Does Climate Change Affect Firm Sales? Identifying Supply Effects

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Abstract

We estimate the supply-side effects of climate change on firm sales by exploiting variation in local average temperature across suppliers of the same client. A 1°C increase in temperature leads to a 2.5% decline in annual sales. This effect is nonlinear, with stronger effects among suppliers in regions with the largest temperature increases and in cooler regions. Manufacturing and heat-sensitive industries are more affected, consistent with a reduction in labor productivity and labor supply when local temperatures rise. Non-diversified and financially constrained firms are also more affected, supporting the importance of operational and financial flexibility in adapting to climate change.

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I. Introduction

A central question for policymakers is whether the economic effects of climate change originate on the supply side—through reductions in productive capacity, labor productivity, and operational resilience—or mostly reflect demand-side responses. This distinction matters for the design of policies: supply-driven effects call for fiscal support and structural policies that strengthen productive capacity and firm resilience, while demand-driven effects are better addressed through monetary policy. In this paper, we identify the supply-side effect of temperature shocks on firm sales using an identification strategy that isolates supply-side variation within production networks.

Existing evidence establishes that temperature shocks can have important economic effects, but provides limited guidance on whether these effects operate through the supply or demand side of the economy. Early cross-sectional evidence shows that countries with higher temperatures tend to have lower income (Gallup, Sachs, and Mellinger (1999), Dell, Jones, and Olken (2009)), and subsequent work documents negative effects of temperature on aggregate economic activity and labor productivity (Hsiang (2010), Dell, Jones, and Olken (2012), Graff-Zivin and Neidell (2014)). At the firm level, however, evidence on sales is less conclusive: Pankratz, Bauer, and Derwall (2023) find negative effects, whereas Addoum, Ng, and Ortiz-Bobea (2020, 2023) find limited average effects and significant cross-industry heterogeneity. One reason for these mixed findings may be that temperature shocks simultaneously affect firms' productive capacity and the demand they face. Existing estimates that do not separate these channels therefore need not recover the underlying supply-side effect. We address this identification challenge by exploiting production networks to isolate variation in firm sales that originates from temperature-induced supply disruptions.

Identifying supply-side effects is empirically challenging not only because weather shocks affect both supply and demand at the same time, but also because many firms are geographically clustered with their suppliers, leading to correlated exposure (Ellison and Glaeser (1997)). In this paper, we estimate supply-side effects by leveraging a data set that combines supplier-by-customer sales data for the production network of publicly traded nonfinancial U.S. firms (sourced from the Compustat segment files) with the precise location of suppliers' headquarters and establishments (from Compustat and the National Establishment Time Series, NETS) and high-resolution temperature and precipitation data for the United States (from the PRISM Climate Group). Following an identification strategy similar to Khwaja and Mian (2008), we introduce client-by-year (or supplier-industry-by-client-by-year) fixed effects in our empirical specifications to hold demand fixed while comparing sales to the same client in the same year across suppliers exposed to different temperature shocks. We proxy the suppliers' exposure to the local temperature both through the location of their main headquarters and through the average exposure of the suppliers' establishments to local temperature.

We find that higher local temperatures significantly reduce supplier sales relative to other suppliers serving the same client, indicating economically meaningful supply-side effects. A 1°C increase in average local temperature leads to about a 2.5% decline in annual supplier sales relative to other suppliers serving the same client, with stronger effects in manufacturing and other heat-sensitive industries. The effects operate mainly at the intensive margin, as we do not observe systematic termination of supplier-client relationships. Our findings imply that climate policy should devote attention to adaptation measures that strengthen firms' operational resilience, such as cooling technologies, process innovation, and supply-chain risk management.

The relation between firm sales and average temperature changes may be nonlinear. We investigate whether the effect is heterogeneous across the magnitude of temperature changes and across temperature normals (i.e., long-term historical average temperature). Intuitively, larger and more unusual increases in average temperatures are likely to be more disruptive to firms than smaller changes. Consistent with this idea, we expect larger declines in sales among firms experiencing larger increases in average temperature. Our results show that firms exposed to average temperature changes in the top quintile of the distribution experience a 4.3% to 5.9% greater decline in sales than those in the bottom quintile. We also expect the effects to be more pronounced for firms located in areas that do not typically experience warm weather. Firms in regions with baseline temperatures below the median, or in areas with larger deviations from normal temperatures, exhibit a 2.5% to 3.1% greater reduction in sales for each 1°C increase in average local temperature.

Our main identifying assumption is that differences in sales growth between the treatment group (i.e., suppliers exposed to a change in the average temperature) and the control group would have followed parallel trends in the absence of the treatment (i.e., weather shocks). We find no evidence of pre-existing differential trends in sales growth between groups of suppliers. Our identification strategy also requires that local temperature changes are exogenous to the suppliers' activity. While it is unequivocal that the real activity of specific firms and industries, particularly in CO_2-intensive industries, affects climate (Intergovernmental Panel on Climate Change (2023)), such an impact is at the global level rather than at the firm-specific or local level. We interpret our coefficients as capturing supply-side effects, as the variation in sales is driven by suppliers' exposure to changes in average temperatures. Nevertheless, our estimates may also partly reflect demand-side responses if clients anticipate disruptions at exposed suppliers and reallocate purchases toward alternative suppliers in response to expected price increases, delivery delays, or deterioration in supplier reliability.

A potential concern with our main estimates is the standard trade-off between internal and external validity. Controlling for demand requires restricting the sample to firms with at least two suppliers and excluding firms that sell directly to end consumers. However, these concerns are unlikely to be consequential in our context for the following reasons. First, excluding firms with only a single supplier has a limited impact on sample size, reducing the number of unique suppliers from 1,774 to 1,405. Second, business-to-business transactions (on which our sample is based) account for a substantial share of economic activity, representing approximately 75% of total final consumption.[1] Finally, as we explain below, the mechanisms we uncover suggest supply-side disruptions are largely independent of whether the final customers are other businesses or end consumers. Nevertheless, we address this concern by reweighting our observations using inverse probability weights based on total sales in each two-digit SIC industry to better reflect the broader firm-level population. Our main results remain quantitatively similar.

Next, we investigate four non-mutually exclusive mechanisms through which changes in temperature can affect firm sales. The first mechanism is labor productivity and labor supply. Our results are more pronounced for manufacturing firms, firms in heat-sensitive industries (i.e., firms in industries with outdoor activities or manufacturing processes), and firms with higher labor intensity (as proxied by the ratio of the number of employees to assets). This is consistent with the idea that higher temperatures lower labor productivity due to absenteeism and more challenging working conditions (Graff-Zivin and Neidell (2014)).

The second mechanism is financial constraints. Financially constrained firms may be unable to adapt due to their lack of funding and inability to raise financing to absorb higher costs

[1] According to data from the U.S. Bureau of Economic Analysis, intermediate consumption in 2023 amounted to $20.6 trillion, while final consumption reached $27.7 trillion.

and investment associated with weather shocks. In contrast, unconstrained firms can better cover the costs and make the investments necessary to mitigate the adverse effects of climate change (e.g., Fried (2022), Gourio and Fries (2020)). Our proxies of financial constraints are credit rating, payout ratio, and the financial constraints composite index of Bartram, Hou, and Kim (2022). We find that the effect of changes in temperature on financially constrained firms is larger than that on unconstrained firms. Our results suggest that financially constrained firms have limited financial resources to overcome weather shocks without affecting sales. These results are consistent with Giroud and Mueller (2019), who find that the propagation of economic shocks through firms' internal networks is more pronounced for financially constrained firms.

The third mechanism is operational flexibility. Larger and diversified firms can use their internal networks to reallocate resources across their business and geographic segments to respond and adapt to weather shocks. In line with this mechanism, the estimates indicate that the effect of higher temperature on firm sales is larger for firms with establishments in fewer counties and firms with less diversified operations. These results suggest that geographic and business diversification can mitigate the effects of temperature changes.

The fourth mechanism is switching costs. Barrot and Sauvagnat (2016) show that switching costs between trade partners due to input specificity are substantial and can explain the propagation of shocks in production networks. We proxy for input specificity and switching costs at the supplier level using the market value of patents and an indicator for industries that sell standardized goods. These measures capture the importance of relationship-specific investments and restrictions on sourcing alternative suppliers. We find that the reduction in sales is more pronounced for suppliers that are more easily substitutable—that is, those providing standardized inputs and lower-value patents. These findings are consistent with the idea that the supplier-specific economic costs of weather shocks are larger when switching costs are lower.

We next examine whether firms can mitigate the adverse effects of temperature shocks through adaptation. Guided by the mechanisms underlying our findings, we focus on three strategies that may enhance firms' resilience: automation, geographic diversification of production, and investment. We find no significant decline in sales following temperature shocks among firms that have recently automated production, expanded their geographic footprint by opening plants in other counties, or increased investment. In contrast, firms that have not adopted these strategies experience substantial declines in sales. These results suggest that firms can mitigate their exposure to temperature shocks by investing in technologies and production structures that increase operational resilience.

We then examine how operational and financial constraints influence firms' ability to adapt. Focusing on automation, proxied as substitution away from heat-sensitive labor, we find that firms that are less operationally or financially constrained are more likely to adopt adaptive strategies. In contrast, constrained firms face a dual challenge: they are both more exposed to temperature shocks and less capable of responding effectively. These findings highlight a key policy priority: supporting operationally and financially constrained firms that lack the resources to adapt independently to climate risks (Fankhauser and Soare, 2013).

We contribute to several strands of the literature. First, we contribute to the literature on the real economic costs of climate change. Initial cross-sectional studies show that countries with higher average temperatures tend to have lower income (Gallup et al. (1999), Dell et al. (2009)). More recent work documents similarly adverse effects of higher temperatures on aggregate economic activity (Hsiang (2010), Jones and Olken (2010), Dell et al. (2012)). Using a worldwide sample, Pankratz et al. (2023) find that increased exposure to extremely high temperatures reduces firms' revenues and operating income. In contrast, Addoum et al. (2020) find that the effect of temperature exposure on firm sales is not significant using establishment-level and firm-level data in the United States. In subsequent work, Addoum et al. (2023) find that extreme temperatures have heterogeneous effects as some industries suffer while others benefit. In short, while previous research documents negative effects of climate change on aggregate economic activity and labor productivity, evidence on firm-level sales and performance is mixed.

There is also evidence that climate change, and related phenomena such as pollution and carbon emissions, increase the consumption of energy and other goods, including air conditioning, air purifiers, and medicine (e.g., Abel, Holloway, Harkey, Meier, Ahl, Limaye, and Patz (2018), Deschênes, Greenstone, and Shapiro (2017), Ito and Zhang (2020)). Relatedly, Benmir, Jaccard, and Vermandel (2021) propose a model in which environmental externalities raise households' willingness to consume goods. This is the first paper to isolate the *supply-side effects* of climate change on firm sales using granular data and high-dimensional fixed effects. This is important because demand-side variation is a confounder and may be ambiguous and heterogeneous across regions and industries. Other papers also rely on high-dimensional fixed effects to exploit geographic differences in exposure to temperature. For example, Jones and Olken (2010) use product-year fixed effects and, thus, exploit differences in temperature across countries that control for *global* changes in demand for each product. The higher degree of granularity in our data allow us to further improve identification by controlling for *local* changes in demand, which can be affected by local climate and weather conditions. This approach allows us to identify supply-side effects of changes in temperature after purging firm-specific demand effects. Our results show that the supply-side effects of temperature changes on firm sales are substantial and help explain the apparent puzzle of why average temperature affects labor productivity but not firm sales or performance.

Second, we contribute to the literature on the effects of temperature extremes on firm output through labor productivity. Graff-Zivin and Neidell (2014) show that extremely hot temperatures reduce hours worked across several heat-sensitive industries. Somanathan et al. (2021) find reduced worker productivity on hot days, which can decrease plant annual output by 2% per degree Celsius. In related work, Zhang, Deschênes, Meng, and Zhang (2018), Chen, Huynh, and Zhang (2019), and Colmer et al. (2019) show that higher local temperature lowers total factor productivity, value-added, and employment in manufacturing using establishment-level or firm-level data. Xiao (2024a, 2024b) shows that extreme heat reduces labor productivity and discourages both firm and job creation, especially in heat-sensitive industries. We contribute to this literature by identifying the mechanisms that drive these supply-side effects and how firms adapt to these shocks. Our results suggest that the decline in sales can be due to lower labor productivity and labor supply, lack of operational flexibility or financial resources to adapt the productive processes, and clients' inability to switch to non-affected suppliers. Importantly, we show that firms that adapt to higher temperatures (for example through automation, geographical diversification or increasing investments) can mitigate the negative effects of higher temperatures.

Finally, our evidence is complementary to research studying the propagation of weather shocks along the supply chain from the supplier to its clients. Barrot and Sauvagnat (2016) find that suppliers affected by major natural disasters in the United States lead to output losses for their clients, especially when they produce a specific input. Carvalho, Nirei, Saito, and Tahbaz-Salehi (2021) find that downstream propagation explains a sizable fraction of the decline in gross output following the Great East Japan Earthquake of 2011. Pankratz and Schiller (2024) show that heat waves and flooding at supplier locations reduce the operating performance of their customers in global supply chains. In contrast to these studies, which examine the downstream propagation of natural disaster shocks, our paper uses production networks as a laboratory to estimate the impact of changes in average temperature on firm sales, while controlling for firm-specific demand.

II. Data and Methodology

A. Sample and Variables

Our sample consists of supplier-client pairs with headquarters in the United States. Regulations SFAS 14 and 131 require publicly listed firms in the United States to disclose, annually, the identity of clients and the sales to clients whose purchases represent more than 10% of total sales.[2] We obtain data on supplier-client links and associated sales from the WRDS Supply Chain database (Compustat Segment IDs) for the 2000-2018 period. This WRDS analytics tool is built on the historical customer segment data and complemented by data contributed by researchers including Cohen and Frazzini (2008) and Cen, Maydew, Zhang, and Zuo (2017). As we restrict the sample to publicly traded firms in Compustat, we cannot identify clients that are private firms, government entities, or firms based outside of the United States. We exclude suppliers that are regulated utilities (SIC codes 4900-4999), financial firms (SIC codes 6000-6999) or public administration (SIC codes 9100-9729).

We obtain temperature and precipitation data from the PRISM Climate Group (2019). PRISM provides climate observations from weather stations across the continental United States

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

and uses sophisticated climate modeling techniques to interpolate weather data for each 4×4 km grid (Daly and Bryant (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 the continental United States.

We map the weather grids in PRISM locations to ZIP codes in the U.S. Census Bureau files. We compute the average daily temperature and precipitation at the ZIP code level for each year. Figure 1 plots the change in average daily temperature aggregated per county and year over the sample period. We match the weather variables for each ZIP code to the firms in Compustat using the location of the firm's 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 ZIP code or county as their headquarters (Campello, Connolly, Kankanhalli, and Steiner (2022)), this proxy of the exposure to temperature could be prone to measurement error. We address this issue by obtaining information on the exact location of the firms' establishments, which we source from the National Establishment Time-Series (NETS) Database produced by Walls & Associates. We calculate a firm-level exposure to temperature by mapping the temperature in each ZIP code to the location of each establishment and averaging the changes in temperature across establishments using the number of employees by establishment as weights. The average change in temperature across establishments is highly correlated with the headquarter-level measure with a correlation coefficient of 0.86.

We obtain extreme weather events data from the National Oceanic and Atmospheric Administration (NOAA) Storm Events Database (NOAA (2025)). This database records the occurrence of significant weather events that have sufficient intensity to cause loss of life, injuries, significant property damage, and/or disruption to commerce.

B. Methodology

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

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

The dependent variable measures the annual growth rate in supplier i's sales to client j between years t–1 and t.[3] The main independent variable, $\Delta\, Temp_{it}$, is the change in average daily temperature in degrees Celsius in the ZIP code where supplier i's headquarters is located from year $t-1$ to year t. Following the climate economics literature (e.g., Dell, Jones, and Olken (2014)), we include the average daily precipitation in millimeters in the ZIP code where supplier i headquarters is located from year t–1 to year t ($Prcp_{it}$). In all specifications, we add a set of lagged supplier characteristics, X_{it-1}, which include firm size as proxied by total assets (*Assets*), the ratio of the market value of assets to book value of assets (*Tobin's Q*), the ratio of cash and equivalents to assets (*Cash*), the ratio of total debt to market value of assets (*Leverage*), and the ratio of net property, plant, and equipment to total assets (*Tangibility*).

Our client-supplier pair data allow us to include client-by-year fixed effects, δ_{jt}, in the regressions. Therefore, identification comes from the variation in the change in temperature across the suppliers of a given client in the same year. As shown by Khwaja and Mian (2008) in the context of shocks to credit supply, firm-by-year fixed effects absorb all unobserved heterogeneity at the firm level in a given year. Thus, we will compare the changes in business transactions across suppliers selling to the same firm. For this reason, our results are unlikely to

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

be driven by changes in aggregate firm-specific demand.[4] The estimated difference in sales can therefore be plausibly attributed to supply-side factors, such as changes in labor supply, changes in productivity or increases in operating costs. In addition, weather shocks can affect the quality of products, or delay deliveries to clients.[5] We also estimate a more stringent specification, which includes (supplier) industry-by-client-by-year fixed effects to absorb time-varying differences across suppliers in the same industry (two-digit SIC) that sell to the same firm.

The main coefficient of interest is β_1, which estimates the effect of changes in temperature on firm sales. A negative β_1 would indicate that firms suffering increases in average daily temperature reduce their sales by larger amounts than otherwise similar firms selling to the same client. In our baseline regressions, we cluster the standard errors at the county level (based on the supplier's headquarters) as firms located in the same region are exposed to correlated weather shocks. Table A.1 in the Appendix provides variable definitions and data sources.

C. Summary Statistics

Panel A of Table 1 contains a year-by-year description of our sample. Our sample consists of 10,730 supplier-client-year observations for 1,405 unique suppliers and 331 unique clients over the period 2000-2018, with about 560 observations per year on average. Sales to clients in our sample account, on average, for 38% 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

[4] Client-year fixed effects account for changes in demand stemming, for example, from changes in temperature in the client county, independently of whether the client is in the same or a different location as the supplier. In our setting, it is particularly important to control for firm-specific demand as weather shocks affecting a client-supplier pair are likely correlated due to co-location in production networks. In fact, 84% of the clients in our sample have at least one of their suppliers with an establishment located in the same county as one of the client's establishments.

[5] Clients may reduce purchases from suppliers hit by a weather shock, for example because higher production costs raise prices or because clients anticipate disruptions in input delivery. Although such reductions are initiated by the client, they are triggered by supply-side changes caused by the weather shock rather than by autonomous shifts in client demand. We cannot, however, completely rule out that anticipatory client substitution contributes to the estimated effect.

change in temperature of about five suppliers per client. The table also shows time-series variation in the average daily temperatures in the ZIP codes where firms are located, ranging from -1.1°C to 0.97°C. The average temperature in the firms' headquarters is similar to that of the establishment-weighted temperature variable, which is consistent with most of the production of firms taking place at the firm's headquarters or in establishments that are located close to the headquarters.

[Insert Table 1 Here]

Panels B and C of Table 1, respectively, contain descriptive statistics for the supplier and client firms in our pair-level sample. Client firms are larger than supplier firms in terms of total assets. This is due to regulation SFAS 14, which only requires the disclosure of the names of clients that account for at least 10% of total sales. Client firms are more leveraged, hold less cash, have more tangible assets, and have a lower Tobin's Q than supplier firms. Consistent with a high degree of geographic co-location of suppliers and clients, the average levels of temperature are similar for client and supplier firms.

D. Identifying Assumptions

An identifying assumption in our estimates is that local temperature changes are exogenous to the suppliers' business transactions or sales. While business transactions among certain firms and industries, particularly in CO_2-intensive sectors, may have a significant effect on climate, this effect operates at the global level rather than the local level. For example, the areas most affected by climate change are often those with lower levels of industrialization and economic development. Therefore, it is difficult to argue that an individual firm's business transactions affect the local temperature. Another assumption is that the sales response for a firm's products or services would have been the same for the treatment group (i.e., suppliers exposed to a change in the average temperature) and the control group absent the weather shocks (i.e., changes in the average temperature). We assess whether the parallel trends assumption is plausible using pre-treatment observations.

Our identification strategy exploits within-client-year variation in temperature across a client's suppliers. This approach follows Khwaja and Mian (2008) in using client-by-year fixed effects to identify supply-side shocks. Paravisini, Rappoport, and Schnabl (2023) argue that an additional identifying assumption of this empirical strategy is that changes in a firm's credit demand are equally spread across all the banks lending to the firm. In our case, this implies that changes in clients' purchases are equally spread across all suppliers, which is more plausible when suppliers are from the same industry. For this reason, we estimate specifications that include supplier industry-by-client-by-year fixed effects, restricting the variation to suppliers within the same industry selling to the same client in each period.

III. Results

A. Average Temperature

Table 2 presents the estimates of the effect of changes in average temperature on changes in firm sales using the regression in equation (1). Panel A reports estimates using changes in temperature in the firm's headquarters location at the ZIP code level. Panel B reports estimates using establishment-level changes in temperature (at the ZIP code level) weighted by the number of employees by establishment. We estimate the regressions using three different sets of fixed effects: year fixed effects in column (1); client-by-year fixed effects in columns (2), (4), and (6); and supplier industry-by-client-by-year fixed effects in columns (3) and (5). In addition, the regressions in columns (4)-(6) include firm-level control variables.

[Insert Table 2 Here]

The results show that the coefficient on changes in average temperature ($\Delta Temp$) is negative and statistically significant across all specifications. The estimates in Panel A indicate that a 1°C yearly increase in the average temperature in the supplier's headquarters ZIP code leads to a 1.6% to 2.6% reduction in sales. A similar pattern emerges in Panel B, where estimates are larger in absolute value, ranging from -2.1% to -3.9%.

Columns (1)-(3) in both Panels A and B show that the inclusion of client-by-year or supplier industry-by-client-by-year fixed effects, which absorbs demand-side variation at the client-year level, magnifies the negative effect of temperature on firm sales by approximately one percentage point. Columns (4) and (5) show that including firm-level control variables does not significantly impact the estimated $\Delta Temp$ coefficient.

These results are consistent with demand-side variation masking supply-driven sales losses in firm-level estimates; we do not identify the sign or magnitude of this demand-side variation. Our results help to understand why the literature has found negative effects of higher temperature on aggregate economic activity and labor productivity (e.g., Hsiang (2010), Dell et al. (2012), Graff-Zivin and Neidell (2014), Somanathan et al. (2021)) but no overall effects on firm-level sales and performance (Addoum et al. (2020)).

Column (6) of Panels A and B shows the dynamic effects of temperature by including lags and leads of the change in temperature ($\Delta Temp$). We find that the negative effect of temperature is significant only in the year of the temperature shock but not before or after. This result supports the assumptions of our identification strategy as there is no evidence of preexisting differential trends between treated and control groups. In addition, the effect on firm sales is not persistent, consistent with firms' ability to adapt in the long run.

In Table 3, we examine whether temperature affects firms' business transactions in a nonlinear way by estimating equation (1) using dummy variables to identify the temperature change quintiles (with the first quintile omitted). As before, Panel A shows results using temperature exposure in the firms' headquarters, while Panel B uses temperature exposure based on firms' establishments. The results show that the effects are concentrated in the highest temperature-change quintile (Q5), consistent with a nonlinear effect of temperature on firms' sales. In fact, firms exposed to average temperature changes in the top quintile of the distribution experience a 4.3% to 5.9% greater decline in sales relative to those in the bottom quintile. Thus, the effect of temperature changes on firm sales is more pronounced in locations where the increase in average temperature is more extreme.

[Insert Table 3 Here]

The effect of temperature on a firm's sales can also depend on the local climate and weather conditions. We expect the disruptive effects to be more pronounced for firms in areas that do not typically experience warm weather or large deviations in temperatures, as firms in these locations might not be prepared to deal with high temperatures or large temperature swings. We analyze the effect of local climate by estimating our specifications separately for firms located in areas with: (1) average daily temperature in each year below and above the median; and (2) temperature normal, defined as the long-term (30-year) averages over the period of 1981 to 2010 (drawn from PRISM) below and above the median.

Panel A of Table 4 presents these estimates using the specification in column (4) of Table 2. In columns (1) and (2), we find that the disruptive effects of temperature are larger for firms in areas with average temperatures below the median, with an estimated impact of -3.2%. In columns (3) and (4), we find the negative effect of temperature is significantly stronger (-3.2%) in areas with below-median normal temperatures.

[Insert Table 4 Here]

We also examine the effect of seasonal variation by focusing on summer temperatures, as high temperatures usually occur during the summer. In columns (1) and (2) of Panel B, Table 4, we define summer using the meteorological definition (i.e. from June to August). In columns (3) and (4), we define summer as the three months with the highest monthly temperature normal (long-term average). This alternative definition allows for differences in weather conditions across the continental United States. Under both definitions of summer, our results show that the negative effects of temperature on firm sales are more pronounced (-3.1%) for firms in areas with summer temperatures below the median.

We assess the effect of temperature swings by examining deviations from the temperature normal. In columns (1) and (2) of Panel C, Table 4, we examine the average positive deviations from the temperature normal. A higher positive deviation implies that the location experiences a hotter year relative to its long-run average temperature.[6] In columns (3) and (4), we examine the average absolute deviations from normal.[7] A higher absolute deviation implies that the location experiences a year with larger deviations (both positive and negative) relative to its long-run average temperature. Under both measures of temperature swings, we find that the negative effects of temperature on firm sales are larger for firms in areas with larger deviations from

[6] Formally, we define positive deviation ($Pos\ Dev_{it}$) for supplier *i* in year *t* as:

$$Pos\ Dev_{it} = \frac{1}{T} \times \sum_{\tau=1}^{T} I_{Temp_{i\tau} > Temp\ Norm_{im}} \times \ (Temp_{i\tau} - Temp\ Norm_{im}),$$

where $Pos\ Dev_{it}$ is the average positive deviations in daily temperature relative to the temperature normal in each month. If the daily temperature on day τ is greater than the temperature normal in month *m*, the positive deviation for day τ is the difference between the daily temperature and temperature normal. If the daily temperature on day τ is lower than the temperature normal in month *m*, the positive deviation for day τ is zero.

[7] Formally, we define absolute deviation ($Abs\ Dev_{it}$) as:

$$Abs\ Dev_{it} = \frac{1}{T} \times \sum_{\tau=1}^{T} |Temp_{i\tau} - Temp\ Norm_{im}|,$$

where $Abs\ Dev_{it}$ is the average absolute deviations in daily temperature relative to the monthly temperature normal.

temperature normal, with estimated effects of -2.7% and -2.9% in columns (3) and (4), respectively.

Overall, these results suggest that firms located in areas that are not typically exposed to high temperatures, heat waves, or large temperature swings are less prepared to cope with warmer average temperatures. For example, these firms may lack air conditioning, heat insulation, or heat-resistant infrastructure, or they may be less likely to adopt measures that mitigate the adverse effects of heat, such as shifting workloads to early-morning or late-evening hours.

B. Extreme Weather Events

We examine supply-side effects of extreme weather events on firm sales. Table 5 shows the effects of extreme weather events on interfirm sales using the specifications in Table 2. We focus on three sets of extreme weather events that are closely related to climate change: (1) cold; (2) heat; and (3) precipitation. To identify weather events recorded in the Storm Events database that are "extreme", we look at events that result in at least one fatality. These events are rare, with the mean values ranging from 0.0002 (Heavy Snow) to 0.0234 (Flood).

[Insert Table 5 Here]

In Panel A, we examine the effects of cold-related extreme weather events on firm sales. We find that the coefficients of these extreme weather event indicators range from -0.141 to -0.381, but they are only statistically significant when estimated with industry-by-client-by-year fixed effects.

In Panel B, we examine the effects of heat-related extreme weather events. The coefficient of the heat event indicator is negative but not statistically significant. We construct an additional variable, *Hot Days*, which counts the number of days in which the local temperature exceeds the corresponding monthly normal by more than five degrees Celsius. We find that this variable is negative and statistically significant at the 10% level.

In Panel C, we examine the effects of precipitation-related extreme weather events. The coefficient of the *Heavy Rain* indicator is positive, whereas that on the *Flood* indicator is negative, but neither is statistically significant at conventional levels.

Taken together, we find some evidence of negative effects of extreme cold and heat events on firm sales; however, possibly due to the rarity of such events, the corresponding coefficients are estimated with lower precision.

IV. How Does Temperature Affect Firm Sales?

Our baseline specifications account for demand-side factors (observed and unobserved, time-varying and time-invariant), allowing us to attribute temperature-induced difference in sales to supply-side factors. These factors might include reductions in firm sales due to lower labor supply or productivity (e.g., absenteeism, working conditions, workforce health, and safety) or higher operating costs (e.g., energy or investment costs for air conditioning, building insulation, equipment cooling or heating systems, and higher transportation costs). In addition, weather shocks can affect the quality or the price of products or delay deliveries to clients, which may lead clients to substitute toward unaffected suppliers. In this section, we exploit the heterogeneity in our data to study the mechanisms through which changes in temperature might affect firm supply and which firm characteristics can alleviate or amplify the effect of weather shocks on firm sales.

A. Labor Supply and Productivity

We explore whether the mechanism behind the adverse effects on firm sales documented in the baseline results might be due to lower labor supply and productivity (Graff-Zivin and

Neidell (2014), Zhang et al. (2018), Chen et al. (2019), Colmer et al. (2019)). If this is the case, we expect our estimates to be larger for firms whose labor supply and productivity are most sensitive to weather conditions. We consider three measures to test for this mechanism: (1) whether a firm operates in manufacturing; (2) occupational exposure to heat; and (3) labor intensity, proxied by the ratio of employees to assets.

[Insert Table 6 Here]

If temperature primarily affects firm performance via a labor productivity channel, manufacturing firms are likely to be more affected. Panel A of Table 6 reports the results split by manufacturing status using the specification in column (4) of Table 2. Column (1) presents the results for manufacturing industries, and column (2) presents the results for other industries. We find that the $\Delta \mathit{Temp}$ coefficient is negative and statistically significant with an estimate of -3.8% in manufacturing, while the $\Delta \mathit{Temp}$ coefficient is not statistically significant for firms in other industries. The difference in coefficients is statistically significant at the 10% level.

Firms in industries with predominantly outdoor activities or manufacturing processes are expected to be more sensitive to heat. Following Xiao (2024b), we construct a measure of heat exposure based on occupational exposure at the industry level. We aggregate job zone scores from the Occupational Information Network, which measure outdoor exposure to weather per occupation, at the three-digit SIC and four-digit NAICS level (based on the crosswalk provided in the Bureau of Labor Statistics' Occupational Employment and Wage Statistics). Panel B of Table 6 reports the results split by whether a firm is above or below the median occupation-based heat sensitivity score (at the industry level). Column (1) reports the results for firms with above-median heat exposure, while column (2) shows results for firms with below-median heat exposure. The coefficient on $\Delta \mathit{Temp}$ is -3.2% and statistically significant for firms with above-median heat exposure. For firms with below-median heat exposure, the coefficient is also negative but not statistically significant. The difference in coefficients is not statistically significant at conventional levels.

Firms with higher labor intensity are expected to be more sensitive because a larger share of their input is labor that can be directly affected by heat, both at work and outside the workplace. Panel C of Table 6 reports the results split by whether a firm is above or below the median of the ratio of the number of employees to assets. Column (1) presents the results for firms with high labor intensity where the Δ*Temp* coefficient is negative and statistically significant at -2.3%. Column (2) presents the results for firms with low labor intensity where the Δ*Temp* coefficient is not statistically significant.

In sum, our results support the view that labor supply and productivity mechanisms drive our results as the effect of temperature changes is concentrated in firms potentially more affected by higher average temperatures.

B. Financial Constraints

Disruptions to firms' production processes might be particularly severe if suppliers are financially constrained and cannot raise financing to absorb the increased costs or investments associated with temperature changes. In contrast, unconstrained firms may be better able to tap capital markets to obtain financing to cope with increases in temperature, for example by hiring additional workers to offset productivity losses, investing in appropriate equipment or infrastructure, and implementing strategies that reduce the firm's exposure to higher temperatures.

To study this mechanism, we estimate our specification separately across subsamples according to the firms' financial constraints. We consider three measures of financial constraints:

(1) whether a firm has a credit rating; (2) whether its payout ratio is above or below the median; and (3) the financial constraints composite index of Bartram et al. (2022).

[Insert Table 7 Here]

Table 7 reports the results. Panel A presents the results split by whether a firm is rated by a credit rating agency or not. Firms with a credit rating have access to public debt markets and, therefore, are less likely to be financially constrained. The Δ*Temp* coefficient is -3.0% for unrated firms (column (1)) and statistically significant. In contrast, there is no statistically significant effect for rated firms (column (2)). The difference in coefficients is statistically significant at the 5% level.

Panel B measures financial constraints based on whether a firm's payout ratio is above or below the median. The payout ratio is defined as the sum of common dividends, preferred dividends, and repurchases of common and preferred stock, divided by income before extraordinary items. Firms with a higher payout ratio are considered less financially constrained. Column (1) presents the results for firms with a below-median payout ratio. The coefficient on Δ*Temp* is -3.8% and statistically significant. In contrast, there is no statistically significant effect for firms with an above-median payout ratio (column (2)). The difference in coefficients is statistically significant at the 1% level.

Panel C measures financial constraints using the composite index of Bartram et al. (2022), based on a firm's KZ index (Kaplan and Zingales (1997)), WW index (Whited and Wu (2006)), size-age (SA) index (Hadlock and Pierce (2010)), size, payout ratio, and credit rating. A firm is assigned to the constrained group if its KZ, WW, or SA index is above the median, if its size or payout ratio is below the median, or if it does not have a credit rating. We then construct the composite financial constraints index by summing the six indicators. A high index value indicates that the firm is more financially constrained. We split the sample into firms with high and low values of the financial constraints composite index based on the median. Column (1) presents the results for firms with a high financial constraints composite index. The coefficient on $\Delta Temp$ is -3.9% and statistically significant. In contrast, the coefficient in column (2) for firms with a low financial constraints composite index is not statistically significant. The difference in coefficients is statistically significant at the 5% level.

Overall, the findings support the financial-constraints mechanism and highlight the role of financial constraints in firms' adaptation to climate change.

C. Operational Constraints

Large firms may be better able to adapt to temperature changes than small firms because economies of scale and scope provide greater operational flexibility and reduce operating constraints. Similarly, geographically diversified firms, as well as conglomerates operating across multiple business segments, may be better able to adapt to temperature changes. Such firms can increase production at unaffected plants or reallocate resources across business segments to offset reductions in activity at affected plants or segments.

[Insert Table 8 Here]

Table 8 estimates the effects of temperature changes across different types of firms: small versus large firms, proxied by below- and above-median assets (Panel A); firms operating in a limited number of counties (below median) versus those with more geographically diversified operations (above median) (Panel B); and firms with less versus more diversified operations, proxied by above- and below-median Herfindahl-Hirschman index (HHI) based on establishment sales. The coefficients in column (1) for small firms, firms that operate in a small number of counties, and firms with less diversified operations are negative and statistically significant. In contrast, the coefficients in column (2) for large firms, firms that are more geographically diversified, and firms with more diversified operations are not statistically significant. The differences in the coefficients are statistically significant at conventional levels.[8]

Overall, these results show that firms with less operational flexibility are more affected by the adverse effects of climate change, as these firms may have greater difficulty (or take longer) to adapt to changes in temperature.

D. Switching Costs

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

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

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

[8] The results for small firms in Panel A are also consistent with the financial constraint channel, as smaller firms are more likely to have fewer financial resources to invest and adapt to weather shocks.

economic value of the firm's patents (Kogan, Papanikolaou, Seru, and Stoffman (2017)); and (3) the duration of the supplier-client relationship over the sample period.

[Insert Table 9 Here]

We identify industries that are more likely to sell standardized products or, in other words, industries with lower costs of switching to other suppliers, following Giannetti, Burkart, and Ellingsen (2011). Panel A of Table 9 reports the subsample results split by whether a firm operates in industries that sell standardized goods or not. The coefficient on $\Delta Temp$ is larger for suppliers selling a standardized good at -3.2% (column (1)) than for suppliers selling a non-standardized good at -2.5% (column (2)), although the difference in coefficients is not statistically significant.

Panel B of Table 9 reports the subsample results split by innovation. Suppliers with valuable patents are likely to have more relationship capital with their clients. Therefore, their clients face higher switching costs and are less likely to switch to other non-disrupted suppliers. We find that the negative effects of temperature on sales are more pronounced for firms whose patents have zero economic value at -2.8% in column (1). In contrast, the effect is not significant for firms whose patents have positive economic value in column (2).

Panel C of Table 9 reports the subsample splits by the duration of the supplier-client relationship. We compute the duration of the relationship as the number of years with non-missing interfirm sales data over our sample period. A shorter duration indicates that the relationship is less persistent and hence reflects lower switching costs for the client.[9] We split the sample into short and long relationships at the median value. As shown in column (1), the

[9] An important caveat is that Regulations SFAS numbers 14 and 131 only require firms to disclose corporate clients who contribute to more than 10% of total sales, some of the missing interfirm sales data may stem from a client falling just under the reporting threshold.

coefficient on $\Delta Temp$ for pairs with a shorter relationship is -3.5%, and it is statistically significant at the 1% level. In contrast, in column (2), the coefficient for pairs with a longer relationship is -1.4%. Although the estimated differential effect is economically relevant, the difference in coefficients is not significant at conventional levels.

In sum, the evidence suggests that the negative sales effects of temperature increases are more pronounced for suppliers that are more easily substitutable (i.e., sell a standardized good or have zero economic value for their patents) as their clients face lower switching costs when they change suppliers.

V. Adaptation

Our evidence on the mechanisms suggests there are potential adaptive strategies that firms can carry out to moderate the negative impacts of temperature changes. While there is extensive empirical evidence on the effectiveness of adaptive strategies in the agricultural sector (see, for example, Seo, McCarl, and Mendelsohn (2010), Kurukulasuriya, Kala, and Mendelsohn (2011), and Wang, Mendelsohn, Dinar, and Huang (2010)), there is limited evidence on adaptive behavior in the business sector (Biesbroek, Klostermann, Termeer, and Kabat (2013) and Fankhauser (2017)). In this section, we assess the effectiveness of adaptation and examine how operational and financial constraints influence firms' ability to implement adaptive strategies.

A. Effectiveness of Adaptation

Building on our finding that labor-intensive firms are more affected by weather shocks, we examine three adaptive strategies that may reduce a firm's exposure to heat: (1) automation; (2) geographic diversification; and (3) investment. If these strategies are effective, we expect the negative effects of weather shocks to be more pronounced among firms that have not adopted them recently. Given the potential time lag in the effects of these strategies, we define adoption as occurring within the previous three years. This restriction reduces the sample size for this set of analyses.

[Insert Table 10 Here]

We first analyze the effects of automation using automation-related patent applications, as identified by Mann and Püttmann (2023). As automation technologies increasingly substitute capital for labor, we hypothesize that firms that have applied for an automation-related patent are less sensitive to weather shocks. Panel A of Table 10 presents these results. We find that the coefficient on Δ*Temp* is negative and statistically significant for firms that have not applied for an automation patent (-0.031) in column (1), but not for firms that have applied in column (2).[10]

In Panel B of Table 10, we examine the role of geographic diversification. As shown in Table 8, firms operating in a greater number of counties are less affected by increases in temperature. Building on this finding, we hypothesize that firms that have not diversified their operations geographically (within the past three years) will be more vulnerable to temperature shocks. Consistent with this hypothesis, our results show that the coefficient on Δ*Temp* is negative and statistically significant only for firms that have not expanded operations into a new county (-0.042) in column (1), whereas it is not statistically significant for firms with geographically diversified operations (see column (2)).

In Panel C of Table 10, we explore the role of investment. We hypothesize that firms with lower investment rates (measured as the ratio of capital expenditures to lagged property, plant, and equipment) are more affected by temperature shocks, as they are less likely to be transitioning toward a more capital-intensive business model. To test this, we split the sample at the median value of the average investment rate over the past three years. We find that the

[10] As the data in Mann and Püttmann (2023) is only available up to 2014, the total number of observations is lower in this set of analyses.

coefficient on $\Delta Temp$ is negative and statistically significant only for firms with below-median investment rates (-0.026) in column (1).

B. The Role of Operational and Financial Constraints on Adaptation

Our evidence suggests that these adaptive strategies are effective in mitigating the negative effects of temperature shocks. As Mendelsohn (2000) argues, firms are likely to undertake substantial adaptation to climate change when the benefits outweigh the costs. However, significant barriers may hinder the implementation of such strategies (e.g., Adger, Agrawala, Mirza, Conde, O'Brien, Pilhin, Pulwarty, Smit, and Takahashi (2007), Moser and Ekstrom (2010), Berkhout (2012), Biesbroek et al. (2013)). In light of this, we further examine the role of operational and financial constraints in shaping firms' adaptive capacity.

We focus on the application of automation patents, as it reflects a shift away from heat-sensitive labor. Since patent applications are firm-level outcomes, the following analyses are conducted at the firm-year level, restricting the sample to suppliers within the client-supplier data set. The dependent variable is an indicator for automation patent applications, which equals one if a firm files an automation-related patent application between years *t* and *t*+2. We examine effects up to two years ahead to account for potential delays in converting innovation into patent applications.

[Insert Table 11 Here]

Table 11 presents the estimates based on sample splits according to financial constraints (proxied by credit rating) and operational constraints (proxied by firm size). In Panel A, we report results for financially or operationally unconstrained firms. Columns (1)-(3) show that firms that have a credit rating are more likely to apply for an automation patent. The coefficient on $\Delta Temp$ ranges from 0.024 to 0.033 and is statistically significant at each horizon. Columns

(4)-(6) show that larger firms (those more likely to have greater operational flexibility) are more likely to apply for automation patents. Although the effects are not statistically significant at conventional levels, the magnitude of the coefficients increases with the time horizon.

In Panel B of Table 11, we report results for financially or operationally constrained firms. We find no evidence that such firms—specifically, those that are unrated (columns (1)-(3)), or are smaller in size (columns (4)-(6))—are more likely to apply for an automation-related patent.

In short, the evidence suggests that less constrained firms are more likely to adapt to increases in local average temperature, whereas more constrained firms are not. Combined with our findings on the underlying economic mechanisms, this indicates that constrained firms are not only more adversely affected by temperature shocks but are also less likely to implement adaptive strategies to mitigate these effects. From a public policy perspective, this highlights the importance of targeting support toward financially and operationally constrained firms, which may lack the capacity to adapt independently (Fankhauser and Soare (2013)).

VI. Discussion and Robustness

In this section, we show extensions and robustness checks of our primary findings and discuss the interpretation of our results. The Internet Appendix presents these results.

A. Aggregate Effects: Establishment and Firm-level Outcomes

Table 12 reports the estimates of establishment-level and firm-level regression of sales and productivity. Panel A reports establishment-level results. The dependent variable is the change in the log of establishment-level sales in columns (1) and (2), and the change in the establishment sales-to-establishment employee ratio in columns (3) and (4). The main independent variable is the change in local temperature at the ZIP code level. Because pair-level sales data are not available at the establishment level, we cannot include client-by-year fixed effects and therefore do not control for firm-specific demand. We find that temperature shocks do not significantly affect establishment-level sales or productivity.

[Insert Table 12 Here]

Panel B reports firm-level results using a sample of U.S. firms drawn from the Compustat Industrial Annual database over the 2000-2018 period. We exclude financial firms (SIC codes 6000-6999) and public administration firms (SIC codes 9100-9729). Panel B1 reports results for the sample of U.S. supplier firms in our client-supplier pair-level data. Panel B2 reports results for the broader Compustat sample, without restricting attention to suppliers in the pair-level data, and therefore includes both consumer-facing and smaller firms. The dependent variables are the change in log sales, the change in sales per employee, the change in EBIT-to-assets (return on assets), and the change in net income-to-assets. The main explanatory variable is the change in average local temperature at the firm's headquarters level. As in establishment-level tests, we are unable to include client-by-year fixed effects to control for firm-specific demand. We find that temperature shocks do not significantly affect firm-level sales, productivity or profitability. Our results are consistent with Addoum et al. (2020), who find no evidence that temperature shocks affect firm performance using establishment-level or firm-level data.

Firm-level regressions need not align in sign with our supplier-client specifications for both econometric and economic reasons. Econometrically, our identification strategy estimates whether a shocked supplier sells less relative to other suppliers of the same client, not whether its absolute sales increase or decrease. Aggregating to the firm level requires the strong assumption that non-shocked suppliers' sales to the same client are unchanged, an assumption unlikely to hold when client demand is heterogeneous. Economically, suppliers facing temperature-induced supply constraints may partially offset disruptions through internal reallocation, shifting production across plants, clients, or product lines toward higher-demand or higher-margin opportunities. Consistent with this interpretation, we find no significant effect of temperature on aggregate firm-level sales, productivity, or profitability. Moreover, geographically diversified firms show greater resilience (Table 8), suggesting that multi-establishment firms can redirect production toward less-affected regions. While our results suggest that demand-side variation contributes to attenuating the firm-level supply effect, we do not have direct evidence on the sign or magnitude of demand responses to temperature shocks. Reconciling aggregate mixed findings requires additional identification of the demand channel, which is beyond the scope of this paper.

B. Importance of Economic Mechanisms

We find evidence consistent with several economic mechanisms: the labor productivity and supply channel, the financial constraints channel, the operational flexibility channel, the switching costs channel, and the adaptation channel. Because these mechanisms are not mutually exclusive and the estimated effects are similar across proxies, our results suggest that all of them contribute to explaining how local temperature affects firm sales. Figure IA.1 in the Internet Appendix summarizes the upper and lower bounds of the effect sizes and their statistical significance for each mechanism. The estimated effects of $\Delta Temp$ are negative across all five channels and are generally larger for the subsamples expected to be more vulnerable, consistent with labor productivity, financial constraints, operational flexibility, switching costs, and adaptation each playing a role in shaping the sales response to temperature changes.

C. External Validity

We rely on supplier-client data to implement our identification strategy, which restricts the analysis to business-to-business transactions. Although such transactions account for a large share of economic activity, it remains unclear whether our findings generalize to firms outside this setting. Broader firm-level data could in principle help address this question, but such data does not allow us to separately identify demand- and supply-side effects. To nonetheless assess external validity, we reweight our sample to better match the broader firm population. Table IA.1 in the Internet Appendix reruns the client-supplier sales growth regressions from Table 2 using inverse probability weights based on total sales within each two-digit SIC industry. The estimated coefficients on temperature shocks are similar in magnitude to those in Table 2, ranging from -1.9% to -2.7%.

In addition, our identification strategy relies on temperature variation within the sample of suppliers selling to the same client in one year. This excludes suppliers selling to only a single client in a given year. However, this exclusion is likely to have a limited impact as the restriction reduces the sample from 1,774 to 1,405 unique suppliers.

D. Robustness

We run additional tests to evaluate the robustness of our results to some of the measurement and estimation choices made for our baseline tests.

Table IA.2 reports the results when we use weather variables at the county level rather than at the ZIP code level. The magnitudes of the coefficients on the change in temperature are similar to those in Table 2, ranging between -1.8% and -3.0%.

Table IA.3 reports the results for the subsample in which the sum of reported firm sales accounts for at least 32% of total sales, corresponding to the median level of supplier sales coverage in our data. This test addresses concerns that the estimated effects on firm sales may be driven by suppliers with limited coverage of inter-firm transactions. While the coefficients on changes in temperature are statistically weaker, their magnitudes remain economically meaningful, ranging from -2.0% to -3.7% when client-by-year fixed effects are included.

Climate shocks are more likely to simultaneously affect the ability of firms to supply products and services as well as demand for such products and services when clients are in the same geographical areas as their suppliers (Ellison and Glaeser (1997)), as they might be affected by the same weather shocks. In our sample, 84% (87%) of the clients have at least one of their suppliers with an establishment located in the same county (state) as one of the client's establishments. In Table IA.4, we restrict the sample to relationships where a client has at least one supplier with an establishment in the same state (Panel A) or county (Panel B) of one of the client's establishments. The results in Table IA.4 are similar to those in Table 2, although coefficients are estimated with less precision in Panel B.

In Table IA.5, we focus on average temperature rather than changes in average temperature. The dependent variable is the logarithm of interfirm sales. The regressions include supplier-by-client fixed effects, so we effectively use deviations relative to the mean to estimate the regressions. The results are overall consistent with the notion that when suppliers experience higher temperatures, there is a negative impact on sales when compared to other suppliers of the same client in the same year. The estimates are larger in magnitude than those in Table 2.

In Table IA.6, we examine the role of seasonal variation by focusing on temperature changes during the summer rather than over the full year. The results are qualitatively consistent with our baseline estimates, although they are not statistically significant. This likely reflects the annual frequency of our client-supplier sales data and the resulting limited statistical power.

Table IA.7 reports the results with the change in precipitation as a control variable. In this test, we address the potential concern that instead of controlling for the level of precipitation, we should control for the change in precipitation. The coefficients on the change in precipitation are not statistically different from zero. The magnitudes of the coefficients on the change in temperature are similar to those in Table 2, ranging between -1.8% and -2.7%.

Table IA.8 reports results using alternative standard-error specifications: clustering at the ZIP code level (Panel A); clustering at the firm level (Panel B); and spatially adjusted standard errors as in Colella, Lalive, Sakalli, and Thoenig (2020) (Panel C), which address the potential concern that weather variables are spatially correlated at a broader scale (Hsiang (2016)). The Δ*Temp* coefficient remains statistically significant across all specifications.

Our baseline results in Table 2 are estimated using supplier-client relationships that persist for at least two consecutive years, because changes in interfirm sales are observed only for continuing relationships. The estimates therefore capture intensive-margin adjustments. In Table IA.9, we estimate an extensive margin regression based on equation (1) but replace the dependent variable with a dummy that takes a value of one if we observe a business transaction in year *t*-1 but not in year *t*, suggesting a termination of the relationship or a significant reduction in transactions between the client and the supplier (below the 10% of sales reporting threshold).

We find that the coefficients are not statistically significant in any of the specifications, suggesting that temperature changes are not likely to lead to the termination (or reduction below the threshold) of supply chain relationships. These results differ from those of Pankratz and Schiller (2024), who find that heatwaves and natural disasters (floods) can disrupt the global supply chain at the extensive margin. Our findings show that within the United States, changes in average temperature are not as likely to have such a disruptive effect on business relationships. This may be explained by the fact that our sample is a domestic supply-chain network rather than a global one, and clients and suppliers may have stronger business relationships and lower information asymmetries due to their geographical proximity (i.e., they are located in the same county). This finding may also reflect the nature of the weather shocks we study: changes in average temperature are less severe than the extreme weather events analyzed by Pankratz and Schiller (2024) and may therefore cause less disruption to supply chain relationships.

Table IA.10 provides additional evidence on the financial constraints channel. We show that the results are driven by more financially constrained firms, as indicated by higher WW, KZ, and SA indices, and a higher proportion of long-term debt maturing within one year.

Table IA.11 provides additional evidence on the switching-cost channel. We test the hypothesis that temperature shocks have stronger effects on supplier firms that are more easily replaceable, i.e., those facing lower switching costs. In particular, we hypothesize that suppliers whose clients have greater international exposure are more substitutable, as such clients are likely to have access to a broader set of alternative suppliers and more flexible sourcing options. Consistent with this hypothesis, we find larger effects for suppliers with low patent citations, low interfirm sales share, low market share, fewer clients over the sample period, and whose clients have greater international exposure.

VII. Conclusion

This paper studies the effects of changes in average temperature in the real economy by exploiting variation in production networks. We compare sales of intermediate goods across suppliers that trade with the same client but are exposed to different changes in temperature, which allows us to isolate supply-side effects from demand-side effects.

We show that changes in local temperature can have sizable effects on firm sales at the intensive margin. A 1°C increase in average local temperature leads to a negative and significant effect of about 2.5% on annual sales. We interpret these effects as supply-driven, since they originate from the supplier's exposure to temperature. Sales declines are more pronounced among firms experiencing larger temperature increases and among firms located in cooler regions.

We examine the mechanisms through which changes in local temperature affect firm sales. First, the reduction in sales due to increases in local temperature is primarily driven by firms operating in heat-sensitive industries, manufacturing industries, and labor-intensive firms, suggesting that lower labor supply and productivity are driving our effects. Second, we find that financially unconstrained firms are better able to deal with the adverse effects of increased local temperature and, therefore, face lower temperature-related reductions in sales. This suggests that financial constraints play an essential role in firms' ability to adapt to climate change. Conglomerates and firms that are geographically diversified also cope better with the effects of climate change as they have more operational flexibility. Finally, input specificity and switching costs are important drivers of the impact of temperature on firm sales. The evidence suggests that suppliers experience a smaller decline in sales when they produce specific inputs or when their clients have higher switching costs.

Overall, our findings suggest that climate change can materially affect firm sales and real economic activity. These results underscore the importance of isolating supply-side channels when designing policy responses to climate change. They also highlight the need to target support toward financially and operationally constrained firms, which may lack the capacity to adapt without external assistance. Credibly identifying the demand-side effects of temperature shocks, and whether they reinforce or offset supply-side losses, remains an important direction for future research.

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Table 1: Summary Statistics - Client-Supplier Pair Sample

Panel A presents the number of observations (supplier-client pairs), number of suppliers, number of clients, average number of suppliers per client, average fraction of the supplier's total sales, and the average temperature and change in temperature at the ZIP codes of supplier firms' headquarters or establishments included in the sample each year. Panels B and C present mean, 25th percentile, 50th percentile (median), 75th percentile, standard deviation, and number of observations for each supplier and client variable. The sample consists of annual observations of Compustat firms from 2000 to 2018. Detailed variable definitions are in Table A.1 in the Appendix.

Panel A: Sample by Year

Year	Observations	Unique Suppliers	Unique Clients	Average Number of Suppliers per Client	Average Supplier Sales Coverage	Average Temperature in Supplier Headquarters	Average Change in Temperature in Supplier Headquarters	Average Temperature in Supplier Establishments	Average Change in Temperature in Supplier Establishments
2000	414	291	94	4.4	0.357	13.9	-0.299	12.9	-0.273
2001	610	412	120	5.1	0.374	14.0	-0.200	12.9	-0.205
2002	620	408	132	4.7	0.390	14.0	0.388	12.9	0.339
2003	675	455	136	5.0	0.370	13.5	-0.558	12.7	-0.484
2004	647	431	130	5.0	0.365	13.8	0.261	13.1	0.232
2005	625	418	121	5.2	0.381	13.9	0.172	13.3	0.155
2006	692	450	131	5.3	0.380	14.5	0.347	13.6	0.315
2007	655	446	127	5.2	0.369	14.2	-0.370	13.3	-0.326
2008	641	437	128	5.0	0.374	14.2	-0.249	12.9	-0.249
2009	574	396	117	4.9	0.358	13.9	-0.146	12.8	-0.126
2010	563	384	113	5.0	0.360	14.2	0.321	12.9	0.228
2011	559	381	111	5.0	0.380	14.1	-0.012	13.1	0.075
2012	543	353	109	5.0	0.376	15.2	0.970	13.9	0.893
2013	542	360	113	4.8	0.378	14.5	-1.058	13.2	-1.007
2014	556	364	119	4.7	0.382	14.0	-0.153	12.8	-0.171
2015	490	325	110	4.5	0.385	14.5	0.671	13.3	0.655
2016	456	303	104	4.4	0.395	15.0	0.605	14.0	0.562
2017	429	287	100	4.3	0.390	14.8	-0.126	14.0	-0.086
2018	439	271	98	4.5	0.412	14.3	-0.544	13.7	-0.515
Total Unique	10,730	1,405	331	–	–	–	–	–	–
Average	–	–	–	4.8	0.377	14.1	-0.001	13.1	-0.004

Table 1: Continued

Panel B: Suppliers

Variable	Mean	25th Percentile	Median	75th Percentile	Standard Deviation	Observations
Δlog(Sales)	0.016	-0.154	0.037	0.223	0.493	10,730
ΔTemp	-0.001	-0.517	0.012	0.529	0.864	10,730
$\Delta Temp^{Est.\ emp.\text{-}weighted}$	-0.004	-0.403	0.006	0.408	0.720	10,697
Temp	14.061	10.398	13.239	17.134	4.452	10,730
$Temp^{Est.\ emp.\text{-}weighted}$	13.140	10.770	12.854	15.422	3.718	10,697
Prcp	2.453	1.287	2.606	3.333	1.228	10,730
$Prcp^{Est.\ emp.\text{-}weighted}$	2.336	1.627	2.411	2.981	0.974	10,697
Log(Assets)	5.954	4.613	5.934	7.242	1.843	10,730
Tobin's Q	1.995	1.124	1.524	2.248	1.489	10,730
Cash	0.244	0.043	0.168	0.390	0.238	10,730
Leverage	0.140	0.001	0.084	0.231	0.160	10,730
Tangibility	0.220	0.069	0.150	0.295	0.212	10,730
Cold/WindChill	0.001	0.000	0.000	0.000	0.032	10,730
Heavy Snow	0.000	0.000	0.000	0.000	0.014	10,730
Heat	0.003	0.000	0.000	0.000	0.053	10,730
Hot Days	40.064	23.000	40.000	56.000	21.303	10,730
Heavy Rain	0.010	0.000	0.000	0.000	0.099	10,730
Flood	0.023	0.000	0.000	0.000	0.151	10,730
Automation Patent Application	0.306	0.000	0.000	1.000	0.461	8,916

Panel C: Clients

Variable	Mean	25th Percentile	Median	75th Percentile	Standard Deviation	Observations
Temp	13.998	10.682	12.688	16.491	4.203	4,256
$Temp^{Est.\ emp.\text{-}weighted}$	12.402	10.659	12.511	13.920	3.072	9,436
Log(Assets)	10.756	9.786	10.759	12.005	1.408	9,423
Tobin's Q	1.807	1.166	1.493	1.988	0.986	9,023
Cash	0.104	0.036	0.069	0.134	0.104	9,423
Leverage	0.174	0.077	0.136	0.223	0.141	9,023
Tangibility	0.289	0.098	0.249	0.499	0.209	9,410

Table 2: Client-Supplier Sales Growth Regressions

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. Panel A reports results using weather variables measured at the corporate headquarters' ZIP code level. Panel B reports results using weather variables measured at the supplier establishments' ZIP code level and aggregated to the firm level using establishment employment as weights. The dependent variable, Δlog(*Sales*), is the change in the log of sales from supplier *i* to client *j* between year *t*-1 and year *t*. Δ*Temp* is the change in average daily temperature in degrees Celsius at the ZIP code of supplier *i*'s corporate headquarters from year *t*-1 to year *t*. *Prcp* is the average daily precipitation in millimeters at the ZIP code of supplier *i*'s corporate headquarters in year *t*. $\Delta Temp^{Est.\ emp\text{-}weighted}$ is the change in average establishment employment-weighted daily temperature in degrees Celsius for supplier *i* from year *t*-1 to year *t*. $Prcp^{Est.\ emp\text{-}weighted}$ is the average establishment employment-weighted daily precipitation in millimeters for supplier *i* in year *t*. *Assets* is total assets. *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. *Leverage* is the ratio of total debt to the market value of assets. *Tangibility* is the ratio of net property, plant, and equipment to total assets. All financial variables are for the supplier and lagged by one year. Detailed variable definitions are provided in Table A.1 in the Appendix. The sample consists of annual observations of Compustat supplier-client pairs from 2000 to 2018. Industry fixed effects are defined at the two-digit SIC level. Robust standard errors are clustered at the supplier headquarters' county level in Panel A and at the supplier establishments' county level in Panel B. *p*-values are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Headquarters

	1	2	3	4	5	6
$\Delta Temp_t$	-0.016**	-0.025***	-0.026**	-0.023***	-0.024**	-0.023**
	(0.016)	(0.000)	(0.015)	(0.001)	(0.018)	(0.030)
$\Delta Temp_{t-1}$						-0.002
						(0.858)
$\Delta Temp_{t+1}$						0.001
						(0.932)
$\Delta Temp_{t+2}$						0.002
						(0.814)
Prcp	-0.002	0.002	-0.004	0.004	-0.002	0.005
	(0.590)	(0.698)	(0.578)	(0.405)	(0.815)	(0.305)
Log(Assets)				0.011***	0.012***	0.002
				(0.000)	(0.003)	(0.533)
Tobin's Q				0.040***	0.036***	0.039***
				(0.000)	(0.000)	(0.000)
Cash				-0.053	-0.037	-0.058
				(0.163)	(0.546)	(0.290)
Leverage				0.021	0.018	0.094*
				(0.535)	(0.747)	(0.077)
Tangibility				0.022	-0.000	0.032
				(0.547)	(0.998)	(0.538)
Observations	10,730	10,730	7,489	10,730	7,489	3,873
R-squared	0.016	0.321	0.392	0.330	0.399	0.397
Year FE	Yes	No	No	No	No	No
Client-Year FE	No	Yes	No	Yes	No	Yes
Ind.-Client-Year FE	No	No	Yes	No	Yes	No

Table 2: Continued

Panel B: Establishments

	1	2	3	4	5	6
$\Delta Temp^{Est.\ emp.\text{-}weighted}_{t}$	-0.021**	-0.027***	-0.030**	-0.025**	-0.027*	-0.039**
	(0.027)	(0.005)	(0.043)	(0.010)	(0.070)	(0.023)
$\Delta Temp^{Est.\ emp.\text{-}weighted}_{t-1}$						-0.002
						(0.906)
$\Delta Temp^{Est.\ emp.\text{-}weighted}_{t+1}$						-0.014
						(0.265)
$\Delta Temp^{Est.\ emp.\text{-}weighted}_{t+2}$						0.003
						(0.856)
$Prcp^{Est.\ emp.\text{-}weighted}$	-0.002	0.005	0.005	0.009	0.010	0.008
	(0.791)	(0.451)	(0.558)	(0.193)	(0.269)	(0.350)
Tobin's Q				0.040***	0.037***	0.037***
				(0.000)	(0.000)	(0.000)
Log(Assets)				0.010***	0.012***	0.002
				(0.000)	(0.003)	(0.412)
Cash				-0.049	-0.033	-0.064
				(0.198)	(0.591)	(0.238)
Leverage				0.022	0.013	0.098*
				(0.523)	(0.803)	(0.059)
Tangibility				0.026	0.000	0.035
				(0.480)	(0.996)	(0.489)
Observations	10,697	10,692	7,459	10,692	7,459	3,856
R-squared	0.016	0.320	0.391	0.329	0.398	0.397
Year FE	Yes	No	No	No	No	No
Client-Year FE	No	Yes	No	Yes	No	Yes
Ind.-Client-Year FE	No	No	Yes	No	Yes	No

Table 3: Temperature Quintiles

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. Panel A reports results using weather variables measured at the corporate headquarters' ZIP code level. Panel B reports results using weather variables measured at the supplier establishments' ZIP code level and aggregated to the firm level using establishment employment as weights. The dependent variable, Δlog(*Sales*), is the change in the log of sales from supplier *i* to client *j* between year *t*-1 and year *t*. $\Delta Temp^{Q2}$,…, $\Delta Temp^{Q5}$ are indicator variables equal to one if Δ*Temp,* the change in average daily temperature in degrees Celsius at the ZIP code of supplier *i*'s corporate headquarters from year *t*-1 to year *t,* is in the 2nd, …, 5th quintile, and zero otherwise. *Prcp* is the average daily precipitation in millimeters at the ZIP code of supplier *i*'s corporate headquarters in year *t*. $\Delta Temp^{Est.\ emp.\text{-}weighted,Q2}$,…, $\Delta Temp^{Est.\ emp.\text{-}weighted,Q5}$ are indicator variables equal to one if $\Delta Temp^{Est.\ emp.\text{-}weighted}$, the change in average establishment employment-weighted daily temperature in degrees Celsius for supplier *i* from year *t*-1 to year *t,* is in the 2nd, …, 5th quintile, and zero otherwise. $Prcp^{Est.\ emp\text{-}weighted}$ is the average establishment employment-weighted daily precipitation in millimeters for supplier *i* in year *t*. Regressions in columns (4) and (5) include the same control variables as those in Table 2 (coefficients not shown). All financial variables are for the supplier and lagged by one year. Detailed variable definitions are provided in Table A.1 in the Appendix. The sample consists of annual observations of Compustat supplier-client pairs from 2000 to 2018. Industry fixed effects are defined at the two-digit SIC level. Robust standard errors are clustered at the supplier headquarters' county level in Panel A and at the supplier establishments' county level in Panel B. *p*-values are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Headquarters

	1	2	3	4	5
$\Delta Temp^{Q2}$	-0.000	-0.006	0.016	-0.011	0.010
	(0.985)	(0.726)	(0.401)	(0.536)	(0.607)
$\Delta Temp^{Q3}$	-0.033**	-0.031*	-0.024	-0.036**	-0.031
	(0.049)	(0.075)	(0.288)	(0.039)	(0.181)
$\Delta Temp^{Q4}$	-0.030*	-0.033	-0.011	-0.031	-0.012
	(0.092)	(0.106)	(0.665)	(0.116)	(0.643)
$\Delta Temp^{Q5}$	-0.043**	-0.059***	-0.056**	-0.058***	-0.056**
	(0.013)	(0.001)	(0.020)	(0.001)	(0.018)
Prcp	-0.003	0.002	-0.002	0.004	-0.000
	(0.578)	(0.647)	(0.743)	(0.398)	(0.955)
Observations	10,730	10,730	7,489	10,730	7,489
R-squared	0.016	0.321	0.392	0.330	0.400
Controls	No	No	No	Yes	Yes
Year FE	Yes	No	No	No	No
Client-Year FE	No	Yes	No	Yes	No
Ind.-Client-Year FE	No	No	Yes	No	Yes

Table 3: Continued

Panel B: Establishments

	1	2	3	4	5
$\Delta Temp^{Est.\ emp.\text{-}weighted,Q2}$	0.008	0.007	-0.002	0.009	-0.003
	(0.638)	(0.670)	(0.937)	(0.605)	(0.900)
$\Delta Temp^{Est.\ emp.\text{-}weighted,Q3}$	-0.033*	-0.036	-0.057*	-0.039*	-0.061*
	(0.078)	(0.100)	(0.067)	(0.077)	(0.057)
$\Delta Temp^{Est.\ emp.\text{-}weighted,Q4}$	-0.027	-0.037	-0.039	-0.034	-0.037
	(0.215)	(0.119)	(0.248)	(0.136)	(0.273)
$\Delta Temp^{Est.\ emp.\text{-}weighted,Q5}$	-0.037*	-0.044**	-0.054*	-0.041*	-0.050*
	(0.088)	(0.037)	(0.059)	(0.054)	(0.078)
$Prcp^{Est.\ emp.\text{-}weighted}$	-0.002	0.005	0.003	0.008	0.007
	(0.776)	(0.503)	(0.717)	(0.262)	(0.423)
Observations	10,697	10,692	7,459	10,692	7,459
R-squared	0.016	0.320	0.391	0.329	0.399
Controls	No	No	No	Yes	Yes
Year FE	Yes	No	No	No	No
Client-Year FE	No	Yes	No	Yes	No
Ind.-Client-Year FE	No	No	Yes	No	Yes

Table 4: Local Climate and Weather Conditions

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 year *t*-1 and year *t*. Δ*Temp* is the change in average daily temperature in degrees Celsius at the ZIP code of supplier *i*'s corporate headquarters from year *t*-1 to year *t*. *Prcp* is the average daily precipitation in millimeters at the ZIP code of supplier *i*'s corporate headquarters in year *t*. Firms are partitioned into groups based on the criteria indicated in each panel, with continuous variables split at the median. Panel A uses annual average temperature (columns (1) and (2)) and temperature normal (columns (3) and (4)). Panel B uses summer temperature defined using calendar months (columns (1) and (2)) and the three consecutive months with the highest temperature normal (columns (3) and (4)). Panel C uses positive (columns (1) and (2)) and absolute deviations from temperature normal (columns (3) and (4)). Regressions include the same control variables as those in Table 2 (coefficients not shown). All financial variables are for the supplier and lagged by one year. Detailed variable definitions are provided in Table A.1 in the Appendix. The sample consists of annual observations of Compustat supplier-client pairs from 2000 to 2018. Robust standard errors are clustered at the supplier headquarters' county level. *p*-values are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Local Climate

	Low Average Temperature	High Average Temperature	Low Temperature Normal	High Temperature Normal
	1	2	3	4
ΔTemp	-0.032**	-0.022	-0.032**	-0.016
	(0.016)	(0.144)	(0.015)	(0.269)
Prcp	0.000	0.004	0.000	0.008
	(0.983)	(0.518)	(0.986)	(0.221)
Observations	4,711	4,753	4,700	4,752
R-squared	0.357	0.381	0.357	0.388
Controls	Yes	Yes	Yes	Yes
Client-Year FE	Yes	Yes	Yes	Yes

Panel B: Summer Temperatures

	Low Summer Temperature (Calendar)	High Summer Temperature (Calendar)	Low Summer Temperature (Average Normal)	High Summer Temperature (Average Normal)
	1	2	3	4
ΔTemp	-0.031**	-0.012	-0.031**	-0.012
	(0.012)	(0.495)	(0.012)	(0.495)
Prcp	-0.001	0.005	-0.001	0.005
	(0.939)	(0.319)	(0.939)	(0.319)
Observations	4,709	4,758	4,709	4,758
R-squared	0.358	0.386	0.358	0.386
Controls	Yes	Yes	Yes	Yes
Client-Year FE	Yes	Yes	Yes	Yes

Table 4: Continued

Panel C: Deviations from Normal

	Low Positive Deviations	High Positive Deviations	Low Absolute Deviations	High Absolute Deviations
	1	2	3	4
ΔTemp	-0.023	-0.029**	-0.008	-0.027***
	(0.156)	(0.011)	(0.540)	(0.009)
Prcp	0.002	-0.003	-0.010	-0.000
	(0.807)	(0.762)	(0.260)	(0.971)
Observations	4,712	4,673	4,775	4,758
R-squared	0.377	0.353	0.359	0.371
Controls	Yes	Yes	Yes	Yes
Client-Year FE	Yes	Yes	Yes	Yes

Table 5: Extreme Weather Events

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier-client pair level. The dependent variable, Δlog(*Sales*), is the change in the log of sales from supplier *i* to client *j* between year *t*-1 and year *t*. *Cold/Windchill*, *Heavy Snow, Heat$_t$*, *Heavy Rain*, and *Flood* are indicator variables equal to one if the relevant extreme weather event (as recorded in NOAA's Storm Events Database) has resulted in fatalities in supplier *i*'s headquarters county in year *t*. *Hot Days* is the number of days when daily mean temperature exceeds the corresponding monthly temperature normal by at least five degrees Celsius at the ZIP code of supplier *i*'s corporate headquarters in year *t*. *Temp* is the average daily temperature in degrees Celsius at the ZIP code of supplier *i*'s corporate headquarters in year *t*. *Prcp* is the average daily precipitation in millimeters at the ZIP code of supplier *i*'s corporate headquarters in year *t*. Regressions include the same control variables as those in Table 2 (coefficients not shown). All financial variables are for the supplier and lagged by one year. Detailed variable definitions are provided in Table A.1 in the Appendix. The sample consists of annual observations of Compustat supplier-client pairs from 2000 to 2018. Robust standard errors are clustered at the supplier headquarters' county level. *p*-values are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Cold-related Extreme Weather Events

	1	2	3	4
Cold/Wind Chill	-0.141	-0.254*		
	(0.140)	(0.089)		
Heavy Snow			-0.284	-0.381**
			(0.154)	(0.047)
Observations	10,730	7,489	10,730	7,489
R-squared	0.329	0.399	0.329	0.399
Controls	Yes	Yes	Yes	Yes
Client-Year FE	Yes	No	Yes	No
Ind.-Client-Year FE	No	Yes	No	Yes

Panel B: Heat-related Extreme Weather Events

	1	2	3	4
Heat	-0.010	-0.074		
	(0.899)	(0.590)		
Hot Days			-0.001*	-0.001*
			(0.059)	(0.069)
Observations	10,730	7,489	10,730	7,489
R-squared	0.329	0.399	0.330	0.399
Controls	Yes	Yes	Yes	Yes
Client-Year FE	Yes	No	Yes	No
Ind.-Client-Year FE	No	Yes	No	Yes

Table 5: Continued

Panel C: Precipitation-related Extreme Weather Events

	1	2	3	4
Heavy Rain	0.029	0.059		
	(0.619)	(0.410)		
Flood			-0.015	-0.040
			(0.510)	(0.265)
Observations	10,730	7,489	10,730	7,489
R-squared	0.329	0.399	0.329	0.399
Controls	Yes	Yes	Yes	Yes
Client-Year FE	Yes	No	Yes	No
Ind.-Client-Year FE	No	Yes	No	Yes

Table 6: Labor Supply and Productivity Channel

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 year *t*-1 and year *t*. Δ*Temp* is the change in average daily temperature in degrees Celsius at the ZIP code of supplier *i*'s corporate headquarters from year *t*-1 to year *t*. *Prcp* is the average daily precipitation in millimeters at the ZIP code of supplier *i*'s corporate headquarters in year *t*. Firms are partitioned into groups based on the criteria indicated in each panel, with continuous variables split at the median. Panel A uses an indicator for manufacturing industries (SIC codes between 2000 and 3999). Panel B uses occupational heat exposure, following Xiao (2024b). Panel C uses labor intensity. Regressions include the same control variables as those in Table 2 (coefficients not shown). All financial variables are for the supplier and lagged by one year. Detailed variable definitions are provided in Table A.1 in the Appendix. The sample consists of annual observations of Compustat supplier-client pairs from 2000 to 2018. Robust standard errors are clustered at the supplier headquarters' county level. *p*-values are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Manufacturing Industries

	Manufacturing Industries	Non-manufacturing Industries
	1	2
ΔTemp	-0.038***	0.002
	(0.000)	(0.932)
Prcp	-0.001	0.002
	(0.832)	(0.861)
Observations	7,648	2,285
R-squared	0.325	0.443
Controls	Yes	Yes
Client-Year FE	Yes	Yes
p-value of difference	0.059	

Panel B: Occupational Heat Exposure

	High Exposure	Low Exposure
	1	2
ΔTemp	-0.032***	-0.013
	(0.003)	(0.202)
Prcp	0.006	0.008
	(0.461)	(0.212)
Observations	4,842	4,787
R-squared	0.344	0.364
Controls	Yes	Yes
Client-Year FE	Yes	Yes
p-value of difference	0.229	

Table 6: Continued

Panel C: Labor Intensity

	High Labor Intensity	Low Labor Intensity
	1	2
ΔTemp	-0.023**	-0.012
	(0.018)	(0.352)
Prcp	0.015**	-0.003
	(0.011)	(0.650)
Observations	4,778	4,768
R-squared	0.366	0.368
Controls	Yes	Yes
Client-Year FE	Yes	Yes
p-value of difference	0.513	

Table 7: Financial Constraints Channel

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 year *t*-1 and year *t*. Δ*Temp* is the change in average daily temperature in degrees Celsius at the ZIP code of supplier *i*'s corporate headquarters from year *t*-1 to year *t*. *Prcp* is the average daily precipitation in millimeters at the ZIP code of supplier *i*'s corporate headquarters in year *t*. Firms are partitioned into groups based on the criteria indicated in each panel, with continuous variables split at the median. Panel A uses an indicator for the presence of an S&P credit rating. Panel B uses the payout ratio. Panel C uses the financial constraints composite index, following Bartram et al. (2022). Regressions include the same control variables as in Table 2, columns (4) and (5) (coefficients not shown). All financial variables are for the supplier and lagged by one year. Detailed variable definitions are provided in Table A.1 in the Appendix. The sample consists of annual observations of Compustat supplier-client pairs from 2000 to 2018. Robust standard errors are clustered at the supplier headquarters' county level. *p*-values are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Credit Rating

	Unrated	Rated
	1	2
ΔTemp	-0.030***	-0.001
	(0.000)	(0.950)
Prcp	0.006	-0.009
	(0.294)	(0.291)
Observations	8,346	1,547
R-squared	0.340	0.439
Controls	Yes	Yes
Client-Year FE	Yes	Yes
p-value of difference	0.037	

Panel B: Payout

	Low Payout	High Payout
	1	2
ΔTemp	-0.038***	-0.003
	(0.000)	(0.708)
Prcp	0.006	0.001
	(0.398)	(0.850)
Observations	5,679	3,861
R-squared	0.359	0.377
Controls	Yes	Yes
Client-Year FE	Yes	Yes
p-value of difference	0.007	

Table 7: Continued

Panel C: Financial Constraints Composite Index

	High Financial Constraints Composite Index	Low Financial Constraints Composite Index
	1	2
ΔTemp	-0.039***	-0.004
	(0.001)	(0.674)
Prcp	0.009	-0.003
	(0.352)	(0.579)
Observations	4,747	4,817
R-squared	0.362	0.382
Controls	Yes	Yes
Client-Year FE	Yes	Yes
p-value of difference	0.013	

Table 8: Operational Constraints Channel

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 year *t*-1 and year *t*. Δ*Temp* is the change in average daily temperature in degrees Celsius at the ZIP code of supplier *i*'s corporate headquarters from year *t*-1 to year *t*. *Prcp* is the average daily precipitation in millimeters at the ZIP code of supplier *i*'s corporate headquarters in year *t*. Firms are partitioned into groups based on the criteria indicated in each panel, with continuous variables split at the median. Panel A uses total assets. Panel B uses the number of counties with an establishment. Panel C uses the Herfindahl-Hirschman Index (HHI) based on establishment sales. Regressions include the same control variables as in Table 2, columns (4) and (5) (coefficients not shown). All financial variables are for the supplier and lagged by one year. Detailed variable definitions are provided in Table A.1 in the Appendix. The sample consists of annual observations of Compustat supplier-client pairs from 2000 to 2018. Robust standard errors are clustered at the supplier headquarters' county level. *p*-values are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Assets

	Low Assets	High Assets
	1	2
ΔTemp	-0.044***	-0.002
	(0.000)	(0.850)
Prcp	0.005	-0.007
	(0.598)	(0.304)
Observations	4,810	4,779
R-squared	0.359	0.399
Controls	Yes	Yes
Client-Year FE	Yes	Yes
p-value of difference	0.009	

Panel B: Number of Counties with an Establishment

	Low Number of Counties	High Number of Counties
	1	2
ΔTemp	-0.036***	-0.004
	(0.004)	(0.637)
Prcp	0.005	0.001
	(0.508)	(0.862)
Observations	5,044	4,485
R-squared	0.361	0.386
Controls	Yes	Yes
Client-Year FE	Yes	Yes
p-value of difference	0.044	

Table 8: Continued

Panel C: HHI Establishment Sales

	High HHI Establishment Sales	Low HHI Establishment Sales
	1	2
ΔTemp	-0.036***	-0.004
	(0.009)	(0.576)
Prcp	0.008	0.003
	(0.305)	(0.658)
Observations	4,730	4,672
R-squared	0.368	0.391
Controls	Yes	Yes
Client-Year FE	Yes	Yes
p-value of difference	0.068	

Table 9: Switching Costs Channel

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 year *t*-1 and year *t*. Δ*Temp* is the change in average daily temperature in degrees Celsius at the ZIP code of supplier *i*'s corporate headquarters from year *t*-1 to year *t*. *Prcp* is the average daily precipitation in millimeters at the ZIP code of supplier *i*'s corporate headquarters in year *t*. Firms are partitioned into groups based on the criteria indicated in each panel, with continuous variables split at the median. Panel A uses an indicator for firms in industries that sell standardized goods, defined as in Giannetti et al. (2011). Panel B uses innovation value, constructed as in Kogan et al. (2017). Panel C uses the duration of the supplier-client relationship. Regressions include the same control variables as in Table 2, columns (4) and (5) (coefficients not shown). All financial variables are for the supplier and lagged by one year. Detailed variable definitions are provided in Table A.1 in the Appendix. The sample consists of annual observations of Compustat supplier-client pairs from 2000 to 2018. Robust standard errors are clustered at the supplier headquarters' county level. *p*-values are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Standardized Goods

	Standardized Goods	Non-Standardized Goods
	1	2
ΔTemp	-0.032**	-0.025***
	(0.039)	(0.006)
Prcp	-0.012	0.009
	(0.245)	(0.138)
Observations	2,379	6,723
R-squared	0.307	0.330
Controls	Yes	Yes
Client-Year FE	Yes	Yes
p-value of difference	0.701	

Panel B: Innovation Value

	Zero Innovation Value	Positive Innovation Value
	1	2
ΔTemp	-0.028***	-0.003
	(0.003)	(0.785)
Prcp	0.010*	-0.008
	(0.095)	(0.421)
Observations	5,504	4,146
R-squared	0.379	0.364
Controls	Yes	Yes
Client-Year FE	Yes	Yes
p-value of difference	0.130	

Table 9: Continued

Panel C: Duration of Supplier-Client Relationship

	Short Relationship	Long Relationship
	1	2
ΔTemp	-0.035***	-0.014*
	(0.006)	(0.094)
Prcp	0.002	0.006
	(0.837)	(0.184)
Observations	5,198	4,703
R-squared	0.373	0.376
Controls	Yes	Yes
Client-Year FE	Yes	Yes
p-value of difference	0.164	

Table 10: Adaptation Channel

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 year *t*-1 and year *t*. Δ*Temp* is the change in average daily temperature in degrees Celsius at the ZIP code of supplier *i*'s corporate headquarters from year *t*-1 to year *t*. *Prcp* is the average daily precipitation in millimeters at the ZIP code of supplier *i*'s corporate headquarters in year *t*. Firms are partitioned into groups based on the criteria indicated in each panel, with continuous variables split at the median. Panel A uses an indicator for automation-related patent applications from year *t*-2 to year *t*, as identified in Mann and Püttmann (2023). Panel B uses an indicator for having a new establishment in a new county over year *t*-2 to year *t*. Panel C uses the three-year average investment rate over year *t*-2 and year *t*. Regressions include the same control variables as those in Table 2 (coefficients not shown). All financial variables are for the supplier and lagged by one year. Detailed variable definitions are provided in Table A.1 in the Appendix. The sample consists of annual observations of Compustat supplier-client pairs from 2000 to 2014 in Panel A, and from 2000 to 2018 in Panels B and C. Robust standard errors are clustered at the supplier headquarters' county level. *p*-values are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Automation Patent Applications

	No Automation	Automation
	1	2
ΔTemp	-0.031**	-0.009
	(0.019)	(0.499)
Prcp	0.003	-0.011
	(0.697)	(0.184)
Observations	4,507	3,414
R-squared	0.355	0.364
Controls	Yes	Yes
Client-Year FE	Yes	Yes
p-value of difference	0.288	

Panel B: Has New Establishments in a New County

	No New County	New County
	1	2
ΔTemp	-0.042***	-0.007
	(0.005)	(0.423)
Prcp	0.003	0.003
	(0.772)	(0.677)
Observations	3,680	5,665
R-squared	0.367	0.390
Controls	Yes	Yes
Client-Year FE	Yes	Yes
p-value of difference	0.047	

Table 10: Continued

Panel C: Investment Rate

	Low Investment Rate		High Investment Rate
	1		2
ΔTemp	-0.026***		-0.020
	(0.009)		(0.143)
Prcp	-0.000		0.011
	(0.977)		(0.101)
Observations	4,663		4,725
R-squared	0.350		0.379
Controls	Yes		Yes
Client-Year FE	Yes		Yes
p-value of difference		0.738	

Table 11: Adaptation - The Role of Operational and Financial Constraints

This table presents estimates of ordinary least squares (OLS) panel regressions at the supplier firm level. The dependent variable, *Automation Patent Application,* is an indicator variable equal to one if supplier *i* has made an automation-related patent application from year *t* to year $t+\tau$, as identified in Mann and Püttmann (2023), and zero otherwise. Δ*Temp* is the change in average daily temperature in degrees Celsius at the ZIP code of supplier *i*'s corporate headquarters from year *t*-1 to year *t*. *Prcp* is the average daily precipitation in millimeters at the ZIP code of supplier *i*'s corporate headquarters in year *t*. Panel A reports the results for supplier firms with low operational and financial constraints. Panel B reports the results for supplier firms with high operational and financial constraints. Firms are partitioned into groups based on the criteria indicated in the column subheadings, with continuous variables split at the median. Columns (1)-(3) use an indicator for the presence of an S&P credit rating. Columns (4)-(6) use total assets. Regressions include the same control variables as those in Table 2 (coefficients not shown). All financial variables are lagged by one period. Detailed variable definitions are provided in Table A.1 in the Appendix. The sample consists of annual observations of Compustat supplier firms from 2000 to 2014. Industry fixed effects are defined at the two-digit SIC level. Robust standard errors are clustered at the supplier headquarters' county level. *p*-values are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Low Operational and Financial Constraints

	Rated			High Assets		
	1	2	3	4	5	6
	[*t*,*t*]	[*t*,*t*+1]	[*t*,*t*+2]	[*t*,*t*]	[*t*,*t*+1]	[*t*,*t*+2]
ΔTemp	0.024*	0.033**	0.031**	0.006	0.008	0.009
	(0.073)	(0.013)	(0.015)	(0.392)	(0.245)	(0.155)
Prcp	0.003	0.006	0.006	-0.017	-0.015	-0.014
	(0.874)	(0.764)	(0.770)	(0.211)	(0.240)	(0.278)
Observations	1,762	1,762	1,762	5,821	5,821	5,821
R-squared	0.488	0.498	0.505	0.458	0.460	0.461
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: High Operational and Financial Constraints

	Unrated			Low Assets		
	1	2	3	4	5	6
	[*t*,*t*]	[*t*,*t*+1]	[*t*,*t*+2]	[*t*,*t*]	[*t*,*t*+1]	[*t*,*t*+2]
$\Delta Temp_t$	-0.000	-0.002	-0.002	0.001	-0.002	-0.004
	(0.996)	(0.542)	(0.580)	(0.841)	(0.601)	(0.451)
Prcp	-0.033***	-0.033***	-0.032***	-0.032***	-0.033***	-0.033***
	(0.006)	(0.005)	(0.007)	(0.004)	(0.004)	(0.008)
Observations	10,515	10,515	10,515	6,448	6,448	6,448
R-squared	0.363	0.371	0.372	0.257	0.284	0.291
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 12: Establishment- and Firm-Level Results

This table presents estimates of ordinary least squares (OLS) panel regressions at the establishment and firm levels. In Panel A, the dependent variable is Δlog(*Sales*^{Est}) in columns (1) and (2), and Δ(*Sale*^{Est}/*Employees*^{Est}) in columns (3) and (4). Δlog(*Sales*^{Est}) is the change in the log of establishment sales between year *t*-1 and year *t*. Δ(*Sale*^{Est}/*Employees*^{Est}) is the change in the log of establishment sales-to-establishment employment between year *t*-1 and year *t*. Δ*Temp*$^{Est.}$ is the change in average daily temperature in degrees Celsius at the ZIP code of the establishment from year *t*-1 to year *t*. *Prcp*$^{Est.}$ is the average daily precipitation in millimeters at the ZIP code of the establishment in year *t*. Log(*Emp*$^{Est.}$) is the log of establishment employment in year *t*-1. In Panels B1 and B2, the dependent variable is Δlog(*Sales*) in columns (1) and (2), Δ(*Sales/Employees*) in columns (3) and (4), Δ*(EBIT/Assets)* in columns (5) and (6), and Δ*(Net Income/Assets)* in columns (7) and (8). Δlog(*Sales*) is the change in the log of total sales between years *t*-1 and *t*. Δ*(Sales/Employees)* is the change in the ratio of total sales in year *t* to total employees in year *t*-1. Δ*(EBIT/Assets)* is the change in the ratio of operating income in year *t* divided by total assets in year *t*-1. Δ*(Net Income/Assets)* is the change in the ratio of net income in year *t* to total assets in year *t*-1. Δ*Temp* is the change in average daily temperature in degrees 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* in year *t*. Detailed variable definitions are provided in Table A.1 in the Appendix. Regressions in Panels B1 and B2 include the same control variables as in Table 2, columns (4) and (5) (coefficients not shown). In Panel A, the sample consists of annual observations of NETS establishments that are linked to Compustat suppliers. In Panel B1, the sample consists of annual observations of Compustat supplier firms. In Panel B2, the sample consists of annual observations for Compustat firms with sales exceeding $5 million. The sample period is from 2000 to 2018. Robust standard errors are clustered at the supplier establishments' county level in Panel A and at the firm headquarters' county level in Panel B. *p*-values are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Establishment-Level Results

Dependent Variable:	Δlog(Sale$^{Est.}$)		Δ(Sale$^{Est.}$/Employees$^{Est.}$)	
	1	2	3	4
ΔTemp$^{Est.}$	-0.001	-0.001	-0.139	-0.142
	(0.217)	(0.219)	(0.548)	(0.534)
Prcp$^{Est.}$	-0.001**	-0.001***	0.180**	0.017
	(0.039)	(0.002)	(0.038)	(0.883)
Log(Emp$^{Est.}$)		-0.016***		-6.253***
		(0.000)		(0.000)
Observations	548,078	548,078	512,852	512,852
R-squared	0.343	0.351	0.216	0.225
Firm-Year FE	Yes	Yes	Yes	Yes

Table 12: Continued

Panel B1: Firm-Level Results - Sample of Suppliers

Dependent Variable:	Δlog(Sales)		Δ(Sales/Employees)	
	1	2	3	4
ΔTemp	-0.005	-0.004	1.220	1.496
	(0.145)	(0.228)	(0.582)	(0.495)
Prcp	-0.005	-0.001	0.370	1.524
	(0.147)	(0.742)	(0.808)	(0.333)
Observations	14,714	14,714	14,070	14,070
R-squared	0.121	0.159	0.169	0.173
Controls	Yes	Yes	Yes	Yes
Ind.-Year FE	Yes	Yes	Yes	Yes

Dependent Variable:	Δ(EBIT/Assets)		Δ(Net Income/Assets)	
	5	6	7	8
ΔTemp	0.000	0.000	0.001	0.001
	(0.914)	(0.891)	(0.587)	(0.544)
Prcp	-0.001	-0.001	-0.002**	-0.001
	(0.165)	(0.477)	(0.035)	(0.267)
Observations	14,644	14,644	14,644	14,644
R-squared	0.061	0.064	0.046	0.050
Controls	Yes	Yes	Yes	Yes
Ind.-Year FE	Yes	Yes	Yes	Yes

Table 12: Continued

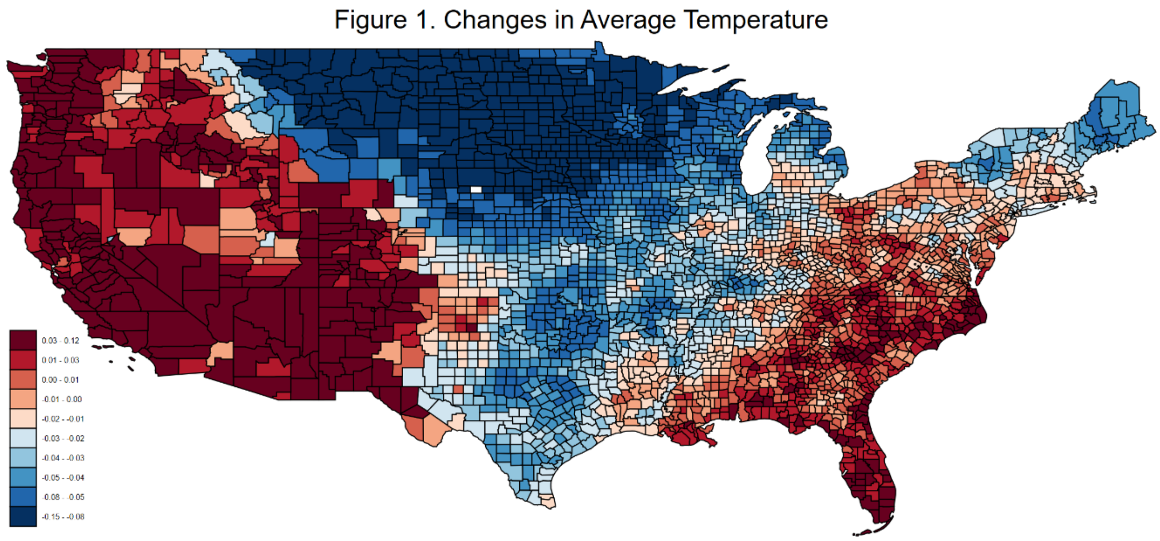
Panel B2: Firm-Level Results - Sample of Compustat Firms

Dependent Variable:	Δlog(Sales)		Δ(Sales/Employees)	
	1	2	3	4
ΔTemp	-0.003	-0.002	0.464	0.608
	(0.151)	(0.337)	(0.666)	(0.572)
Prcp	-0.006**	-0.000	0.497	1.555*
	(0.016)	(0.878)	(0.553)	(0.098)
Observations	32,522	32,522	30,787	30,787
R-squared	0.137	0.186	0.178	0.180
Controls	Yes	Yes	Yes	Yes
Ind.-Year FE	Yes	Yes	Yes	Yes

Dependent Variable:	Δ(EBIT/Assets)		Δ(Net Income/Assets)	
	5	6	7	8
ΔTemp	0.000	0.000	0.002	0.002
	(0.736)	(0.724)	(0.229)	(0.197)
Prcp	-0.001	-0.000	-0.002***	-0.001
	(0.104)	(0.471)	(0.006)	(0.143)
Observations	31,923	31,923	31,940	31,940
R-squared	0.065	0.067	0.043	0.046
Controls	Yes	Yes	Yes	Yes
Ind.-Year FE	Yes	Yes	Yes	Yes

Figure 1: Changes in Average Temperature

This figure plots changes in average daily temperature at the county level. Temperature is averaged by calendar year over the period 2000-2018.



Appendix

Table A.1: Variable Definitions

Variable	Definition
Δlog(Sales)	Change in the logarithm of sales from supplier *i* to client *j* from year *t*-1 to year *t*. (Source: Compustat)
ΔTemp	Change in the annual average daily mean temperature from year *t*-1 to year *t*, measured in degrees Celsius, at the ZIP code of supplier *i*'s corporate headquarters. Daily mean temperature is the average of daily maximum and minimum temperatures. (Source: Compustat and PRISM)
$\Delta\text{Temp}^{\textit{Est. emp.-weighted}}$	Change in the annual average establishment employment-weighted daily mean temperature from year *t*-1 to year *t*, measured in degrees Celsius. Daily mean temperature is the average of daily maximum and minimum temperatures. Establishment-level temperature is measured at the ZIP codes of supplier *i's* establishments, then aggregated to the firm level using the number of employees in each establishment as weights. (Source: Compustat, NETS, and PRISM)
Temp	Annual average daily mean temperature in year *t*, measured in degrees Celsius, at the ZIP code of supplier *i*'s corporate headquarters. Daily mean temperature is the average of daily maximum and minimum temperatures. (Source: Compustat and PRISM)
$\text{Temp}^{\textit{Est. emp.-weighted}}$	Annual average establishment employment-weighted daily mean temperature in year *t*, measured in degrees Celsius. Daily mean temperature is the average of daily maximum and minimum temperatures. Establishment-level temperature is measured at the ZIP codes of supplier *i's* establishments, then aggregated to the firm level using the number of employees in each establishment as weights. (Source: Compustat, NETS, and PRISM)
Prcp	Annual average daily precipitation in year *t*, measured in millimeters, at the ZIP code of supplier *i*'s corporate headquarters. (Source: Compustat and PRISM)
$\text{Prcp}^{\textit{Est. emp.-weighted}}$	Annual average establishment employment-weighted daily precipitation in year *t*, measured in millimeters. Establishment-level precipitation is measured at the ZIP codes of supplier *i*'s establishments, then aggregated to the firm level using the number of employees in each establishment as weights. (Source: Compustat, NETS and PRISM)
Assets	Total assets in year *t*-1. (Source: Compustat AT)
Cash	Cash and cash equivalents in year *t*-1, divided by total assets in year *t*-1. (Compustat CHE / AT)
Leverage	Total debt in year *t*-1, defined as debt in current liabilities plus long-term debt, divided by market value of assets in year *t*-1. (Source: Compustat (DLC + DLTT) / (DLC + DLTT + CSHO × PRCC_F))
Tangibility	Net property, plant and equipment in year *t*-1, divided by total assets in year *t*-1. (Source: Compustat PPENT / AT)
Tobin's Q	Market value of assets in year *t*-1, defined as total assets plus market value of equity minus book value of equity, divided by total assets in year *t*-1. (Source: Compustat (AT + CSHO × PRCC_F - [AT - (LT + PSTKL) + TXDITC]) / AT)
Temperature Normal	30-year average daily mean temperature, measured in degrees Celsius, at the ZIP code of supplier *i*'s corporate headquarters from 1981 to 2010. (Source: Compustat and PRISM)
Positive Deviation	Annual average positive temperature deviations in year *t*, measured in degrees Celsius, at the ZIP code of supplier *i*'s corporate headquarters. For each day, the positive temperature deviation is calculated as the difference between daily mean temperature and monthly temperature normal if the daily mean temperature exceeds the monthly temperature normal, and zero otherwise. (Source: Compustat and PRISM)

Table A.1: Continued

Variable	Definition
Absolute Deviation	Annual average absolute temperature deviations in year *t*, measured in degrees Celsius, at the ZIP code of supplier *i*'s corporate headquarters. For each day, the absolute temperature deviation is calculated as the absolute value of the difference between daily mean temperature and monthly temperature normal. (Source: Compustat and PRISM)
Summer Temperature (Calendar)	Seasonal average of daily mean temperatures during meteorological summer (i.e. from June to August) in year *t*, measured in degrees Celsius, at the ZIP code of supplier *i*'s corporate headquarters. (Source: Compustat and PRISM)
Summer Temperature (Average Normal)	Seasonal average of daily mean temperature during summer, defined as the three months with the highest monthly temperature normals, in year *t*, measured in degrees Celsius, at the ZIP code of supplier *i*'s corporate headquarters. (Source: Compustat and PRISM)
Cold/Wind Chill	Indicator variable equal to one if the county of supplier *i*'s corporate headquarters has experienced a cold/wind chill event that has resulted in at least one fatality in year *t*, and zero otherwise. A cold/wind chill event is a period of low temperatures or wind chill temperatures reaching or exceeding locally/regionally defined advisory conditions. (Source: Compustat and NOAA)
Heavy Snow	Indicator variable equal to one if the county of supplier *i*'s corporate headquarters has experienced a heavy snow event that has resulted in at least one fatality in year *t*, and zero otherwise. A heavy snow event happens when snow accumulation meets or exceeds locally/regionally defined 12 and/or 24 hours warning criteria. (Source: Compustat and NOAA)
Heat	Indicator variable equal to one if the county of supplier *i*'s corporate headquarters has experienced a heat event that has resulted in at least one fatality in year *t*, and zero otherwise. A heat event is a period of heat resulting from the combination of high temperatures (above normal) and relative humidity. (Source: Compustat and NOAA)
Hot Days	Number of days in year *t* for which the daily mean temperature exceeds the corresponding monthly temperature normal by at least five degree Celsius at the ZIP code of supplier *i*'s corporate headquarters. (Source: Compustat and PRISM)
Heavy Rain	Indicator variable equal to one if the county of supplier *i*'s corporate headquarters has experienced a heavy rain event that has resulted in at least one fatality in year *t*, and zero otherwise. A heavy rain event is an unusually large amount of rain that does not cause a flash flood or flood event, but causes damage, e.g., roof collapse or other human/economic impact. (Source: Compustat and NOAA)
Flood	Indicator variable equal to one if the county of supplier *i*'s corporate headquarters has experienced a flood event that has resulted in at least one fatality in year *t*, and zero otherwise. A flood event is any high flow, overflow, or inundation by water which causes damage. (Source: Compustat and NOAA)
Manufacturing Industries	Industries with SIC codes between 2000 and 3999. (Source: Compustat)
Occupational Heat Exposure	Job zone scores aggregated at three-digit SIC or four-digit NAICS levels. (Source: Occupational Information Network and Bureau of Labor Statistics' Occupational Employment and Wage Statistics)
Labor Intensity	Number of employees in year *t*-1 divided by total assets in year *t*-1. (Source: Compustat EMP / AT)
Credit Rating	Indicator variable equal to one if supplier *i* has a credit rating from S&P in year *t*-1, and zero otherwise. (Source: Compustat)
Payout Ratio	Payout in year *t*-1, defined as the sum of preferred dividends, common dividends, and purchases of common and preferred stocks, divided by income before extraordinary items in year *t*-1. (Source: Compustat (DVP + DVC + PRSTKC) / IB)

Table A.1: Continued

Variable	Definition
Financial Constraints Composite Index	Composite financial constraints index in year *t*-1, following Bartram et al. (2022). The index is constructed as the sum of indicator variables based on the KZ Index, WW Index, SA Index, size, payout ratio, and credit rating, where each indicator reflects whether the firm is classified as financially constrained according to the respective measure. (Source: Compustat)
Number of Counties with Establishment	Number of counties where supplier *i* has at least one establishment. (Source: Compustat and NETS)
HHI Establishment Sales	Herfindahl-Hirschman Index of establishment-level sales for supplier *i* in year *t*-1, computed as the sum of squared shares of each establishment's sales in supplier *i*'s total sales. (Source: NETS)
Standardized Goods	Indicator variable equal to one if supplier *i* belongs to an industry that is more likely to sell standardized products as defined in Giannetti et al. (2011), and zero otherwise. (Source: Compustat)
Innovation Value	Market-adjusted stock returns on the three-day window around the patent issue date. (Source: Kogan et al. (2017))
Duration of Supplier-Client Relationship	Number of years when supplier *i* has a transaction with client *j* over the sample period. (Source: Compustat)
Automation Patent Application	Indicator variable equal to one if supplier *i* has made an automation-related patent application in year *t*, based on the definition in Mann and Püttmann (2023). (Source: Mann and Püttmann (2023))
Investment Rate	Capital expenditures in year *t*, divided by net property, plant, and equipment in year *t*-1. (Source: Compustat CAPEX/PPENT)
Δlog(Sales$^{Est.}$)	Change in the logarithm of sales at establishment *e* from year *t*-1 to year *t*. (Source: NETS)
Δ(Sales$^{Est.}$ /Emp$^{Est.}$)	Change in the ratio of establishment sales-to-establishment employment from year *t*-1 to year *t* (Source: NETS).
ΔTemp$^{Est.}$	Change in the annual average daily mean temperature from year *t*-1 to year *t*, measured in degrees Celsius, at the ZIP code of establishment *e*. Daily mean temperature is the average of daily maximum and minimum temperatures. (Source: NETS and PRISM)
Prcp$^{Est.}$	Annual average daily precipitation in year *t*, measured in millimeters, at the ZIP code of establishment *e.* (Source: NETS and PRISM)
Δlog(Sales)	Change in the logarithm of total sales for supplier *i* from year *t*-1 to year *t*. (Source: Compustat)
Δ(Sales/Employees)	Change in the ratio of total sales in year *t* to total employees in year *t*-1. (Source: Compustat)
Δ(EBIT/Assets)	Change in the ratio of operating income in year *t* divided by total assets in year *t*-1. (Source: Compustat)
Δ(Net Income/Assets)	Change in the ratio of net income in year *t* to total assets in year *t*-1. (Source: Compustat)
Log(Emp$^{Est.}$)	Logarithm of employment at establishment *e* in year *t*-1. (Source: NETS)

Internet Appendix for

Does Climate Change Affect Firm Sales? Identifying Supply Effects

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Figure IA.1: Mechanisms - Summary of Effect Sizes and Significance Levels

This figure summarizes the effect sizes and significance levels of the coefficient on $\Delta Temp$ from the sample splits in Tables 6-10. Each subfigure plots the point estimates and 95% confidence intervals for subsamples supporting the corresponding economic mechanism.

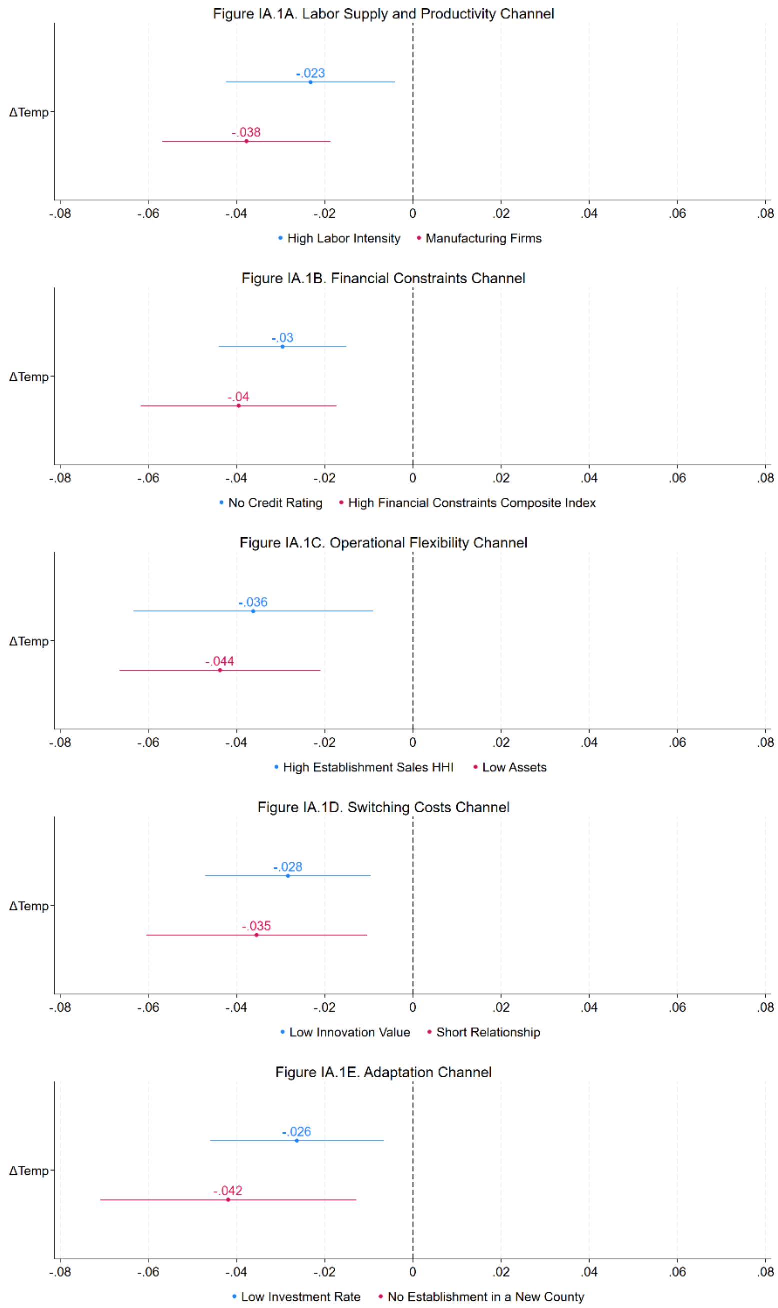

Table IA.1: Client-Supplier Sales Growth Regressions: Alternative Weights

This table presents estimates from ordinary least squares (OLS) panel regressions at the supplier-client pair level, weighted by inverse probability weights constructed from total sales within each two-digit SIC industry. The dependent variable, Δlog(*Sales*), is the change in the log of sales from supplier *i* to client *j* between year *t*-1 and year *t*. Δ*Temp* is the change in average daily temperature in degrees Celsius at the ZIP code of supplier *i*'s corporate headquarters from year *t*-1 to year *t*. *Prcp* is the average daily precipitation in millimeters at the ZIP code of supplier *i*'s corporate headquarters in year *t*. *Assets* is total assets. *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. *Leverage* is the ratio of total debt to the market value of assets. *Tangibility* is the ratio of net property, plant, and equipment to total assets. All financial variables are for the supplier and lagged by one year. Detailed variable definitions are provided in Table A.1 in the Appendix. The sample consists of annual observations of Compustat supplier-client pairs from 2000 to 2018. Industry fixed effects are defined at the two-digit SIC level. Robust standard errors are clustered at the supplier headquarters' county level. *p*-values are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	1	2	3	4	5	6
$\Delta Temp_t$	-0.019**	-0.025***	-0.025**	-0.023***	-0.024**	-0.027**
	(0.013)	(0.001)	(0.027)	(0.003)	(0.031)	(0.026)
$\Delta Temp_{t-1}$						-0.008
						(0.518)
$\Delta Temp_{t+1}$						0.003
						(0.766)
$\Delta Temp_{t+2}$						-0.002
						(0.838)
Prcp	-0.000	0.003	-0.005	0.006	-0.003	0.004
	(0.975)	(0.552)	(0.499)	(0.287)	(0.691)	(0.455)
Log(Assets)				0.040***	0.038***	0.043***
				(0.000)	(0.000)	(0.000)
Tobin's Q				0.013***	0.015***	0.002
				(0.000)	(0.000)	(0.517)
Cash				-0.006	0.013	-0.021
				(0.871)	(0.824)	(0.706)
Leverage				0.043	0.041	0.136**
				(0.309)	(0.494)	(0.031)
Tangibility				0.073	0.044	0.048
				(0.113)	(0.490)	(0.308)
Observations	10,730	10,730	7,489	10,730	7,489	3,873
R-squared	0.013	0.342	0.409	0.351	0.418	0.434
Year FE	Yes	No	No	No	No	No
Client-Year FE	No	Yes	No	Yes	No	Yes
Ind.-Client-Year FE	No	No	Yes	No	Yes	No

Table IA.2: Client-Supplier Sales Growth Regressions - County 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 year *t*-1 and year *t*. $\Delta Temp^{County}$ is the change in average daily temperature in degrees Celsius at the county of supplier *i*'s corporate headquarters from year *t*-1 to year *t*. $Prcp^{County}$ is the average daily precipitation in millimeters at the county of supplier *i*'s corporate headquarters in year *t*. *Assets* is total assets. *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. *Leverage* is the ratio of total debt to the market value of assets. *Tangibility* is the ratio of net property, plant, and equipment to total assets. All financial variables are for the supplier and lagged by one year. Detailed variable definitions are provided in Table A.1 in the Appendix. The sample consists of annual observations of Compustat supplier-client pairs from 2000 to 2018. Industry fixed effects are defined at the two-digit SIC level. Robust standard errors are clustered at the supplier headquarters' county level. *p*-values are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	1	2	3	4	5	6
$\Delta Temp^{County}_{t}$	-0.018***	-0.027***	-0.030***	-0.026***	-0.029***	-0.025**
	(0.006)	(0.000)	(0.006)	(0.000)	(0.007)	(0.017)
$\Delta Temp^{County}_{t-1}$						-0.005
						(0.694)
$\Delta Temp^{County}_{t+1}$						0.001
						(0.916)
$\Delta Temp^{County}_{t+2}$						0.000
						(0.990)
$Prcp^{County}$	-0.005	0.001	-0.007	0.002	-0.006	0.006
	(0.344)	(0.924)	(0.317)	(0.756)	(0.403)	(0.305)
Log(Assets)				0.011***	0.012***	0.002
				(0.000)	(0.003)	(0.545)
Tobin's Q				0.039***	0.036***	0.039***
				(0.000)	(0.000)	(0.000)
Cash				-0.055	-0.037	-0.059
				(0.151)	(0.544)	(0.277)
Leverage				0.023	0.021	0.095*
				(0.509)	(0.700)	(0.074)
Tangibility				0.022	-0.001	0.031
				(0.552)	(0.989)	(0.552)
Observations	10,730	10,730	7,489	10,730	7,489	3,873
R-squared	0.016	0.321	0.392	0.330	0.400	0.397
Year FE	Yes	No	No	No	No	No
Client-Year FE	No	Yes	No	Yes	No	Yes
Ind.-Client-Year FE	No	No	Yes	No	Yes	No

Table IA.3: 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 year *t*-1 and year *t*. Δ*Temp* is the change in average daily temperature in degrees Celsius at the ZIP code of supplier *i*'s corporate headquarters from year *t*-1 to year *t*. *Prcp* is the average daily precipitation in millimeters at the ZIP code of supplier *i*'s corporate headquarters in year *t*. *Assets* is total assets. *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. *Leverage* is the ratio of total debt to the market value of assets. *Tangibility* is the ratio of net property, plant, and equipment to total assets. All financial variables are for the supplier and lagged by one year. Detailed variable definitions are provided in Table A.1 in the Appendix. The sample is restricted to suppliers with client sales coverage (sum of sales to major corporate clients divided by total sales) above median. Industry fixed effects are defined at the two-digit SIC level. Robust standard errors are clustered at the supplier headquarters' county level. *p*-values are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	1	2	3	4	5
ΔTemp	-0.005	-0.023*	-0.037*	-0.020	-0.034*
	(0.580)	(0.086)	(0.064)	(0.113)	(0.076)
Prcp	0.001	0.011*	0.003	0.011*	0.002
	(0.801)	(0.095)	(0.836)	(0.073)	(0.889)
Log(Assets)				0.005	0.007
				(0.296)	(0.322)
Tobin's Q				0.041***	0.034***
				(0.000)	(0.002)
Cash				-0.047	-0.090
				(0.474)	(0.337)
Leverage				0.001	-0.005
				(0.978)	(0.951)
Tangibility				0.068	-0.122
				(0.423)	(0.233)
Observations	5,364	4,682	3,146	4,682	3,146
R-squared	0.013	0.341	0.394	0.352	0.401
Year FE	Yes	No	No	No	No
Client-Year FE	No	Yes	No	Yes	No
Ind.-Client-Year FE	No	No	Yes	No	Yes

Table IA.4: Client-Supplier Sales Growth Regressions - Co-location Sample

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 year *t*-1 and year *t*. Δ*Temp* is the change in average daily temperature in degrees Celsius at the ZIP code of supplier *i*'s corporate headquarters from year *t*-1 to year *t*. *Prcp* is the average daily precipitation in millimeters at the ZIP code of supplier *i*'s corporate headquarters in year *t*. *Assets* is total assets. *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. *Leverage* is the ratio of total debt to the market value of assets. *Tangibility* is the ratio of net property, plant, and equipment to total assets. All financial variables are for the supplier and lagged by one year. Detailed variable definitions are provided in Table A.1 in the Appendix. The sample consists of annual observations of Compustat supplier-client pairs from 2000 to 2018. Panel A restricts the sample to pairs where a client has at least one supplier with an establishment in the same state as one of the client's establishments. Panel B further restricts the sample to pairs where a client has at least one supplier with an establishment in the same county. Industry fixed effects are defined at the two-digit SIC level. Robust standard errors are clustered at the supplier headquarters' county level. *p*-values are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Co-location by Establishments' States

	1	2	3	4	5
ΔTemp	-0.013**	-0.020***	-0.019*	-0.019***	-0.018*
	(0.030)	(0.003)	(0.060)	(0.004)	(0.068)
Prcp	-0.003	0.001	-0.003	0.003	-0.001
	(0.545)	(0.848)	(0.677)	(0.572)	(0.925)
Log(Assets)				0.010***	0.010***
				(0.001)	(0.006)
Tobin's Q				0.038***	0.036***
				(0.000)	(0.000)
Cash				-0.055	-0.029
				(0.168)	(0.660)
Leverage				0.002	0.005
				(0.959)	(0.935)
Tangibility				0.049	0.019
				(0.205)	(0.770)
Observations	9,313	9,313	6,560	9,313	6,560
R-squared	0.017	0.312	0.398	0.321	0.406
Year FE	Yes	No	No	No	No
Client-Year FE	No	Yes	No	Yes	No
Ind.-Client-Year FE	No	No	Yes	No	Yes

Table IA.4: Continued

Panel B: Co-location by Establishments' Counties

	1	2	3	4	5
ΔTemp	-0.013**	-0.018***	-0.016	-0.017***	-0.014
	(0.037)	(0.007)	(0.113)	(0.010)	(0.135)
Prcp	-0.000	0.002	-0.002	0.004	0.001
	(0.926)	(0.755)	(0.785)	(0.474)	(0.936)
Log(Assets)				0.010***	0.010***
				(0.001)	(0.009)
Tobin's Q				0.038***	0.037***
				(0.000)	(0.000)
Cash				-0.051	-0.039
				(0.213)	(0.552)
Leverage				0.014	0.008
				(0.682)	(0.887)
Tangibility				0.042	-0.010
				(0.284)	(0.876)
Observations	9,039	9,039	6,364	9,039	6,364
R-squared	0.017	0.306	0.398	0.316	0.406
Year FE	Yes	No	No	No	No
Client-Year FE	No	Yes	No	Yes	No
Ind.-Client-Year FE	No	No	Yes	No	Yes

Table IA.5: Average Temperature

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 year *t*-1 and year *t*. *Temp* is the average daily temperature in degrees Celsius at the ZIP code of supplier *i*'s corporate headquarters in year *t*. *Prcp* is the average daily precipitation in millimeters at the ZIP code of supplier *i*'s corporate headquarters in year *t*. *Assets* is total assets. *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. *Leverage* is the ratio of total debt to the market value of assets. *Tangibility* is the ratio of net property, plant, and equipment to total assets. All financial variables are for the supplier and lagged by one year. Detailed variable definitions are provided in Table A.1 in the Appendix. The sample consists of annual observations of Compustat supplier-client pairs from 2000 to 2018. Industry fixed effects are defined at the two-digit SIC level. Robust standard errors are clustered at the supplier headquarters' county level. *p*-values are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	1	2	3	4	5
Temp	-0.026**	-0.040***	-0.057***	-0.033***	-0.041**
	(0.036)	(0.001)	(0.007)	(0.002)	(0.020)
Prcp	-0.039*	-0.014	-0.018	-0.012	-0.018
	(0.070)	(0.350)	(0.413)	(0.343)	(0.271)
Log(Assets)				0.549***	0.552***
				(0.000)	(0.000)
Tobin's Q				0.054***	0.047***
				(0.000)	(0.003)
Cash				-0.437***	-0.446***
				(0.000)	(0.001)
Leverage				-0.514***	-0.608***
				(0.000)	(0.001)
Tangibility				0.297	0.413
				(0.214)	(0.161)
Observations	9,843	9,680	6,683	9,680	6,683
R-squared	0.942	0.964	0.969	0.970	0.975
Supplier-Client FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	No	No
Client-Year FE	No	Yes	No	Yes	No
Ind.-Client-Year FE	No	No	Yes	No	Yes

Table IA.6: Changes in Summer Temperature

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 year *t*-1 and year *t*. Δ*Summer Temp* is the change in average daily temperature between June and August in degrees Celsius at the ZIP code of supplier *i*'s corporate headquarters from year *t*-1 to year *t*. *Prcp* is the average daily precipitation in millimeters at the ZIP code of supplier *i*'s corporate headquarters in year *t*. *Assets* is total assets. *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. *Leverage* is the ratio of total debt to the market value of assets. *Tangibility* is the ratio of net property, plant, and equipment to total assets. All financial variables are for the supplier and lagged by one year. Detailed variable definitions are provided in Table A.1 in the Appendix. The sample consists of annual observations of Compustat supplier-client pairs from 2000 to 2018. Industry fixed effects are defined at the two-digit SIC level. Robust standard errors are clustered at the supplier headquarters' county level. *p*-values are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	1	2	3	4	5
ΔSummer Temp	0.002	-0.003	-0.007	-0.002	-0.006
	(0.771)	(0.677)	(0.467)	(0.753)	(0.528)
Prcp	-0.001	0.003	-0.003	0.005	-0.001
	(0.755)	(0.558)	(0.657)	(0.301)	(0.918)
Log(Assets)				0.040***	0.037***
				(0.000)	(0.000)
Tobin's Q				0.011***	0.012***
				(0.000)	(0.004)
Cash				-0.053	-0.037
				(0.168)	(0.547)
Leverage				0.020	0.016
				(0.555)	(0.766)
Tangibility				0.023	0.001
				(0.524)	(0.993)
Observations	10,730	10,730	7,489	10,730	7,489
R-squared	0.015	0.320	0.391	0.329	0.399
Year FE	Yes	No	No	No	No
Client-Year FE	No	Yes	No	Yes	No
Ind.-Client-Year FE	No	No	Yes	No	Yes

Table IA.7: 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 year *t*-1 and year *t*. Δ*Temp* is the change in average daily temperature in degrees Celsius at the ZIP code of supplier *i*'s corporate headquarters from year *t*-1 to year *t*. Δ*Prcp* is the change in average daily precipitation in millimeters at the ZIP code of supplier *i*'s corporate headquarters from year *t*-1 to year *t*. *Assets* is total assets. *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. *Leverage* is the ratio of total debt to the market value of assets. *Tangibility* is the ratio of net property, plant, and equipment to total assets. All financial variables are for the supplier and lagged by one year. Detailed variable definitions are provided in Table A.1 in the Appendix. The sample consists of annual observations of Compustat supplier-client pairs from 2000 to 2018. Industry fixed effects are defined at the two-digit SIC level. Robust standard errors are clustered at the supplier headquarters' county level. *p*-values are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	1	2	3	4	5
ΔTemp	-0.018***	-0.026***	-0.027**	-0.025***	-0.026**
	(0.006)	(0.000)	(0.011)	(0.000)	(0.013)
ΔPrcp	-0.016*	-0.006	-0.010	-0.005	-0.009
	(0.073)	(0.460)	(0.390)	(0.489)	(0.414)
Log(Assets)				0.010***	0.012***
				(0.000)	(0.003)
Tobin's Q				0.039***	0.036***
				(0.000)	(0.000)
Cash				-0.056	-0.037
				(0.143)	(0.541)
Leverage				0.024	0.017
				(0.485)	(0.752)
Tangibility				0.023	-0.001
				(0.539)	(0.989)
Observations	10,730	10,730	7,489	10,730	7,489
R-squared	0.016	0.321	0.392	0.330	0.399
Year FE	Yes	No	No	No	No
Client-Year FE	No	Yes	No	Yes	No
Ind.-Client-Year FE	No	No	Yes	No	Yes

Table IA.8: Alternative Standard-Error Clustering

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 year *t*-1 and year *t*. Δ*Temp* is the change in average daily temperature in degrees Celsius at the ZIP code of supplier *i*'s corporate headquarters from year *t*-1 to year *t*. *Prcp* is the average daily precipitation in millimeters at the ZIP code of supplier *i*'s corporate headquarters in year *t*. *Assets* is total assets. *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. *Leverage* is the ratio of total debt to the market value of assets. *Tangibility* is the ratio of net property, plant, and equipment to total assets. All financial variables are for the supplier and lagged by one year. Detailed variable definitions are provided in Table A.1 in the Appendix. The sample consists of annual observations of Compustat supplier-client pairs from 2000 to 2018. Industry fixed effects are defined at the two-digit SIC level. In Panel A, robust standard errors are clustered at the supplier headquarters' ZIP code level. In Panel B, robust standard errors are clustered at the firm level. In Panel C, spatially-adjusted standard errors with a distance cutoff of 500 km are calculated following Colella et al. (2020). *p*-values are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Standard Errors Clustered at ZIP Code Level

	1	2	3	4	5
ΔTemp	-0.016**	-0.025***	-0.026**	-0.023***	-0.024**
	(0.019)	(0.002)	(0.020)	(0.003)	(0.024)
Prcp	-0.002	0.002	-0.004	0.004	-0.002
	(0.578)	(0.688)	(0.588)	(0.401)	(0.824)
Log(Assets)				0.011***	0.012***
				(0.001)	(0.004)
Tobin's Q				0.040***	0.036***
				(0.000)	(0.000)
Cash				-0.053	-0.037
				(0.165)	(0.497)
Leverage				0.021	0.018
				(0.588)	(0.731)
Tangibility				0.022	-0.000
				(0.550)	(0.998)
Observations	10,730	10,730	7,489	10,730	7,489
R-squared	0.016	0.321	0.392	0.330	0.399
Year FE	Yes	No	No	No	No
Client-Year FE	No	Yes	No	Yes	No
Ind.-Client-Year FE	No	No	Yes	No	Yes

Table IA.8: Continued

Panel B: Standard Errors Clustered at Firm Level

	1	2	3	4	5
ΔTemp	-0.016**	-0.025***	-0.026**	-0.023***	-0.024**
	(0.018)	(0.002)	(0.018)	(0.003)	(0.021)
Prcp	-0.002	0.002	-0.004	0.004	-0.002
	(0.599)	(0.703)	(0.594)	(0.426)	(0.829)
Log(Assets)				0.011***	0.012***
				(0.001)	(0.007)
Tobin's Q				0.040***	0.036***
				(0.000)	(0.000)
Cash				-0.053	-0.037
				(0.184)	(0.503)
Leverage				0.021	0.018
				(0.589)	(0.735)
Tangibility				0.022	-0.000
				(0.568)	(0.998)
Observations	10,730	10,730	7,489	10,730	7,489
R-squared	0.016	0.321	0.392	0.330	0.399
Year FE	Yes	No	No	No	No
Client-Year FE	No	Yes	No	Yes	No
Ind.-Client-Year FE	No	No	Yes	No	Yes

Table IA.8: Continued

Panel C: Spatially-Adjusted Standard Errors

	1	2	3	4	5
ΔTemp	-0.016**	-0.025***	-0.026***	-0.023***	-0.024***
	(0.024)	(0.001)	(0.003)	(0.001)	(0.003)
Prcp	-0.002	0.002	-0.004	0.004	-0.002
	(0.660)	(0.618)	(0.430)	(0.300)	(0.747)
Tobin's Q				0.040***	0.036***
				(0.000)	(0.000)
Log(Assets)				0.011***	0.012***
				(0.000)	(0.001)
Cash				-0.053	-0.037
				(0.105)	(0.464)
Leverage				0.021	0.018
				(0.544)	(0.675)
Tangibility				0.022	-0.000
				(0.526)	(0.998)
Observations	10,730	10,730	7,489	10,730	7,489
R-squared	0.016	0.321	0.392	0.330	0.399
Year FE	Yes	No	No	No	No
Client-Year FE	No	Yes	No	Yes	No
Ind.-Client-Year FE	No	No	Yes	No	Yes

Table IA.9: 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 equals one if there is a business transaction between supplier *i* and client *j* in year *t*-1 but not in year *t*, and zero otherwise. Δ*Temp* is the change in average daily temperature in degrees Celsius at the ZIP code of supplier *i*'s corporate headquarters from year *t*-1 to year *t*. *Prcp* is the average daily precipitation in millimeters at the ZIP code of supplier *i*'s corporate headquarters in year *t*. *Assets* is total assets. *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. *Leverage* is the ratio of total debt to the market value of assets. *Tangibility* is the ratio of net property, plant, and equipment to total assets. All financial variables are for the supplier and lagged by one year. Detailed variable definitions are provided in Table A.1 in the Appendix. The sample consists of annual observations of Compustat supplier-client pairs from 2000 to 2018. Industry fixed effects are defined at the two-digit SIC level. Robust standard errors are clustered at the supplier headquarters' county level. *p*-values are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	1	2	3	4	5
ΔTemp	0.003	0.003	0.001	0.003	0.002
	(0.278)	(0.392)	(0.709)	(0.311)	(0.606)
Prcp	-0.004	0.002	-0.002	0.002	-0.002
	(0.616)	(0.831)	(0.820)	(0.796)	(0.842)
Log(Assets)				0.012	0.012
				(0.690)	(0.740)
Tobin's Q				0.004	0.007*
				(0.245)	(0.073)
Cash				-0.015***	-0.009*
				(0.001)	(0.086)
Tangibility				0.060	0.087*
				(0.225)	(0.071)
Leverage				-0.060	-0.026
				(0.327)	(0.706)
Observations	32,819	32,819	24,117	32,819	24,117
R-squared	0.013	0.265	0.371	0.269	0.373
Year FE	Yes	No	No	No	No
Client-Year FE	No	Yes	No	Yes	No
Ind.-Client-Year FE	No	No	Yes	No	Yes

Table IA.10: Financial Constraints Channel - Additional 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 year *t*-1 and year *t*. Δ*Temp* is the change in average daily temperature in degrees Celsius at the ZIP code of supplier *i*'s corporate headquarters from year *t*-1 to year *t*. *Prcp* is the average daily precipitation in millimeters at the ZIP code of supplier *i*'s corporate headquarters in year *t*. Firms are partitioned into groups based on the criteria indicated in each panel, with continuous variables split at the median. Panel A uses the WW index, constructed as in Whited and Wu (2006). Panel B uses the KZ index, constructed as in Lamont et al. (2001). Panel C uses the SA index, constructed as in Hadlock and Pierce (2010). Panel D uses long-term debt maturing within one year scaled by total assets. Regressions include the same control variables as in Table 2, columns (4) and (5) (coefficients not shown). All financial variables are for the supplier and lagged by one year. Detailed variable definitions are provided in Table A.1 in the Appendix. The sample consists of annual observations of Compustat supplier-client pairs from 2000 to 2018. Robust standard errors are clustered at the supplier headquarters' county level. *p*-values are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Whited-Wu (WW) Index

	High WW Index	Low WW Index
	1	2
ΔTemp	-0.039***	-0.013
	(0.003)	(0.279)
Prcp	0.005	0.005
	(0.543)	(0.395)
Observations	4,746	4,693
R-squared	0.377	0.360
Controls	Yes	Yes
Client-Year FE	Yes	Yes
p-value of difference	0.162	

Panel B: Kaplan-Zingales (KZ) Index

	High KZ Index	Low KZ Index
	1	2
ΔTemp	-0.025**	-0.017
	(0.045)	(0.207)
Prcp	0.010	-0.006
	(0.219)	(0.431)
Observations	3,994	4,032
R-squared	0.387	0.377
Controls	Yes	Yes
Client-Year FE	Yes	Yes
p-value of difference	0.693	

Table IA.10: Continued

Panel C: Size-Age (SA) Index

	High SA Index	Low SA Index
	1	2
ΔTemp	-0.025**	-0.009
	(0.022)	(0.303)
Prcp	0.013	-0.002
	(0.179)	(0.703)
Observations	4,752	4,704
R-squared	0.368	0.377
Controls	Yes	Yes
Client-Year FE	Yes	Yes
p-value of difference	0.278	

Panel D: Long-term Debt Maturing

	High Long-Term Debt Maturing	Low Long-Term Debt Maturing
	1	2
ΔTemp	-0.025**	-0.012
	(0.012)	(0.377)
Prcp	0.009	0.000
	(0.246)	(0.946)
Observations	4,587	4,624
R-squared	0.357	0.383
Controls	Yes	Yes
Client-Year FE	Yes	Yes
p-value of difference	0.278	

Table IA.11: Switching Costs Channel - Additional 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 year *t*-1 and year *t*. Δ*Temp* is the change in average daily temperature in degrees Celsius at the ZIP code of supplier *i*'s corporate headquarters from year *t*-1 to year *t*. *Prcp* is the average daily precipitation in millimeters at the ZIP code of supplier *i*'s corporate headquarters in year *t*. Firms are partitioned into groups based on the criteria indicated in each panel, with continuous variables split at the median. Panel A uses an indicator for positive forward patent citations, following Kogan et al. (2017). Panel B uses interfirm sales share. Panel C uses market share defined at the two-digit SIC level. Panel D uses the number of clients. Panel E uses international client exposure. Regressions include the same control variables as in Table 2, columns (4) and (5) (coefficients not shown). All financial variables are for the supplier and lagged by one year. Detailed variable definitions are provided in Table A.1 in the Appendix. The sample consists of annual observations of Compustat supplier-client pairs from 2000 to 2018. Robust standard errors are clustered at the supplier headquarters' county level. *p*-values are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Patent Citations

	No Citations	Positive Citations
	1	2
ΔTemp	-0.026***	-0.014
	(0.004)	(0.321)
Prcp	0.008	-0.011
	(0.169)	(0.230)
Observations	5,856	3,805
R-squared	0.369	0.378
Controls	Yes	Yes
Client-Year FE	Yes	Yes
p-value of difference	0.492	

Panel B: Interfirm Sales Share

	Low Interfirm Sales Share	High Interfirm Sales Share
	1	2
ΔTemp	-0.033***	-0.020
	(0.001)	(0.113)
Prcp	-0.004	0.011*
	(0.558)	(0.073)
Observations	4,690	4,682
R-squared	0.415	0.352
Controls	Yes	Yes
Client-Year FE	Yes	Yes
p-value of difference	0.474	

Table IA.11: Continued

Panel C: Market Share

	Low Market Share	High Market Share
	1	2
ΔTemp	-0.051***	-0.002
	(0.000)	(0.776)
Prcp	0.004	-0.003
	(0.640)	(0.549)
Observations	4,824	4,792
R-squared	0.371	0.402
Controls	Yes	Yes
Client-Year FE	Yes	Yes
p-value of difference	0.001	

Panel D: Number of Clients

	Low Number of Clients	High Number of Clients
	1	2
ΔTemp	-0.031***	-0.010
	(0.001)	(0.512)
Prcp	-0.002	0.003
	(0.813)	(0.803)
Observations	7,595	2,247
R-squared	0.342	0.372
Controls	Yes	Yes
Client-Year FE	Yes	Yes
p-value of difference	0.257	

Panel E: International Client Exposure

	High International Client Exposure	Low International Client Exposure
	1	2
ΔTemp	-0.041***	0.000
	(0.000)	(0.990)
Prcp	-0.002	0.007
	(0.852)	(0.227)
Observations	4,723	4,732
R-squared	0.335	0.298
Controls	Yes	Yes
Client-Year FE	Yes	Yes
p-value of difference	0.002	

Table IA.A1: Additional Variable Definitions

Variable	Definition
WW Index	Financial constraints index, as constructed in Whited and Wu (2006). (Source: Compustat)
KZ Index	Financial constraints index in Kaplan and Zingales (1997), as constructed in Lamont, Polk, and Saá-Requejo (2001). (Source: Compustat)
SA Index	Financial constraints index, as constructed in Hadlock and Pierce (2010). (Source: Compustat)
Long-Term Debt Maturing	Long-term debt maturing within one year in year *t*-1, divided by total assets in year *t*-1. (Source: Compustat DD1/AT)
Patent Citations	Total forward citations received by the patents owned by supplier *i* in year *t*-1. (Source: Kogan et al. (2017))
Interfirm Sales Share	Sales from supplier *i* to client *j* in year t, divided by supplier *i*'s total sales in year *t*. (Source: Compustat SALES / SALE)
Market Share	Sales-based market share in year *t*-1, computed as supplier *i*'s sales divided by industry-level sales defined at the two-digit SIC level. (Source: Compustat)
Number of Clients	Number of corporate clients for firm *i* over the sample period. (Source: Compustat)
International Client Exposure	Client *j*'s sales outside of the United States in year *t*-1, divided by client *j*'s total sales in year *t*-1. (Source: Compustat $\sum SALES/SALE$)