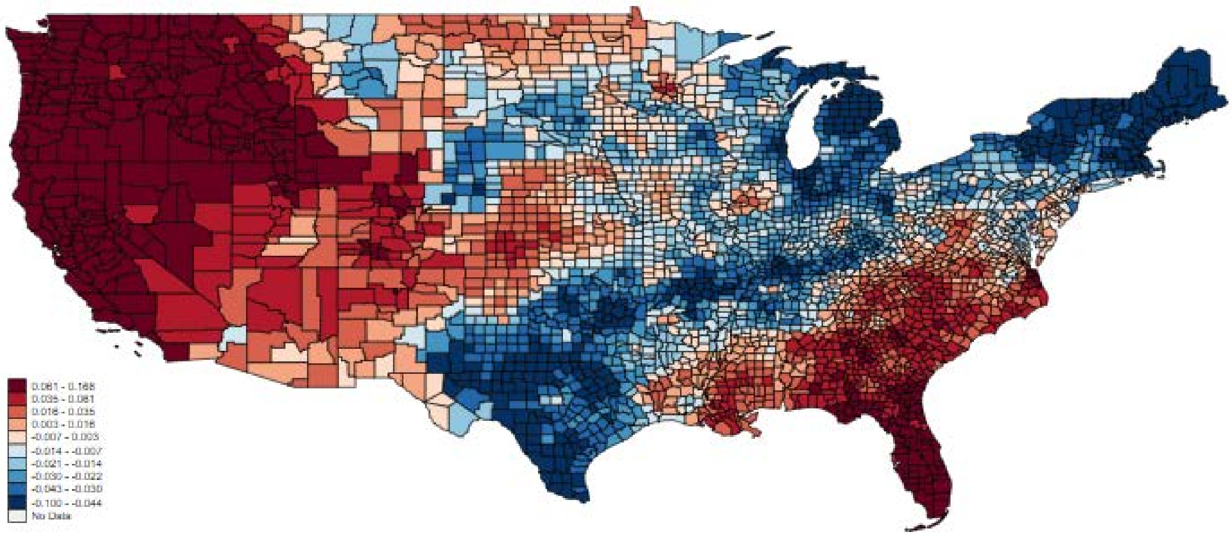
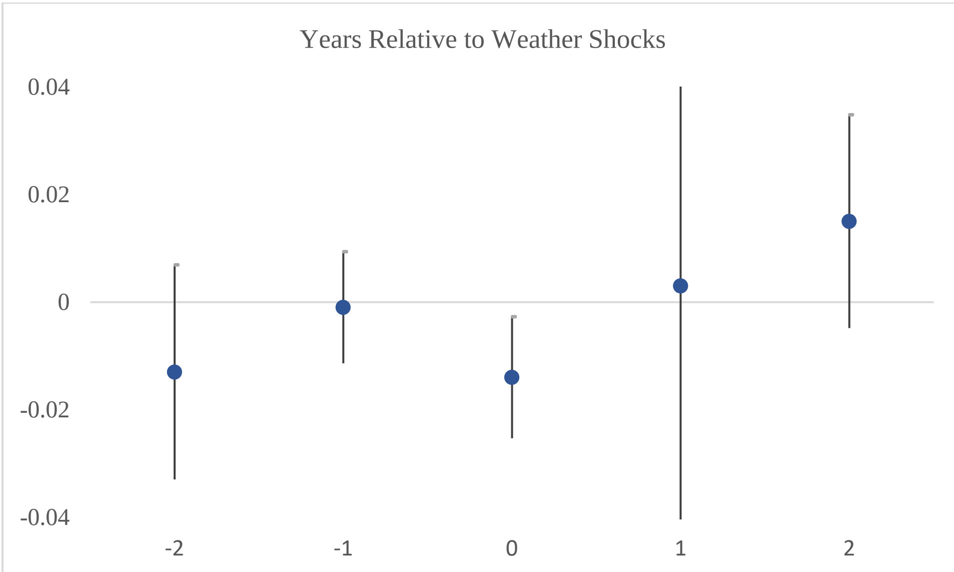


Figure 2: Placebo Regression

This figure shows the coefficient and 95% confidence intervals of the change in temperature in ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable is Δlog(*Sales*), defined as the change in the log of sales from supplier *i* to client *j* between years *t*+*k*-1 and *t*+*k* (k = -3,-2,...,+3). The horizontal axis represents the index *k*. The regressions include the same control variables and client-by-year fixed effects as in column (1) of Table 2. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period.



Appendix

Table A.1: Variable Definitions

Variable	**Definition**
Δlog(Sales)	Change in the log of sales from supplier *i* to client *j* (Compustat).
Temp	Average daily temperature in a county in year *t* in degree Celsius (PRISM).
ΔTemp	Change in average daily temperature in a county from year *t*-1 to t in degree Celsius (PRISM).
Prcp	Average daily precipitation in a county in year *t* in millimeters (PRISM).
Cold Events	Number of cold events in a county recorded in NOAA Storm Events Database. A Cold event is an episode (a period) of low temperature (or wind chill temperatures) that reaches or exceeds locally/regionally defined advisory conditions (typical value is -18 degrees Fahrenheit or colder) (NOAA Storm Events Database).
Heat Events	Number of heat events in a county recorded in NOAA Storm Events Database. A Heat event is an episode where heat index values meet or exceed locally/regionally established advisory thresholds (NOAA Storm Events Database).
Tobin's Q	Total assets plus market value of equity minus book value of equity divided by total assets (Compustat AT + CSHO × PRCC_F - [AT - (LT + PSTKL) + TXDITC] / AT).
Cash	Cash and cash equivalents (Compustat CHE).
Assets	Total assets (Compustat AT).
Tangibility	Net property, plant and equipment divided by total assets (Compustat PPENT / AT).
Leverage	Total debt, defined as debt in current liabilities plus long-term debt, divided by market value of assets (Compustat (DLC + DLTT) / (DLC + DLTT + CSHO ´ PRCC_F).
Long-Term Debt Maturing	Ratio of long-term debt maturing within one year to total long-term debt (Compustat DD1/(DD1 + DDLT)).
Credit Rating	Firms with a bond credit rating (Compustat).
Number of Employees	Total number of employees (Compustat EMP).
Number of Segments	Number of business segments (Compustat).
Patents	Number of patent applications by a firm (NBER patent database).
Distance	Geographical distance in kilometers between corporate headquarters of client and supplier.

Internet Appendix for
How Does Climate Change Affect Firm Sales? Identifying Supply Effects

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Table IA.1: Summary Statistics - Firm-Level Sample

This table presents mean, median, 25th percentile, 75th percentile, standard deviation, and number of observations for firm-level variables. The sample consists of yearly observations of Compustat firms in the 2000-2015 period. Δlog(Sales) is the change in the log of total sales between years *t*-1 and *t*. Variable definitions are provided in Table A.1 in the Appendix.

Variable	Mean	25th Percentile	Median	75th Percentile	Standard Deviation	Observations
Δlog(Sales)	0.0733	-0.0525	0.0614	0.1887	0.4157	40,662
Temp	14.0663	10.4941	13.3446	17.1437	4.4286	40,662
ΔTemp	-0.0096	-0.5383	0.0524	0.5265	0.8492	40,662
Prcp	2.7258	1.9225	2.8938	3.5042	1.1632	40,662
Cold Events	0.0010	0	0	0	0.0351	40,662
Heat Events	0.0071	0	0	0	0.1465	40,662
Tobin's Q	2.8243	1.0807	1.4980	2.3940	5.8275	40,662
Cash	0.1264	0.0211	0.0689	0.1683	0.1570	40,662
Log(Assets)	5.3724	3.6975	5.5103	7.1014	2.4579	40,662
Tangibility	0.2725	0.0840	0.1947	0.4009	0.2377	40,662
Leverage	0.2624	0.0566	0.1873	0.4021	0.2487	40,662

Table IA.2: Interaction of Labor Productivity and Financial Constraints - Manufacturing Industries

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable Δlog(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. Δ *Temp* is the change in average daily temperature in degree Celsius in the county of the corporate headquarters for supplier *i* from year *t*-1 to year *t*. *Prcp* is the average daily precipitation in millimeters in the county of the corporate headquarters for supplier *i* in between years *t*-1 and *t*. The rated and unrated groups consist of those firms with a credit rating and without a credit rating. The high and low long-term debt maturing groups consist of those firms that are above and below the median of the ratio of long-term debt maturing within one year to total long-term debt. The high and low assets groups consist of those firms that are above and below the median. The high and low assets groups consist of those firms that are above and below the median. The high and low number of employees groups consist of those firms that are above and below the median. The multi- and single-segment groups consist of those firms with one business segment and more than one business segment. Manufacturing industries are defined as industries with SIC codes between 2000 and 3999. All financial variables are for the supplier and lagged one period. Regressions include the same control variables as in Table 2 (coefficients not shown). Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. Industry fixed effects are defined by 2-digit SIC code. Robust *p*-values clustered at the supplier county level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Credit Rating

	Rated and Manufacturing			Unrated and Manufacturing		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔTemp	0.008	0.010	0.011	-0.033***	-0.034***	-0.035**
	(0.584)	(0.475)	(0.507)	(0.007)	(0.007)	(0.011)
Prcp	0.003	0.008	0.007	-0.014*	-0.013	-0.015
	(0.775)	(0.390)	(0.480)	(0.096)	(0.139)	(0.106)
Observations	2,008	2,008	1,957	5,965	5,964	5,926
R-squared	0.393	0.403	0.448	0.321	0.324	0.339
	Rated and Non-Manufacturing			Unrated and Non-Manufacturing		
	(7)	(8)	(9)	(10)	(11)	(12)
ΔTemp	0.073***	0.058**	0.087***	0.018	0.022	0.006
	(0.010)	(0.048)	(0.009)	(0.472)	(0.382)	(0.833)
Prcp	-0.023	-0.042	-0.048*	0.002	-0.002	-0.009
	(0.430)	(0.161)	(0.068)	(0.852)	(0.837)	(0.468)
Observations	611	611	545	2,075	2,075	2,008
R-squared	0.462	0.477	0.560	0.382	0.398	0.469
Client-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No
Industry-Year FE	No	No	Yes	No	No	Yes

Table IA.2: Continued

Panel B: Long-Term Debt Maturing Next Year

	Low Long-Term Debt Maturing and Manufacturing			High Long-Term Debt Maturing and Manufacturing		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔTemp	0.005	0.005	0.003	-0.045***	-0.044***	-0.045***
	(0.743)	(0.729)	(0.879)	(0.003)	(0.003)	(0.006)
Prcp	-0.018	-0.015	-0.016	0.010	0.011	0.009
	(0.101)	(0.157)	(0.158)	(0.389)	(0.355)	(0.501)
Observations	2,665	2,665	2,593	2,884	2,884	2,836
R-squared	0.375	0.380	0.421	0.392	0.397	0.423
	Low Long-Term Debt Maturing and Non-Manufacturing			High Long-Term Debt Maturing and Non-Manufacturing		
	(7)	(8)	(9)	(10)	(11)	(12)
ΔTemp	0.034	0.021	0.031	0.006	-0.006	0.041
	(0.271)	(0.506)	(0.363)	(0.879)	(0.890)	(0.440)
Prcp	-0.032*	-0.042**	-0.041**	0.006	-0.001	0.031
	(0.096)	(0.038)	(0.024)	(0.746)	(0.960)	(0.245)
Observations	1,039	1,033	976	711	711	627
R-squared	0.435	0.442	0.488	0.430	0.461	0.584
Client-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No
Industry-Year FE	No	No	Yes	No	No	Yes

Table IA.2: Continued

Panel C: Assets

	High Assets and Manufacturing			Low Assets and Manufacturing		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔTemp	0.002	0.003	0.004	-0.053***	-0.054***	-0.060***
	(0.869)	(0.822)	(0.742)	(0.004)	(0.003)	(0.004)
Prcp	-0.008	-0.007	-0.007	-0.019*	-0.018	-0.023*
	(0.249)	(0.282)	(0.300)	(0.093)	(0.131)	(0.075)
Observations	3,931	3,929	3,881	3,837	3,837	3,779
R-squared	0.373	0.377	0.406	0.364	0.369	0.387
	High Assets and Non-Manufacturing			Low Assets and Non-Manufacturing		
	(7)	(8)	(9)	(10)	(11)	(12)
ΔTemp	0.026	0.017	0.010	0.040	0.039	0.020
	(0.260)	(0.457)	(0.618)	(0.271)	(0.291)	(0.639)
Prcp	-0.008	-0.022	-0.028	-0.017	-0.023	-0.039**
	(0.717)	(0.288)	(0.132)	(0.321)	(0.209)	(0.032)
Observations	1,345	1,341	1,297	1,201	1,199	1,128
R-squared	0.422	0.437	0.502	0.420	0.440	0.515
Client-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No
Industry-Year FE	No	No	Yes	No	No	Yes

Table IA.2: Continued

Panel D: Number of Employees

	High Number of Employees and Manufacturing			Low Number of Employees and Manufacturing		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔTemp	-0.004	-0.003	-0.002	-0.035	-0.036	-0.037
	(0.708)	(0.766)	(0.819)	(0.122)	(0.105)	(0.132)
Prcp	0.001	0.004	0.002	-0.024**	-0.023*	-0.027**
	(0.846)	(0.613)	(0.830)	(0.033)	(0.058)	(0.037)
Observations	3,949	3,949	3,910	3,697	3,697	3,634
R-squared	0.367	0.373	0.417	0.343	0.349	0.367
	High Number of Employees and Non-Manufacturing			Low Number of Employees and Non-Manufacturing		
	(7)	(8)	(9)	(10)	(11)	(12)
ΔTemp	-0.015	-0.015	-0.030	0.018	0.016	0.030
	(0.575)	(0.566)	(0.220)	(0.668)	(0.682)	(0.534)
Prcp	0.012	0.008	0.007	-0.027	-0.026	-0.044**
	(0.523)	(0.643)	(0.634)	(0.168)	(0.173)	(0.019)
Observations	1,148	1,148	1,107	1,216	1,216	1,155
R-squared	0.401	0.424	0.515	0.442	0.469	0.526
Client-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No
Industry-Year FE	No	No	Yes	No	No	Yes

Table IA.2: Continued

Panel E: Number of Business Segments

	Multi Segment and Manufacturing			Single Segment and Manufacturing		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔTemp	0.010	0.008	0.013	-0.030***	-0.030***	-0.028**
	(0.614)	(0.688)	(0.499)	(0.005)	(0.005)	(0.020)
Prcp	0.016	0.020	0.024*	-0.013	-0.012	-0.013
	(0.207)	(0.136)	(0.085)	(0.146)	(0.189)	(0.196)
Observations	1,663	1,663	1,594	6,114	6,114	6,053
R-squared	0.333	0.341	0.446	0.321	0.323	0.336
	Multi Segment and Non-Manufacturing			Single Segment and Non-Manufacturing		
	(7)	(8)	(9)	(10)	(11)	(12)
ΔTemp	-0.019	-0.006	0.024	0.020	0.020	0.013
	(0.770)	(0.929)	(0.812)	(0.390)	(0.381)	(0.590)
Prcp	0.028	0.002	0.004	-0.025**	-0.028**	-0.035***
	(0.467)	(0.956)	(0.947)	(0.036)	(0.025)	(0.002)
Observations	310	309	230	2,272	2,272	2,209
R-squared	0.575	0.622	0.680	0.378	0.386	0.465
Client-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No
Industry-Year FE	No	No	Yes	No	No	Yes

Table IA.3: Interaction of Labor Productivity and Financial Constraints - Heat Sensitive Industries

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable Δlog(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. Δ *Temp* is the change in average daily temperature in degree Celsius in the county of the corporate headquarters for supplier *i* from year *t*-1 to year *t*. *Prcp* is the average daily precipitation in millimeters in the county of the corporate headquarters for supplier *i* in between years *t*-1 and *t*. The rated and unrated groups consist of those firms with a credit rating and without a credit rating. The high and low long-term debt maturing groups consist of those firms that are above and below the median of the ratio of long-term debt maturing within one year to total long-term debt. The high and low assets groups consist of those firms that are above and below the median. The high and low assets groups consist of those firms that are above and below the median. The high and low number of employees groups consist of those firms that are above and below the median. The multi- and single-segment groups consist of those firms with one business segment and more than one business segment. Heat sensitive industries are defined as in Graff-Zivin and Neidell (2014). All financial variables are for the supplier and lagged one period. Regressions include the same control variables as in Table 2 (coefficients not shown). Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. Industry fixed effects are defined by 2-digit SIC code. Robust *p*-values clustered at the supplier county level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Credit Rating

	Rated and Heat Sensitive			Unrated and Heat Sensitive		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔTemp	0.022*	0.018	0.017	-0.032***	-0.033***	-0.036***
	(0.090)	(0.146)	(0.260)	(0.008)	(0.006)	(0.005)
Prcp	-0.002	-0.004	-0.005	-0.012	-0.012	-0.016*
	(0.852)	(0.717)	(0.576)	(0.128)	(0.138)	(0.068)
Observations	2,575	2,575	2,487	6,869	6,867	6,790
R-squared	0.402	0.418	0.489	0.332	0.335	0.361
	Rated and Non-Heat Sensitive			Unrated and Non-Heat Sensitive		
	(7)	(8)	(9)	(10)	(11)	(12)
ΔTemp	0.139**	0.130	0.139	0.024	0.022	0.021
	(0.050)	(0.117)	(0.127)	(0.340)	(0.367)	(0.412)
Prcp	-0.005	-0.042	-0.046	0.006	-0.001	-0.003
	(0.961)	(0.754)	(0.737)	(0.684)	(0.950)	(0.806)
Observations	76	76	66	1,220	1,220	1,191
R-squared	0.602	0.645	0.631	0.377	0.387	0.450
Client-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No
Industry-Year FE	No	No	Yes	No	No	Yes

Table IA.3: Continued

Panel B: Long-Term Debt Maturing Next Year

	Low Long-Term Debt Maturing and Heat Sensitive			Long-Term Debt Maturing and Heat Sensitive		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔTemp	0.009	0.007	0.006	-0.042***	-0.042***	-0.042**
	(0.537)	(0.637)	(0.685)	(0.006)	(0.007)	(0.012)
Prcp	-0.020**	-0.023**	-0.024**	0.010	0.012	0.012
	(0.029)	(0.013)	(0.010)	(0.339)	(0.295)	(0.343)
Observations	3,587	3,586	3,473	3,165	3,163	3,064
R-squared	0.378	0.388	0.440	0.388	0.396	0.435
	Low Long-Term Debt Maturing and Non-Heat Sensitive			High Long-Term Debt Maturing and Non-Heat Sensitive		
	(7)	(8)	(9)	(10)	(11)	(12)
ΔTemp	-0.023	-0.027	-0.007	-0.060	-0.063	0.006
	(0.702)	(0.680)	(0.913)	(0.237)	(0.230)	(0.919)
Prcp	0.011	0.021	0.025	-0.009	-0.023	0.009
	(0.760)	(0.571)	(0.546)	(0.705)	(0.396)	(0.743)
Observations	171	169	158	462	462	426
R-squared	0.562	0.517	0.505	0.478	0.490	0.605
Client-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No
Industry-Year FE	No	No	Yes	No	No	Yes

Table IA.3: Continued

Panel C: Assets

	High Assets and Heat Sensitive			Low Assets and Heat Sensitive		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔTemp	0.002	0.001	0.001	-0.047***	-0.048***	-0.057***
	(0.839)	(0.932)	(0.914)	(0.006)	(0.005)	(0.004)
Prcp	-0.012*	-0.014**	-0.015**	-0.016	-0.017	-0.025**
	(0.092)	(0.039)	(0.025)	(0.134)	(0.145)	(0.043)
Observations	4,930	4,928	4,866	4,288	4,286	4,183
R-squared	0.381	0.389	0.433	0.372	0.379	0.407
	High Assets and Non-Heat Sensitive			Low Assets and Non-Heat Sensitive		
	(7)	(8)	(9)	(10)	(11)	(12)
ΔTemp	0.006	0.009	-0.005	0.054	0.049	0.049
	(0.787)	(0.664)	(0.838)	(0.178)	(0.211)	(0.241)
Prcp	0.020	0.014	0.010	-0.011	-0.020	-0.030
	(0.188)	(0.432)	(0.570)	(0.642)	(0.413)	(0.198)
Observations	384	380	360	809	809	782
R-squared	0.411	0.424	0.461	0.410	0.424	0.503
Client-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No
Industry-Year FE	No	No	Yes	No	No	Yes

Table IA.3: Continued

Panel D: Number of Employees

	High Number of Employees and Heat Sensitive			Low Number of Employees and Heat Sensitive		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔTemp	-0.003	-0.004	-0.007	-0.030	-0.031	-0.035
	(0.722)	(0.695)	(0.504)	(0.153)	(0.130)	(0.105)
Prcp	-0.001	-0.001	-0.002	-0.024**	-0.025**	-0.031***
	(0.921)	(0.934)	(0.752)	(0.014)	(0.022)	(0.005)
Observations	4,590	4,590	4,529	4,452	4,449	4,350
R-squared	0.380	0.387	0.451	0.361	0.368	0.394
	High Number of Employees and Non-Heat Sensitive			Low Number of Employees and Non-Heat Sensitive		
	(7)	(8)	(9)	(10)	(11)	(12)
ΔTemp	0.021	0.024	0.007	0.036	0.033	0.049
	(0.349)	(0.310)	(0.787)	(0.510)	(0.540)	(0.392)
Prcp	0.009	0.014	0.016	-0.005	-0.010	-0.034
	(0.580)	(0.362)	(0.283)	(0.871)	(0.750)	(0.290)
Observations	547	547	525	553	553	516
R-squared	0.460	0.477	0.488	0.409	0.427	0.510
Client-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No
Industry-Year FE	No	No	Yes	No	No	Yes

Table IA.3: Continued

Panel E: Number of Business Segments

	Multi Segment and Heat Sensitive			Single Segment and Heat Sensitive		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔTemp	0.006	0.002	0.007	-0.027***	-0.028***	-0.027**
	(0.726)	(0.899)	(0.710)	(0.005)	(0.004)	(0.016)
Prcp	0.013	0.017	0.023*	-0.015*	-0.016**	-0.018**
	(0.255)	(0.181)	(0.077)	(0.064)	(0.038)	(0.032)
Observations	1,937	1,937	1,820	7,307	7,307	7,220
R-squared	0.370	0.384	0.480	0.330	0.334	0.361
	Multi Segment and Non-Heat Sensitive			Single Segment and Non-Heat Sensitive		
	(7)	(8)	(9)	(10)	(11)	(12)
ΔTemp	0.135	0.117	0.244	0.032	0.031	0.037
	(0.120)	(0.270)	(0.440)	(0.212)	(0.238)	(0.147)
Prcp	0.001	-0.046	-0.037	0.003	0.002	-0.007
	(0.988)	(0.607)	(0.779)	(0.798)	(0.872)	(0.567)
Observations	88	88	57	1,120	1,120	1,095
R-squared	0.598	0.656	0.542	0.376	0.379	0.461
Client-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No
Industry-Year FE	No	No	Yes	No	No	Yes

Table IA.4: Sample with Above Median Sales Coverage

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable Δlog(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. Δ*Temp* is the change in average daily temperature in degree Celsius in the county of the corporate headquarters for supplier *i* from year *t*-1 to year *t*. *Prcp* is the average daily precipitation in millimeters in the county of the corporate headquarters for supplier *i* between years *t*-1 and *t*. *Tobin's Q* is the ratio of the market value of assets to book value of assets. *Cash* is the ratio of cash and equivalents to total assets. *Assets* is total assets. *Tangibility* is the ratio of net property, plant and equipment to total assets. *Leverage* is the ratio of total debt to the market value of assets. All financial variables are for the supplier and lagged one period. Variable definitions are provided in Table A.1 in the Appendix. The sample is restricted to suppliers for which client sales coverage is above median. Industry fixed effects are defined by two-digit SIC code. Robust *p*-values clustered at the supplier county level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
ΔTemp	-0.016*	-0.017*	-0.019*	-0.017*	-0.019**	-0.022*
	(0.084)	(0.057)	(0.069)	(0.071)	(0.045)	(0.051)
Prcp				-0.007	-0.008	-0.011
				(0.345)	(0.272)	(0.216)
Tobin's Q	0.016***	0.016***	0.016***	0.016***	0.016***	0.016***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cash	-0.110	-0.105	-0.113	-0.111	-0.106	-0.115
	(0.126)	(0.156)	(0.168)	(0.119)	(0.150)	(0.159)
Log(Assets)	0.006	0.006	0.005	0.006	0.006	0.005
	(0.222)	(0.267)	(0.395)	(0.239)	(0.265)	(0.390)
Tangibility	-0.062	-0.083	-0.121*	-0.062	-0.081	-0.119*
	(0.316)	(0.214)	(0.091)	(0.320)	(0.227)	(0.099)
Leverage	-0.061*	-0.049	-0.051	-0.060*	-0.049	-0.052
	(0.055)	(0.146)	(0.156)	(0.058)	(0.143)	(0.151)
Observations	7,286	7,284	7,222	7,286	7,284	7,222
R-squared	0.310	0.317	0.359	0.311	0.317	0.359
Client-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No
Industry-Year FE	No	No	Yes	No	No	Yes

Table IA.5: Quadratic Weather Variables

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable Δlog(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. Δ*Temp* is the change in average daily temperature in degree Celsius in the county of the corporate headquarters for supplier *i* from year *t*-1 to year *t*. Δ*Temp Sq* is the square of Δ*Temp*. *Prcp* is the average daily precipitation in millimeters in the county of the corporate headquarters for supplier *i* between years *t*-1 and *t*. *Prcp Sq* is the square of Prcp. *Tobin's Q* is the ratio of the market value of assets to book value of assets. *Cash* is the ratio of cash and equivalents to total assets. *Assets* is total assets. *Tangibility* is the ratio of net property, plant and equipment to total assets. *Leverage* is the ratio of total debt to the market value of assets. All financial variables are for the supplier and lagged one period. Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. Industry fixed effects are defined by two-digit SIC code. Robust *p*-values clustered at the supplier county level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
ΔTemp	-0.012*	-0.012*	-0.017**	-0.013*	-0.014*	-0.018**
	(0.095)	(0.079)	(0.024)	(0.083)	(0.062)	(0.016)
ΔTemp Sq	0.003	0.003	-0.000	0.004	0.004	0.001
	(0.486)	(0.549)	(0.997)	(0.415)	(0.428)	(0.821)
Prcp				0.001	-0.003	-0.007
				(0.957)	(0.876)	(0.748)
Prcp Sq				-0.002	-0.001	-0.000
				(0.675)	(0.803)	(0.927)
Tobin's Q	0.013***	0.013***	0.014***	0.013***	0.013***	0.014***
	(0.002)	(0.001)	(0.000)	(0.002)	(0.001)	(0.000)
Cash	-0.082	-0.076	-0.072	-0.084	-0.078	-0.075
	(0.138)	(0.182)	(0.221)	(0.128)	(0.166)	(0.201)
Log(Assets)	0.014***	0.013***	0.013***	0.014***	0.013***	0.013***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Tangibility	-0.015	-0.045	-0.044	-0.016	-0.046	-0.045
	(0.651)	(0.299)	(0.326)	(0.642)	(0.301)	(0.325)
Leverage	-0.053**	-0.051**	-0.047*	-0.052**	-0.050**	-0.046*
	(0.019)	(0.031)	(0.072)	(0.024)	(0.035)	(0.079)
Observations	12,439	12,439	12,439	12,439	12,439	12,439
R-squared	0.298	0.302	0.333	0.299	0.302	0.334
Client-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No
Industry-Year FE	No	No	Yes	No	No	Yes

Table IA.6: Change in Precipitation as Control

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable Δlog(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. Δ*Temp* is the change in average daily temperature in degree Celsius in the county of the corporate headquarters for supplier *i* from year *t*-1 to year *t*. Δ*Prcp* is the change in average daily precipitation in millimeters in the county of the corporate headquarters for supplier *i* between years *t*-1 and *t*. *Tobin's Q* is the ratio of the market value of assets to book value of assets. *Cash* is the ratio of cash and equivalents to total assets. *Assets* is total assets. *Tangibility* is the ratio of net property, plant and equipment to total assets. *Leverage* is the ratio of total debt to the market value of assets. All financial variables are for the supplier and lagged one period. Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. Industry fixed effects are defined by two-digit SIC code. Robust *p*-values clustered at the supplier county level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
ΔTemp	-0.013*	-0.013*	-0.018**
	(0.100)	(0.084)	(0.021)
ΔPrcp	-0.002	-0.002	-0.006
	(0.843)	(0.806)	(0.496)
Tobin's Q	0.013***	0.013***	0.014***
	(0.002)	(0.001)	(0.000)
Cash/Assets	-0.082	-0.076	-0.072
	(0.137)	(0.180)	(0.221)
Log(Assets)	0.014***	0.013***	0.013***
	(0.000)	(0.000)	(0.001)
Tangibility	-0.014	-0.045	-0.044
	(0.674)	(0.309)	(0.328)
Leverage	-0.053**	-0.051**	-0.047*
	(0.019)	(0.031)	(0.073)
Observations	12,439	12,439	12,439
R-squared	0.298	0.302	0.333
Client-Year FE	Yes	Yes	Yes
Industry FE	No	Yes	No
Industry-Year FE	No	No	Yes

Table IA.7: Standard Errors Clustered at the State Level

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable Δlog(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. Δ*Temp* is the change in average daily temperature in degree Celsius in the county of the corporate headquarters for supplier *i* from year *t*-1 to year *t*. *Prcp Chg* is the change in average daily precipitation in millimeters in the county of the corporate headquarters for supplier *i* between years *t*-1 and *t*. *Tobin's Q* is the ratio of the market value of assets to book value of assets. *Cash* is the ratio of cash and equivalents to total assets. *Assets* is total assets. *Tangibility* is the ratio of net property, plant and equipment to total assets. *Leverage* is the ratio of total debt to the market value of assets. All financial variables are for the supplier and lagged one period. Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. Industry fixed effects are defined by two-digit SIC code. Robust *p*-values clustered at the supplier state level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
ΔTemp	-0.012*	-0.013*	-0.017**	-0.014*	-0.014*	-0.019**
	(0.080)	(0.062)	(0.037)	(0.070)	(0.050)	(0.026)
Prcp				-0.007	-0.008	-0.009
				(0.208)	(0.155)	(0.109)
Tobin's Q	0.013***	0.013***	0.014***	0.013***	0.013***	0.014***
	(0.002)	(0.001)	(0.000)	(0.002)	(0.001)	(0.000)
Cash/Assets	-0.082	-0.076	-0.072	-0.084	-0.078	-0.075
	(0.184)	(0.223)	(0.245)	(0.168)	(0.202)	(0.220)
Log(Assets)	0.014***	0.013***	0.013***	0.014***	0.013***	0.013***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Tangibility	-0.014	-0.045	-0.044	-0.014	-0.045	-0.044
	(0.726)	(0.354)	(0.344)	(0.723)	(0.349)	(0.336)
Leverage	-0.053**	-0.051**	-0.047*	-0.052**	-0.050*	-0.046
	(0.024)	(0.047)	(0.096)	(0.027)	(0.051)	(0.104)
Observations	12,439	12,439	12,439	12,439	12,439	12,439
R-squared	0.298	0.302	0.333	0.298	0.302	0.334
Client-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No
Industry-Year FE	No	No	Yes	No	No	Yes

Table IA.8: Weather Variables at the Zip Code Level

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable Δlog(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. Δ*Temp* (zip code) is the change in average daily temperature in degree Celsius in the zip code of the corporate headquarters for supplier *i* from year *t*-1 to year *t. Prcp (zip code)* is the average daily precipitation in millimeters in the zip code of the corporate headquarters for supplier *i* between years *t*-1 and *t*. *Tobin's Q* is the ratio of the market value of assets to book value of assets. *Cash* is the ratio of cash and equivalents to total assets. *Assets* is total assets. *Tangibility* is the ratio of net property, plant and equipment to total assets. *Leverage* is the ratio of total debt to the market value of assets. All financial variables are for the supplier and lagged one period. Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. Industry fixed effects are defined by two-digit SIC code. Robust *p*-values clustered at the supplier county level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
ΔTemp (zip code)	-0.012*	-0.013*	-0.016**	-0.013*	-0.014**	-0.018**
	(0.067)	(0.055)	(0.021)	(0.058)	(0.042)	(0.015)
Prcp (zip code)				-0.005	-0.006	-0.007
				(0.391)	(0.292)	(0.226)
Tobin's Q	0.013***	0.013***	0.015***	0.013***	0.013***	0.014***
	(0.002)	(0.001)	(0.000)	(0.002)	(0.001)	(0.000)
Cash/Assets	-0.083	-0.078	-0.074	-0.085	-0.080	-0.076
	(0.132)	(0.174)	(0.215)	(0.126)	(0.165)	(0.202)
Log(Assets)	0.014***	0.013***	0.013***	0.014***	0.013***	0.013***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Tangibility	-0.014	-0.044	-0.044	-0.014	-0.044	-0.044
	(0.687)	(0.308)	(0.331)	(0.689)	(0.314)	(0.333)
Leverage	-0.054**	-0.052**	-0.047*	-0.053**	-0.051**	-0.046*
	(0.015)	(0.025)	(0.065)	(0.019)	(0.030)	(0.075)
Observations	12,362	12,362	12,362	12,362	12,362	12,362
R-squared	0.296	0.299	0.331	0.296	0.299	0.331
Client-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No
Industry-Year FE	No	No	Yes	No	No	Yes

Table IA.9: Alternative Fixed Effects

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable Δlog(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. Δ*Temp* is the change in average daily temperature in degree Celsius in the county of the corporate headquarters for supplier *i* from year *t*-1 to year *t. Prcp* is the average daily precipitation in millimeters in the county of the corporate headquarters for supplier *i* between years *t*-1 and *t*. *Tobin's Q* is the ratio of the market value of assets to book value of assets. *Cash* is the ratio of cash and equivalents to total assets. *Assets* is total assets. *Tangibility* is the ratio of net property, plant and equipment to total assets. *Leverage* is the ratio of total debt to the market value of assets. All financial variables are for the supplier and lagged one period. Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. Industry fixed effects are defined at the three-digit SIC code level. Robust *p*-values clustered at the supplier county level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
ΔTemp	-0.012*	-0.013*	-0.015*	-0.014*	-0.015**	-0.018**
	(0.085)	(0.064)	(0.072)	(0.069)	(0.045)	(0.040)
Prcp				-0.007	-0.010	-0.014**
				(0.236)	(0.116)	(0.049)
Tobin's Q	0.013***	0.013***	0.015***	0.013***	0.013***	0.015***
	(0.002)	(0.001)	(0.000)	(0.002)	(0.001)	(0.000)
Cash/Assets	-0.082	-0.067	-0.053	-0.084	-0.070	-0.056
	(0.137)	(0.264)	(0.421)	(0.127)	(0.246)	(0.390)
Log(Assets)	0.014***	0.012***	0.013***	0.014***	0.012***	0.013***
	(0.000)	(0.002)	(0.004)	(0.000)	(0.001)	(0.002)
Tangibility	-0.014	-0.028	-0.023	-0.014	-0.030	-0.025
	(0.673)	(0.552)	(0.677)	(0.675)	(0.541)	(0.658)
Leverage	-0.053**	-0.058**	-0.038	-0.052**	-0.057**	-0.037
	(0.018)	(0.040)	(0.270)	(0.023)	(0.043)	(0.281)
Observations	12,439	12,427	11,832	12,439	12,427	11,832
R-squared	0.298	0.311	0.378	0.298	0.311	0.379
Client-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No
Industry-Year FE	No	No	Yes	No	No	Yes

Table IA.10: Extensive Margin and Extreme Weather Events

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable is a dummy variable that takes a value of one if the client-supplier relationship has been terminated in year *t*, and zero otherwise. *Cold Events* is the number of cold events recorded in the county of corporate headquarters between years *t*-1 and *t*. *Heat Events* is the number of heat events recorded in the county of corporate headquarters between years *t*-1 and *t*. *Temp* is the average daily temperature in degree Celsius in the county of the corporate headquarters for supplier *i* between years *t*-1 and *t*. *Prcp* is the average daily precipitation in millimeters in the county of the corporate headquarters for supplier *i* between years *t*-1 and *t*. *Tobin's Q* is the ratio of the market value of assets to book value of assets. *Cash* is the ratio of cash and equivalents to total assets. *Assets* is total assets. *Tangibility* is the ratio of net property, plant and equipment to total assets. *Leverage* is the ratio of total debt to the market value of assets. All financial variables are for the supplier and lagged one period. Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. Industry fixed effects are defined by two-digit SIC code. Robust *p*-values clustered at the supplier county level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Heat Events	0.034	0.038*	0.044			
	(0.104)	(0.084)	(0.192)			
Cold Events				0.041	0.044	0.061
				(0.582)	(0.552)	(0.491)
Temp	-0.007	-0.007	-0.008	-0.007	-0.007	-0.008
	(0.226)	(0.214)	(0.147)	(0.232)	(0.220)	(0.153)
Prcp	-0.007	-0.007	-0.005	-0.007	-0.007	-0.005
	(0.273)	(0.237)	(0.374)	(0.274)	(0.238)	(0.376)
Tobin's Q	0.003*	0.003	0.003	0.003*	0.003	0.003
	(0.095)	(0.132)	(0.163)	(0.097)	(0.134)	(0.165)
Cash	-0.024	-0.027	-0.021	-0.024	-0.027	-0.020
	(0.475)	(0.418)	(0.547)	(0.482)	(0.425)	(0.555)
Log(Assets)	-0.023***	-0.019***	-0.018***	-0.023***	-0.019***	-0.018***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
Tangibility	-0.106**	-0.101*	-0.098	-0.106**	-0.102*	-0.098
	(0.034)	(0.083)	(0.111)	(0.034)	(0.083)	(0.112)
Leverage	0.092***	0.089***	0.102***	0.092***	0.089***	0.102***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	23,179	23,179	23,178	23,179	23,179	23,178
R-squared	0.478	0.486	0.501	0.478	0.486	0.500
Client-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No
Industry-Year FE	No	No	Yes	No	No	Yes

Table IA.11: Firm-Level Changes in Sales, Productivity and Profitability - Changes

This table presents estimates of ordinary least squares (OLS) panel regressions at the firm level. In columns (1) and (2), the dependent variable Δlog(*Sales*) is the change in the log of sales between years *t*-1 and *t*. In columns (3) and (4), the dependent variable Δ(*Sales/Employees)* is the change in the ratio of sales in year *t* to total employees in year *t*-1. In columns (5) and (6), the dependent variable Δ*(EBIT/Assets)* is the change in the ratio of operating income in year *t* to total assets in year *t*-1. In columns (7) and (8), the dependent variable Δ*(Net Income/Assets)* is the change in the ratio of net income in year *t* to total assets in year *t*-1. Δ*Temp* is the change in average daily temperature in degree Celsius in the county of the corporate headquarters for supplier *i* from year *t*-1 to year *t*. *Prcp* is the average daily precipitation in millimeters in the county of the corporate headquarters for firm *i* between years *t*-1 and *t*. *Tobin's Q* is the ratio of the market value of assets to book value of assets. *Cash* is the ratio of cash and equivalents to total assets. *Assets* is total assets. *Tangibility* is the ratio of net property, plant and equipment to total assets. *Leverage* is the ratio of total debt to the market value of assets. All financial variables are lagged one period. Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat firms in the 2000-2015 period. Industry fixed effects are defined by two-digit SIC code. Robust *p*-values clustered at the supplier county level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Δlog(Sales)		Δ(Sales/Employees)		Δ(EBIT/Assets)		Δ(Net Income/Assets)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔTemp	-0.002	-0.002	-0.000	-0.000	0.000	0.000	0.002	0.002
	(0.427)	(0.431)	(0.929)	(0.947)	(0.963)	(0.586)	(0.639)	(0.679)
Prcp	-0.000	-0.002	-0.006***	-0.006***	0.003	-0.003**	-0.001	-0.001
	(0.948)	(0.741)	(0.009)	(0.009)	(0.519)	(0.012)	(0.883)	(0.929)
Tobin's Q		0.006***		0.000		0.000		-0.002
		(0.000)		(0.184)		(0.327)		(0.223)
Cash		0.111***		0.034***		0.001		0.318***
		(0.000)		(0.000)		(0.909)		(0.000)
Log(Assets)		0.006***		-0.000		-0.001**		-0.002
		(0.001)		(0.176)		(0.023)		(0.224)
Tangibility		0.042**		0.026***		0.006*		-0.063***
		(0.014)		(0.000)		(0.081)		(0.009)
Leverage		-0.173***		-0.004		0.001		0.051***
		(0.000)		(0.324)		(0.856)		(0.000)
Observations	42,516	42,516	39,845	39,845	42,017	42,017	42,017	42,017
R-squared	0.093	0.110	0.166	0.167	0.043	0.052	0.033	0.041
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.12: Firm-Level Sales, Productivity and Profitability - Firm Fixed Effects

This table presents estimates of ordinary least squares (OLS) panel regressions at the firm level. In Columns (1) and (2), the dependent variable log(*Sales*) is the log of sales in years *t*. In Columns (3) and (4), the dependent variable *Sales/Employees* is the ratio of sales in year *t* to total employees in year *t*-1. In Columns (5) and (6), the dependent variable *EBIT/Assets* is the ratio of operating income in year *t* to total assets in year *t*-1. In Columns (7) and (8), the dependent variable *Net Income/Assets* is the ratio of net income in year *t* to total assets in year *t*-1. *Temp* is the average daily temperature in degree Celsius in the county of the corporate headquarters for supplier *i* between year *t*-1 and year *t*. *Prcp* is the average daily precipitation in millimeters in the county of the corporate headquarters for firm *i* between years *t*-1 and *t*. *Tobin's Q* is the ratio of the market value of assets to book value of assets. *Cash* is the ratio of cash and equivalents to total assets. *Assets* is total assets. *Tangibility* is the ratio of net property, plant and equipment to total assets. *Leverage* is the ratio of total debt to the market value of assets. All financial variables are lagged one period. Variable definitions are provided in Table A.1 in the Appendix. The sample consists of yearly observations of Compustat firms in the 2000-2015 period. Industry fixed effects are defined by two-digit SIC code. Robust *p*-values clustered at the supplier county level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	log(Sales)		Sales/Employees		EBIT/Assets		Net Income/Assets	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Temp	0.005	0.003	0.003	0.003	0.000	-0.003	0.000	-0.003
	(0.408)	(0.477)	(0.240)	(0.259)	(0.929)	(0.368)	(0.958)	(0.465)
Prcp	-0.002	-0.003	-0.003	-0.003	-0.002	-0.000	-0.007	-0.005
	(0.802)	(0.596)	(0.318)	(0.273)	(0.565)	(0.961)	(0.126)	(0.229)
Tobin's Q		0.012***		0.001		-0.050***		-0.054***
		(0.000)		(0.536)		(0.000)		(0.000)
Cash		-0.495***		0.011		0.050		0.186***
		(0.000)		(0.624)		(0.336)		(0.002)
Log(Assets)		0.629***		0.011		0.107***		0.139***
		(0.000)		(0.210)		(0.000)		(0.000)
Tangibility		0.262***		-0.146***		-0.231***		-0.189**
		(0.002)		(0.000)		(0.001)		(0.025)
Leverage		-0.215***		-0.070***		-0.139***		-0.198***
		(0.000)		(0.000)		(0.000)		(0.000)
Observations	42,516	42,516	41,084	41,084	42,516	42,516	42,516	42,516
R-squared	0.957	0.970	0.850	0.851	0.713	0.808	0.680	0.757
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes