# The Economic Costs of Climate Change

Cláudia Custódio
Imperial College Business School, CEPR, ECGI

Miguel A. Ferreira
Nova School of Business and Economics, CEPR, ECGI

Emilia Garcia-Appendini
University of Zurich

Adrian Lam
Imperial College Business School

This Version: October 8, 2020

**Abstract**

We estimate the economic costs of climate change by exploiting production networks. Specifically, we estimate the impact of changes in local temperature by comparing sales of intermediate goods across suppliers located in different regions that are selling to the same client. We find that a 1°C increase in average daily temperature leads to a reduction in supplier sales of about 2%. The effect is more pronounced among suppliers in manufacturing and heat-sensitive industries, which is consistent with reduced labor supply when temperatures are higher. Financially constrained and small firms are more affected, which suggests that these firms have difficulties to adapt to changes in temperatures. We also find that episodes of extremely hot and cold weather lead to significantly stronger reductions in sales. Our results suggest that the supply-side effects of climate change are large.

**JEL classification:** G31, G32, L11, L14, Q54

**Keywords:** Climate change, Global warming, Production networks, Economic costs, Firm supply

## 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- to late-21st century (Intergovernmental Panel on Climate Change, 2007, 2012, 2014, 2019). This increase is expected to be associated with more frequent extreme weather events such as droughts, storms, and floods, as well as the rise in sea levels and heat waves (Barriopedro et al., 2011). But what is the impact of such weather shocks for the real economy? Several studies focus on the direct economic consequences of weather shocks on agricultural outcomes and farmland value (Mendelsohn et al. (1994), Schlenker et al. (2005), Deschênes and Greenstone (2007), Schlenker and Roberts (2009), Schlenker and Lobell (2010), Chevet et al. (2011), and Roberts et al. (2012)). There is also growing evidence on the impact of climate change on total factor productivity (Graff-Zivin and Kahn (2016), Chen et al. (2018), and Zhang et al. (2018)). However, it is unclear whether and how these shocks affect firm value. In particular, it is challenging to distinguish demand from supply effects as weather shocks can affect both the supply and the demand for a firm's products.

In this paper, we use production networks as an empirical setting to estimate the impact of changes in average temperature on firm supply while accounting for demand shocks. We use variation in average temperatures across suppliers of the same client in a given year to obtain an estimate of the impact of weather shocks on firm sales controlling for firm-specific demand. We obtain supplier-client pair sales data from Compustat Segment sales, gridded weather data from PRISM Climate Group (2019), and extreme weather events from the National Oceanic and Atmospheric Administration (NOAA) Storm Events Database. To quantify the impact of weather shocks to supplier-client sales, we use an empirical strategy similar to Khwaja and Mian (2008), which consists of including client-by-year fixed effects to explicitly control for demand shocks to a client in a given year. We also control for observable supplier financial characteristics and include supplier-industry fixed effects and supplier county fixed effects to account for unobserved heterogeneity.

We find that increases in temperature lead to declines in supplier sales. A 1°C increase in the average daily temperature in supplier counties is associated with a decrease in sales of about 2%.[1] In addition, we find that extreme heat events, and especially extreme cold events, can have a disruptive effect on sales at -8% and -36%, respectively. While these results show that weather shocks affect the intensive margin of sales of intermediate goods, we do not find evidence of similar effects on the extensive margin, i.e., we do not find that weather shocks lead to termination of supply chain relationships. Our estimated difference in sales can be arguably attributed to supply-side factors, such as changes in labor supply or productivity of suppliers and increases in operating costs, which can lead to lower output.

We investigate several channels through which weather shocks can affect firm supply. We show that our results are mostly driven by manufacturing firms and heat-sensitive industries, suggesting that our findings can be explained by a labor supply and productivity channel as weather shocks can negatively affect productivity due to workers' absence or harder working conditions. We also test the hypothesis that financial constraints and operational flexibility can mediate the effect of weather shocks on sales. We find that the effect of weather shocks on sales is 1.5 to 2 times larger than our baseline estimates for financially constrained firms as proxied by the ratio of long-term debt maturing next year to total long-term debt, credit rating, firm size and number of business segments. In addition, we find that the effect of weather shocks is larger for firms with less

[1] A 1°C increase in the average temperature in a county might seem large compared to the expected increase in worldwide temperature of 2°C over several decades (IPCC, 2019). However, increases of temperature in the order of 1°C are not uncommon *at the local* (county) level in a given year. The standard deviation of the change in average temperature in our sample is 0.85°C.

operational flexibility such as small firms and single-segment firms. Our results suggest that financially constrained firms and firms with less operational flexibility do not have the resources or the flexibility to adapt and overcome weather shocks without affecting production.

We explore whether input specificity and client-supplier relationship capital can amplify or mitigate the effect of weather shocks on supplier sales. Clients buying standardized goods might avoid delays related to disruptions in the production of shocked suppliers by switching to other suppliers. In addition, clients could more easily identify if suppliers compromise product quality. Thus, we expect a stronger negative effect of weather shocks for suppliers in industries producing standardized goods relative to industries producing differentiated goods. We find that the reduction in sales is more pronounced in industries that sell standardized goods and for firms that do not file for patents, which arguably sell less specialized goods. We also find that the reduction in sales is stronger when the supplier is geographically distant from the client. Distant suppliers are less likely to be part of a local production network and the relationship is more likely to be transactional. These findings are consistent with the idea that the supplier-specific economic costs of weather shocks are larger when client switching costs are lower.[2]

This paper contributes to the literature on the indirect costs of climate change on the economy. Graff-Zivin and Kahn (2016), Chen et al. (2018) and Zhang et al. (2018) find that heat affects total factor productivity. We complement these findings by showing that higher temperature affects supplier-client sales via a labor productivity channel. Addoum, Ng, and Ortiz-Bobea (2020) find no evidence that location-specific temperatures affect sales, productivity, and profitability using establishment-level data in the U.S. We improve on the identification of the effect of temperature on sales by using detailed information of sales from suppliers to clients, which allows us to control for confounding demand effects at the client level by including client-by-time fixed effects.

[2] Clients may be less informed about suppliers that are further away and for that reason respond to supplier weather shocks more for precautionary reasons.

We contribute to this literature by showing that climate change affects firm supply. We show for the same client buying from different suppliers, its purchases from suppliers affected by weather shocks decline significantly. The effects are economically significant and cannot be explained by changes in demand for the supplier's products or services. Our results can be explained by labor supply, financial constraints, and input specificity. Our evidence suggests that the decline in sales due to higher temperatures can be due both to firms' lack of flexibility or resources to adapt their productive processes to the changing climate conditions, and to clients' ability to switch to other non-disrupted suppliers. In addition, our results show the role of financial constraints in amplifying the costs of climate change on firm value, with important policy implications as firms emerge from the Covid-19 pandemic with increased levels of leverage.

We also contribute to the literature on climate change and the supply chain. Dasaklis and Pappis (2013) outline how climate change may affect the supply chain qualitatively. Pankratz and Schiller (2019) find that heat waves and flooding at supplier locations lead to termination of relationships in global supply chain and reduction in client sales. We contribute to this literature by showing that, controlling for shocks to client demand, both average weather shocks and extreme weather events lead to changes in supplier-client sales in the intensive margin, but not in the extensive margin.

## 2. Data and Methodology

### *2.1. Sample and variables*

Our sample consists of supplier-client pairs whose headquarters are located in the U.S. To obtain this data, we rely on regulations SFAS numbers 14 and 131, which requires that publicly listed firms in the U.S. must disclose, on a yearly basis, the identity of clients and the sales to clients whose purchases represent more than 10% of total sales. 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 U.S. Similarly, the reporting regulations imply that we cannot identify clients that buy small amounts or aggregate clients.

We obtain temperature and precipitation data from the PRISM Climate Group (2019). PRISM gathers climate observations from weather stations in continental U.S. and uses sophisticated climate modelling techniques to interpolate weather data at each 4 km $\times$ 4 km grid (PRISM (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 U.S.

We obtain extreme weather events data from the National Oceanic and Atmospheric Administration (NOAA) Storm 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 (2018)).

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. 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, which is likely to bias our results against finding any effect on a firm's sales.

### *2.2. Summary statistics*

Panel A of Table I 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 slightly less than 800 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 minus 1.4°C to 0.88°C.The order of magnitude of these changes in temperature might seem large when compared to an expected increase in average worldwide temperature of 2°C relative to pre-industrial levels. However, changes in the annual average temperature of the order of 1°C or higher are not uncommon at the *local* (county) level. Panels B and C show that the annual increase in average temperature is higher than 0.53°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 I 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 both in terms of total assets and number of employees. This is due to regulation SFAS 14, which only requires disclose of the names of clients that account for at least 10% of the suppliers' total sales. Client firms more levered, hold less cash, have more tangible assets, and have a lower Tobin's Q than supplier firms. Average daily temperature and average daily precipitation in headquarters counties for both client firms and supplier firms are similar. Table IA.I in the Internet Appendix contains descriptive statistics for our firm-level sample.

### *2.3. Methodology*

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

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

where indices $i$ and $j$ denote suppliers and clients respectively. The dependent variable measures the percentage change in the supplier's sales to each client.[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 $t$ ($Prcp_{it}$) as a control variable. In all specifications, we add a set of lagged supplier controls, $X_{it-1}$, which include firm size (*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*). The inclusion of these firm-level controls, which affect the level of sales, reduces the variance of the estimated coefficients of the weather variables.

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

Importantly, our client-supplier data allows us to include client-by-year fixed effects, $\delta_{jt}$. This ensures that identification comes from the variation in the change in temperature across the suppliers of a given client in the same year. Client-by-year fixed effects absorb all unobserved heterogeneity at the client level in a given year and allow us to compare the changes in economic activity across suppliers selling to the same firm. Thus, our results are unlikely to be driven by changes in firm-specific demand. 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. In more stringent specifications, we include supplier industry fixed effects or supplier industry-by-year fixed effects to absorb non-time varying or time varying unobserved heterogeneity at the supplier industry level. In more stringent specifications, we include supplier industry fixed effects, $\delta_s$, to control for time-invariant differences across industries, and supplier industry-by-year fixed effects, $\delta_{st}$, to control for time-varying differences across industries.

The main coefficient of interest is $\beta_1$, which estimates the effect of changes in temperature on supplier-client sales. A negative $\beta_1$ 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. Table A.I in the Appendix provides variable definitions and data sources.

## 3. Results

### *3.1. Main results*

Table II 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. The inclusion of precipitation as a control does not significantly affect the estimates. Our estimates indicate that a 1°C yearly increase in the average temperature in the supplier county leads to a 1.2% to 1.9% reduction in supplier-client sales. A 1°C increase in temperature is not uncommon at the local (county) level, where the standard deviation in the annual change in temperature corresponds to 0.85°C over our sample period. Therefore, our estimates of the average effect of temperature on suppliers' sales are economically meaningful. In addition, the inclusion of client-by-year fixed effects in all our specifications absorb all 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. This might explain the differences of our results with respect to studies relying on firm- or establishment-level data to estimate the effect of climate change on firm-level outcomes is insignificant (e.g., Addoum, Ng, and Ortiz-Bobea (2020)). We will address this issue in Section 3.5.

### *3.2. Mechanisms*

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, lower productivity of employees) or higher operating costs (e.g., energy or investment costs for air conditioning, equipment cooling or heating systems, higher costs of transportation due to disruptions in the local transportation network). 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 channel through which changes in the weather might affect firms supply, and which firm characteristics can mitigate or amplify the effect of weather shocks on firm sales.

### *3.2.1. Labor supply and productivity*

We first explore whether the mechanism behind the negative effects on supplier revenue documented in the baseline results might be due to lower labor supply and productivity, consistently with the results in Graff-Zivin and Kahn (2016), Chen et al. (2018), 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 in manufacturing industries; and (3) the ratio of the number of employees to assets as a proxy for labor intensity.

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 A of Table III reports the subsample results split by whether a firm is in heat-sensitive industries. Columns (1)-(3) present the results for firms not in heat-sensitive industries. The coefficient of $\Delta Temp$ is not statistically different from zero. Columns (4)-(6) present the results for firms in heat-sensitive industries. The coefficient of $\Delta Temp$ is -2.2%, and is statistically significant across specifications.

Colmer et al. (2019) find that higher local temperature lowers the value-added and employment in French manufacturing firms. Using plant level data, Chen et al. (2018) document that higher local temperature lowers total factor productivity. If temperature primarily affects economic performance via a productivity channel, firms in the manufacturing industries are likely to be driving the results. Panel B of Table III reports the subsample results split by whether a firm is in manufacturing industries. Columns (1)-(3) present the results for firms in other industries. The coefficient of $\Delta Temp$ is not statistically different from zero. Columns (4)-(6) present the results for firms in manufacturing industries. The coefficient of $\Delta Temp$ ranges from -2.0% to -2.3%, and is statistically significant across specifications.

Firms with higher labor intensity are expected to be more sensitive to heat. Panel C of Table III 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 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 specifications.

### *3.2.2. Financial constraints and adaptability*

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 environment more easily than small firms due to economies of scale and economies of scope. In addition, 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 or segments.

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

Table IV reports the results. Panel A 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., 2011). 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 $\Delta Temp$ is not statistically different from zero. Columns (4)-(6) presents the results for firm with a higher ratio of debt maturing. The coefficient of $\Delta Temp$ ranges from -3.8% to -4.2%, and is statistically significant across specifications. The magnitude is more pronounced than the baseline estimates in Table II.

We use whether a firm has a credit rating as a proxy for financial constraints. Firms with a credit rating have access to public debt markets and therefore are less financially constrained. Panel B presents the subsample results split by whether a firm is rated by a credit rating agency. Columns (1)-(3) present the results for firms with a credit rating. The coefficient of $\Delta Temp$ 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 $\Delta Temp$ ranges from -2.4% to -3.1%, and is statistically significant across all specifications. Similar to Panel A, the magnitude is also more pronounced than the baseline estimates in Table II.

Firm size can proxy for operational flexibility and financial constraints. Larger firms have more operational flexibility and less financial constraints than smaller firms. Panel C of Table IV 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 higher total assets. The coefficient of $\Delta Temp$ is not statistically different from zero. Columns (4)-(6) present the results for firms with lower total assets. 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 find that the negative effects are driven by smaller firms.

The number of business segments can also proxy for operational flexibility and financial constraints. 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 a conglomerate, i.e. multi-segment. Columns (1)-(3) present the results for conglomerate firms. The coefficient of $\Delta Temp$ is not statistically different from zero. 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 are driven by single-segment firms.

Overall, we find that the negative effects of climate change are driven by firms with less operational flexibility and more financial constraints as these firms can have more difficulties (or can take more time) to adapt to changes in temperature.

### *3.2.3. Client-supplier relationship*

In this subsection, we explore 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. 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. 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-supplier pairs.

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. Following Burkart, Ellingsen and Giannetti (2011), we identify industries that are more likely to sell standardized products or, in other words, industries with lower costs of switching to other suppliers. Panel A of Table V reports the subsample results split by whether a firm is industries that sell standardized goods. Columns (1)-(3) present the results for firms in industries that sell less standardized goods. The coefficient of $\Delta Temp$ is not statistically different from zero. Columns (4)-(6) present the results for firms in such industries. The coefficient of $\Delta Temp$ ranges is -3.6%, is statistically significant at the 10% level across specifications.

An alternative measure of input specificity and relationship capital is given by patents. Panel B of Table V reports the subsample results split by the whether a firm filed for patents or not. Columns (1)-(3) present the results for firms without a patent. The coefficient of $\Delta Temp$ ranges from -0.7% to -1.2%, but is not statistically significant. Columns (4)-(6) present the results for firms with at least one patent. The coefficient of $\Delta Temp$ ranges from -1.4% to -1.9%, is marginally insignificant in columns (4) and (5) 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 V 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 $\Delta Temp$ is not statistically significant. Columns (4)-(6) present the results for client-supplier pairs that are farther apart. The coefficient of $\Delta Temp$ ranges from -2.9% to -3.1%, and is statistically significant across specifications.

### *3.3. Extreme weather events*

We next examine whether extreme weather events affect firms' economic activity. In columns (1)-(3) of Table VI, we test whether excessive heat in supplier counties affects supplier-client 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 I 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 VI, we test whether extreme cold events in supplier counties affect supplier-client 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 firms' sale than the extreme heat events. Firms hit an extreme cold event suffer an additional reduction in their sales of 31.3% to 35.7%. These results suggest that extreme cold events, even if less often, can have a more disruptive effect on the firm's economic activity.

### *3.4. Extensive margin*

Our baseline results in Table II are determined 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*. A positive and statistically significant coefficient of change in temperature indicates that suppliers exposed to increases in temperature suffer a significant decrease in sales, such that sales to the client falls below the 10% reporting threshold and eventually to zero. Table VII presents these 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 Tables VII contrast with those of Pankratz and Schiller (2019), who find that heatwaves and natural disasters (floods) can disrupt the global supply chain in the extensive margin. Our findings show that within the U.S., 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.

### *3.5. Robustness*

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

Table IA.II reports the results for the subsample with the sum of reported sales represents at least 24.0% of total sales (the median). In this test, we address the potential concern that the effects in Table II are driven by suppliers where inter-firm trade is less important. During our 2000-2015 sample period, the sum of reported sales represents on average of 31.2% of total sales (the median is 24.0%). The magnitudes of the coefficients of the change in temperature are similar at about -1.9% to -2.2%.

Table IA.III reports the results with squared weather variables. In this test, we address the potential concern that the impact of weather shocks affects firm sales quadratically. 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.IV 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 Table II at about -1.3% to -1.8%.

Table IA.V 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.VI reports the results with postcode 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 postcode level temperature are similar to Table II at about -1.2% to -1.8%.

Table IA.VII reports the results with industry fixed effects at the 3-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 Table II at about -1.2% to -1.8%.

Table IA.VIII reports the results of extreme weather effects on the extensive margin. Columns (1)-(3) show that the coefficients of Heat Events on the termination indicator is positive, but only significant in one specification. Columns (4)-(6) show that the coefficients of Cold Events on the termination indicator are positive but statistically insignificant.

Table IA.IX reports the results with leads and lags of the dependent variable, $\Delta\log(Sales)$. In this test, we conduct a placebo test using the specification used to generate the results in Column (1) of Table II. We estimate the coefficient of the change in temperature in regressions in which we fix the weather shock at time 0, and vary the depdent variable over a period between -2 and +2 years. 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. Figure 1 shows the coefficients of the change in temperature and the 95% confidence intervals. The coefficient at time 0 is -0.014, as shown in Table II. The coefficients for year $t$-2, $t$-1, $t$+1 and $t + 2$ are not statistically different from zero. Figure 1 provides a visual representation of the coefficients.

Table IA.X reports the effects of weather variables on firm level sales and measures of profitability. Consistent with Addoum, Ng and Ortiz-Bobea (2020), we find that local temperature does not significantly affect firm-level sales or profitability on average. Failing to account for changes in demand for the firms' products leads us to find no effects of the increase in temperature on firm sales, similarly to the results in Addoum, Ng, and Ortiz-Bobea (2020).

## 4. Conclusion

This paper studies the economic costs of changes in local temperature using production networks as a laboratory. We compare sales of intermediate goods across suppliers that trade with the same client but are exposed to different weather shocks, which allow us to distinguish supply from demand effects.

We show that changes in local temperature can have important effects on supply-chain networks activity at the intensive margin. A 1°C increase in local temperature in supplier counties leads to a reduction in sales of about 2%. We also show that suppliers exposed to episodes of extremely hot and cold weather suffer large reductions in sales.

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

Overall, these results suggest that climate change can have important economic effects. Suppliers more likely to be affected by climate change can suffer significant decreases in sales, and financial constraints may amplify the effects. Policy makers should consider supply-side effects when they design policies to address climate change challenges.

## References


Addoum, Jawad M., David T. Ng, and Ariel Ortiz-Bobea. (2020). "Temperature Shocks and Establishment Sales." *Review of Financial Studies*, 33: 1331-1366.

Bernanke, Ben S., Mark Gertler, and Simon Glichrist, (1996). "The Financial Accelerator and the Flight to Quality." *Review of Economics and Statistics*, 78: 1-15

Chen, Chen, Thanh D. Huynh and Bohui Zhang. (2019). "Temperature and Productivity: Evidence from Plant-Level Data." *Working Paper*.

Chevet, Jean-Michel, Sébastien Lecocq, and Michael Visser. 2011. "Climate, Grapevine Phenology, Wine Production, and Prices: Pauillac (1800-2009)." *American Economic Review*, 101: 142-146.

Colmer, Jonathan., Ralf Martin, Mirabelle Muuls and Ulrich Wagner. 2019. "Temperature and Production in a Globalized World- Evidence from French Manufacturing Firms." *Working Paper*.

Dasaklis, Thomas K., and Costas P. Pappis. 2013. "Supply Chain Management in View of Climate Change: An Overview of Possible Impacts and the Road Ahead." *Journal of Industrial Engineering and Management*, 6: 1124-1138.

Deschênes, Olivier, and Michael Greenstone. 2007. "The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather." *American Economic Review*, 97: 354-385.

Fazzari, Steven M., R. Glenn Hubbard, and Bruce C. Petersen. 1988. "Financing Constraints and Corporate Investment." *Brookings Papers on Economic Activity*, 1988: 141-206.

Giannetti, Mariassunta, Mike Burkart, and Tore Ellingsen. 2011. "What you sell is what you lend? Explaining trade credit contracts." *Review of Financial Studies*, 24: 1261-1298.

Graff-Zivin, Joshua, and Mathew Neidell. 2014. "Temperature and the Allocation of Time: Implications for Climate Change." *Journal of Labor Economics*, 32: 1-26.

Graff-Zivin, Joshua, and Matthew Kahn. 2016. "Industrial Productivity in a Hotter World: The Aggregate Implications of Heterogeneous Firm Investment in Air Conditioning." *NBER Working Paper 22962*.

Hong, Harrison, Frank Weikai Li, and Jiangmin Xu. 2019. "Climate Risks and Market Efficiency." *Journal of Econometrics*, 208: 265-281.

Hsiang, Solomon. 2016. "Climate Econometrics", *Annual Review of Resource Economics*, 8: 43-75.

Intergovernmental Panel on Climate Change. 2007. "Climate Change 2007: Synthesis Report." URL: https://www.ipcc.ch/report/ar4/syr/

Intergovernmental Panel on Climate Change. 2012. "Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation." URL: https://www.ipcc.ch/report/managing-the-risks-of-extreme-events-and-disasters-to-advance-climate-change-adaptation/

Intergovernmental Panel on Climate Change. 2014. "Climate Change 2014: Synthesis Report." URL: https://www.ipcc.ch/report/ar5/syr/

Intergovernmental Panel on Climate Change. 2019. "Special Report on Global Warming of 1.5 Degree Celsius." URL: https://www.ipcc.ch/sr15/download/

Khwaja, Asim Ijaz and Atif Mian. 2008. "Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market." *America Economic Review*, 98: 1413-42.

Levermann, Anders. 2014. "Climate Economics: Make Supply Chains Climate-Smart." *Nature*, 506: 27-29.

Mendelsohn, Robert, William D. Nordhaus, and Daigee Shaw. 1994. "The Impact of Global Warming on Agriculture: A Ricardian Analysis." *American Economic Review*, 84: 753-771.

Pankratz, Nora M.C., and Christoph M. Schiller. 2019. "Climate Change and Adaptation in Global Supply-Chain Networks." *Working Paper*.

Pew Research Centre. 2019. "Climate Change Still Seen as the Top Global Threat, but Cyberattacks a Rising Concern." *Pew Research Centre Global Report 2018*.

PRISM Climate Group. 2019. "PRISM Gridded Climate Data." http://prism.oregonstate.edu.

Roberts, Michael J., Wolfram Schlenker, and Jonathan Eyer. 2012. "Agronomic Weather Measures in Econometric Models of Crop Yield with Implications for Climate Change." *American Journal of Agricultural Economics*, 95: 236-243.

Schlenker, Wolfram, W Michael Hanemann, and Anthony C Fisher. 2005. "Will U.S. Agriculture Really Benefit from Global Warming? Accounting for Irrigation in the Hedonic Approach." *American Economic Review*, 95: 395-406.

Schlenker, Wolfram, and David B. Lobell. 2010. "Robust Negative Impacts of Climate Change on African Agriculture." *Environmental Research Letters*, 5: 1-8.

Schlenker, Wolfram, and Michael J. Roberts. 2009. "Nonlinear Temperature Effects Indicate Severe Damages to U.S. Crop Yields under Climate Change." *Proceedings of the National Academy of Sciences*, 106: 15594-15598.

Zhang, Peng, Olivier Deschênes, Kyle Meng and Junjie Zhang. 2018. "Temperature Effects on Productivity and Factor Reallocation." *Journal of Environmental Economics and Management*, 88: 1-17.

## Table I: Sample Description and Summary Statistics

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, respectively. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period. Panel D presents mean, median, 25th percentile, 75th percentile, standard deviation, and number of observations for firm-level variables. Panel E presents mean, median, 25th percentile, 75th percentile, standard deviation, and number of observations for firm-segment level variables. The sample consists of yearly observations of Compustat firms in the 2000-2015 period. Variable definitions are in Table A.I in the Appendix.

**Panel A: Sample Description by Year**

| Year | Obs | 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 |
| Unique | -- | 1,856 | 419 | -- | -- | 307 | 99 |
| Total | 12,439 | -- | -- | -- | -- | -- | -- |

## Table I: Continued

**Panel B: Suppliers**

| Variable | Mean | 25th Pct. | 50th Pct. | 75th Pct. | Std. Dev. | Obs. |
|---|---|---|---|---|---|---|
| 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 Pct. | 50th Pct. | 75th Pct. | Std. Dev. | Obs. |
|---|---|---|---|---|---|---|
| Δlog(Sales) | 0.0159 | -0.1641 | 0.0363 | 0.2253 | 0.5081 | 1,2439 |
| 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 II: Baseline Results

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.I 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 III: Labor Supply and Productivity

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable $\Delta$log(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. $\Delta$*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 II (coefficients not shown). Variable definitions are provided in Table A.I 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 vs Non-Manufacturing Industries**

| | Non-Manufacturing Industries | | | Manufacturing Industries | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| ΔTemp | 0.023 | 0.024 | 0.011 | -0.022** | -0.022** | -0.022** |
| | (0.239) | (0.223) | (0.635) | (0.015) | (0.013) | (0.025) |
| Prcp | -0.014 | -0.020* | -0.024** | -0.010 | -0.009 | -0.010 |
| | (0.179) | (0.079) | (0.020) | (0.158) | (0.226) | (0.180) |
| 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 vs Non-Heat Sensitive Industries**

| | Non-Heat Sensitive Industries | | | Heat Sensitive Industries | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| ΔTemp | 0.035 | 0.034 | 0.034 | -0.020** | -0.021** | -0.023** |
| | (0.111) | (0.124) | (0.141) | (0.015) | (0.010) | (0.011) |
| Prcp | 0.002 | -0.004 | -0.008 | -0.010* | -0.011* | -0.013** |
| | (0.855) | (0.790) | (0.575) | (0.096) | (0.083) | (0.043) |
| 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 III: Continued

**Panel C: High vs Low 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 IV: Financial Constraints and Adaptability

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 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 rated and non-rated groups consist of those firms with a credit rating and without a credit rating. 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 employee 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. All financial variables are for the supplier and lagged one period. Regressions include the same control variables as in Table II (coefficients not shown). Variable definitions are provided in Table A.I 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: High vs Low 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 | 3,975 | 3,975 | 3,842 | 4,026 | 4,025 | 3,892 |
| R-squared | 0.363 | 0.373 | 0.430 | 0.367 | 0.378 | 0.438 |
| 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: Rated vs Non-Rated**

| | Rated | | | Non-Rated | | |
|---|---|---|---|---|---|---|
| | (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 |

## Table IV: Continued

**Panel C: High vs Low 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: High vs Low Number of Employee**

| | High Number of Employee | | | Low Number of Employee | | |
|---|---|---|---|---|---|---|
| | (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: Multi- vs Single-Segment Firms**

| | Multi-Segment Firms | | | Single-Segment Firms | | |
|---|---|---|---|---|---|---|
| | (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 V: Client-Supplier Relationship

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). Firms with patents are firms with at least one patent filed. The high and low distance between supplier and client groups consist of those firms that are above and below the median. All financial variables are for the supplier and lagged one period. Regressions include the same control variables as in Table II (coefficients not shown). Variable definitions are provided in Table A.I 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 vs Non-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 | 3,120 | 3,120 | 3,103 | 7,247 | 7,247 | 7,232 |
| R-squared | 0.278 | 0.280 | 0.288 | 0.313 | 0.317 | 0.348 |
| 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: Firms with Patents vs Firms with Zero Patents**

| | Firms with Patents | | | Firms with 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 V: Continued

**Panel C: High Distance vs Low 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 | 3,470 | 3,465 | 3,315 | 3,488 | 3,488 | 3,341 |
| R-squared | 0.358 | 0.367 | 0.419 | 0.337 | 0.346 | 0.425 |
| 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 VI: Extreme Weather Events

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable $\Delta\log(Sales)$ 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.I 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 |

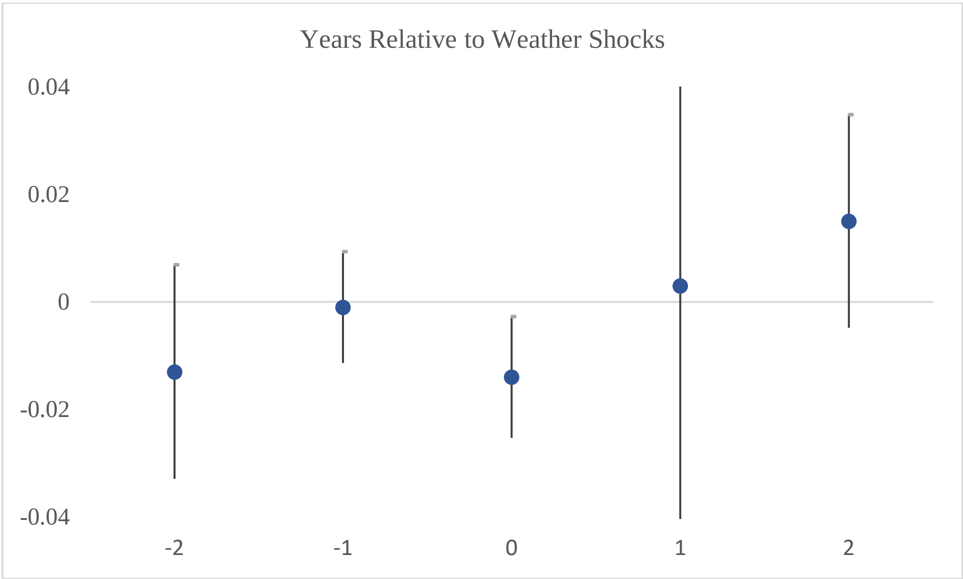
## Table VII: Extensive Margin

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable is an indicator variable that takes a value of one if the client-supplier relationship has been terminated. $\Delta$*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.I 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: 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 for column (1) of Table II. The sample consists of yearly observations of Compustat supplier-client pairs in the 2000-2015 period.



## Appendix

**Table A.I: 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 Employee | 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
# The Economic Costs of Climate Change

Cláudia Custódio
Imperial College Business School, CEPR, ECGI

Miguel A. Ferreira
Nova School of Business and Economics, CEPR, ECGI

Emilia Garcia-Appendini
University of Zurich

Adrian Lam
Imperial College Business School

## Table IA.I: Sample Description and Summary Statistics

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. Variable definitions are in Table A.I in the Appendix.

| Variable | Mean | 25th Pct. | 50th Pct. | 75th Pct. | Std. Dev. | Obs. |
|---|---|---|---|---|---|---|
| $\Delta$log(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 |
| $\Delta$Temp | -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.II: 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.I in the Appendix. The sample is restricted to suppliers for which client sales coverage is above (28.7%). 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.III: Baseline Results with Quadratic Weather Variables

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable $\Delta$log(*Sales*) is the change in the log of sales from supplier *i* to client *j* between years *t*-1 and *t*. $\Delta$*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.* $\Delta$*Temp Sq* is the square of $\Delta$*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.I 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) |
|---|---|---|---|---|---|---|
| $\Delta$Temp | -0.012* | -0.012* | -0.017** | -0.013* | -0.014* | -0.018** |
| | (0.095) | (0.079) | (0.024) | (0.083) | (0.062) | (0.016) |
| $\Delta$Temp 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.IV: Baseline Results with 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*. *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.I 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) |
| Δ Prcp | -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.V: Baseline Results with State Level Clusters

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.I 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.VI: Baseline Results with Postcode Level 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* (Postcode) is the change in average daily temperature in degree Celsius in the postcode of the corporate headquarters for supplier *i* from year *t*-1 to year *t*. *Prcp (Postcode)* is the average daily precipitation in millimeters in the postcode 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.I 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 (Postcode) | -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 (Postcode) | | | | -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.VII: Baseline Results with 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.I 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 3-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* | -0.015* | -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.VIII: Extreme Weather Events and Extensive Margin

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable is an indicator variable that takes a value of one if the client-supplier relationship has been terminated in year *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.I 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.IX: 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.I 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 IA.X: Firm Level Performance

This table presents estimates of ordinary least squares (OLS) panel regressions at the firm level. In Column (1), the dependent variable Δlog(*Sales*) is the change in the log of sales between years *t*-1 and *t*. In Column (2), the dependent variable *Net Sales/Assets* is net sales in year *t* scaled by total assets in year *t*-1. In Column (3), the dependent variable *EBIT/Assets* is operating profit in year *t* scaled by total assets in year *t*-1. In Column (4), the dependent variable *Net Income/Assets* is net income in year *t* scaled by 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.I 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) | ΔNet Sale / Assets | ΔEBIT / Assets | ΔNet Income / Assets |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| ΔTemp | -0.002 | -0.003 | -0.000 | 0.004 |
| | (0.520) | (0.265) | (0.966) | (0.258) |
| Prcp | 0.001 | -0.003 | -0.002 | -0.007 |
| | (0.891) | (0.544) | (0.445) | (0.127) |
| Tobin's Q | 0.006*** | 0.006*** | -0.003*** | -0.005*** |
| | (0.000) | (0.000) | (0.004) | (0.001) |
| Cash | 0.111*** | -0.029 | -0.046*** | -0.002 |
| | (0.000) | (0.126) | (0.004) | (0.919) |
| Log(Assets) | 0.006*** | -0.006*** | -0.006*** | -0.006*** |
| | (0.002) | (0.000) | (0.000) | (0.000) |
| Tangibility | 0.035** | -0.028 | 0.022* | 0.032* |
| | (0.043) | (0.180) | (0.059) | (0.056) |
| Leverage | -0.171*** | -0.198*** | 0.041*** | 0.094*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Observations | 40,662 | 40,662 | 40,662 | 40,662 |
| R-squared | 0.109 | 0.134 | 0.063 | 0.055 |
| County FE | Yes | Yes | Yes | Yes |
| Industry-Year FE | Yes | Yes | Yes | Yes |