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The Economic Costs of Temperature Uncertainty

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ABSTRACT: Beyond its environmental damage, climate change is predicted to produce significant economic costs. Combining novel high-frequency geospatial temperature data from satellites with measures of economic activity for the universe of US listed firms, this article examines a potentially important channel through which global warming can lead to economic costs: temperature uncertainty. The results show that temperature uncertainty—by increasing power outages, reducing labor productivity, and increasing the degree of exposure of firms to environmental and non-political risks, as well as economic uncertainty at the firm-level—persistently reduce firms' investment and sales. This effect varies across firms, with those characterized by tighter financial constraints being disproportionally more affected.

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I. Introduction

Climate change is a key challenge to current and future economic prosperity. World-wide economic costs associated with climate change events—increases in average and extreme temperatures and in the frequency of climate-related natural disasters—may arise to over 125 trillion dollars by 2050, if climate policy actions are not intensified (IMF 2019, UNFCCC. 2021).

Apart from increasing temperatures and natural disasters, another, but not yet well-studied, channel through which climate change can negatively affect the economy is temperature uncertainty, defined as the volatility of daily temperatures. Temperature volatility is on the rise globally (Alessandri and Mumtaz 2022), and in the US has increased even more than the average temperature in the past 30 years (Figure 1). In this paper, we show that this phenomenon has important economic implications by conducting the first study to provide direct evidence on how exposure to temperature uncertainty affects US firms' economic performance.

To be able to quantify the economic costs of temperature uncertainty, we match granular geospatial satellite temperature data at the zip code level with a panel dataset consisting of the universe of US listed firms and quarterly time series data over the period 1961Q1-2018Q4. The detailed geospatial and the high-frequency firm-level dataset, stretching over a 60-year period, enable us to address endogeneity issues related to potential reverse impact of firm emissions on local climate, and provide more generalizable longer-term firm-level evidence.

We employ this data in a local projection framework (Jorda 2005) to estimate the dynamic response of firms' investment decisions to temperature uncertainty, measured as the standard deviation of daily temperatures within quarters of year. The results suggest that temperature uncertainty has sizeable and persistent negative effects on firms' investment. In particular, we find that a 1-degree Celsius increase in temperature volatility causes a reduction in investment of 0.4 percent after four quarters and about 1.4 percent after 20 quarters. In contrast, and consistently with previous evidence for the US (Addoum, Ng and Ortiz-Beboa 2020), we do not find evidence that neither increases in average temperature levels, nor the occurrence of heat or cold waves, nor initial levels of temperature volatility have statistically significant effects on firms' investment. These results are robust to a battery of sensitivity checks.

In addition to investment, we also find negative effects of temperature volatility on firms' sale, labor productivity, and employment. To generalize the results for the entire US economy, we also analyze the effect of temperature volatility using Metropolitan Area employment and unemployment data. The results point to larger effects (more than double) than those obtained with publicly listed firms data, suggesting that the results obtained with the latter are likely to underestimate the true negative effects of temperature volatility.

To understand the mechanisms that channel the effect of temperature uncertainty on economic performance, we test the relevance of (i) increased energy costs (higher frequency of power outages and electricity disruptions), (ii) reduced labor productivity (via sickness and the absenteeism of workers), (iii) financial constraints (via investment uncertainty and climate risks). Hereby, we resort to highly granular data on number of sickness days of one occupational group (in our context teachers), the number of power outages, as well as firms' realized stock market volatility, and exposure to climate change and non-political risks using transcripts of earning calls. Our estimates highlight that all these channels play a key role in driving the effect of temperature uncertainty on the economy.

Finally, by assessing heterogeneity on the way temperature volatility affects firms across economic sectors and firms' characteristics, we show that the effect of temperature volatility is larger for firms operating in manufacturing than in services, and in heat-sensitive industries (as those identified by Graff-Zivin and Neidell 2014). Across firms, and consistent with the literature on uncertainty and firms' financial constraints, we also find that the effect of temperature uncertainty is larger for firms that face higher financial constraints—such as smaller and younger firms, and those with a higher share of short-term liabilities.

The rest of the paper is organized as follows. Section II provides a review of the literature on the economic effects of climate changes and discusses our contribution. Section III describes the data. Section IV presents the main empirical framework. Section V discusses the results on the effect of temperature volatility on economic outcomes, including several robustness checks, and the key channels through which temperature uncertainty can affect economic activity. Section VI examines how the effect of temperature volatility varies across sectors and firms. Section VII concludes.

II. Literature Review

To quantify the economic costs of climate change, studies have mainly focused on the effects of increasing temperatures and natural disasters (Stern 2008, Nordhaus 2019). Most of this research relies on aggregate historical temperature variations across countries or larger subnational regions. Burke, Hsiang, and Miguel (2015) find that economic productivity peaks at average temperatures of 13°C, with a sharp decline at higher temperatures reducing agricultural and industrial output, irrespective of country income levels. Dell, Jones, and Olken (2012) and Acevedo, Mrkaic, Novta, and Pugacheva (2020) detect an adverse impact of higher average temperatures on agricultural and industrial labor productivity primarily in poor countries. The increased frequency of climate-related natural disasters such as storms and drought has further been shown to reduce economic output and jobs (see, among others, Hsiang and Narita 2012; Kalkuhl and Wenz 2020). While these studies provide important new insights, the reliance on cross-country data does not allow us to adequately address macroeconomic and unobservable institutional characteristics which raises endogeneity-related concerns (see, for example, Durlauf et al., 2009; or Hauk and Wacziarg, 2009).

To overcome these issues, several recent studies have used microeconomic data to measure the economic impact of climate change. For instance, Burke and Tanutama (2019) assemble panel data on economic output from over 11,000 districts across 37 countries and find that district-level growth declines for higher average temperatures. Hsiang et al. (2017) develop a spatial, dynamic general equilibrium model which is calibrated with empirical results using firm-level data to analyze the economic damages from climate-related events in the U.S. over a period of two decades. They find that cyclone events in the upper 90th percentile reduce per capita incomes by 7.4 percent relative to their pre-disaster trend.[1] Basker and Miranda (2018) further show that firms that faced capital destruction from hurricane Katrina have significantly lower survival rates than those that did not.[2] Ponticelli et al. (2023), using plant-level data from the US Census Bureau, find that warmer than average temperatures increase energy costs and decrease plant productivity, with the effect that only materializes for small manufacturing plants. Nath (2022) uses firm-level panel data from a wide range of countries to show that extreme heat reduces productivity in agriculture, while manufacturing and services are less affected. In contrast, Addoum, Ng and Ortiz-Beboa (2020) match granular daily data on temperatures across the continental United States with detailed establishment data from 1990 to 2015, and do not find evidence that temperature exposure significantly affects establishment-level sales or productivity, including among industries traditionally classified as heat sensitive.

We contribute to this literature by identifying the impact of temperature uncertainty, rather than average temperature changes or weather impacts, on the US economy. Moreover, we assemble a very detailed geospatial temperature and firm-level data to overcome the limitations of more aggregate county or cross-country data (see below). Compared to Addoum, Ng and Ortiz-Beboa (2020), we also cover a much longer time period, going back to the early 60s, and we use quarterly data which allow to better identify the causal effects of temperature shocks.

More recently, few studies have focused on the potential negative economic impact of temperature volatility. Kotz et al. (2021), for example, find that higher day-to-day temperature variability reduce GDP growth beyond changes in annual average temperatures among 1,537 larger subnational regions in 77 countries over 40 years, with an extra degree of variability reducing average regional growth by five percentage points.[3] Moreover, Donadelli et al. (2021) use monthly aggregate data on UK temperatures for the period 1659–2015 to build an intra-annual temperature volatility index. They find that annual temperature volatility reduces TFP growth in the post-war period (i.e., 1950–2015) and raised it before (i.e., 1800–1950). Calel et al. (2020) embeds climate uncertainty into a climate–economy model and calibrate it to historical data, showing that even modest variability in temperature implies trillions of dollars of previously unaccounted for economic damages. We differ from these studies in relying on more detailed geographical climate and firm-level data for rich time series information within the controlled institutional environment of a single country.

This paper is also related to a literature studying the impact channels of climate change. Specifically, the literature identifies three major channels with sizeable negative impacts on economic activity: lower labor productivity, disruption in energy markets, and higher investment uncertainty. Carleton and Hsiang (2016) find that increasing temperatures facilitate the spread of vector- and water-borne diseases on human health, reducing workers' health and thus labor productivity. Somanathan et al. (2021) use microdata from selected firms in India to show that plant output falls by about 2 percent per 1°C as hot days lower worker productivity by increasing absenteeism. Deryugina and Hsiang (2014) estimate that labor productivity declines by about 1.7 percent for each 1°C once the average daily temperature in US counties exceeds 15°C. The paper further emphasizes the

[1] Moreover, Bastos, Busso, and Miller (2013) use local rainfall data to measure the impact of droughts in Brazil. Related studies have also focused on the indirect impact of climate change on firm performances through carbon pricing policies and regulations on firm performances (Commins et al., 2011; Hall et al., 2021; Shen et al., 2021).

[2] Pelli and Tschopp (2017) and Pelli et al. (2023) show that capital gets allocated more toward comparative advantage and better-performing industries after hurricanes.

[3] For more studies on the economic impact of climate volatility based on more aggregate climate data see also Mumtaz and Alessandri (2021).

need to strengthen the resilience of electrical grids to climate volatility to reduce its impact on power system blackouts.

Relatedly, Khan et al. (2021) apply mean temperature changes across U.S. states to demonstrate a large impact on electric capacity and investment needs. They find that temperatures variability may cause direct damages to infrastructures such as electricity disruption, especially in countries, such as the US., relying on overhead power cables. Panteli and Mancarella (2015) also highlight the need to reduce the impact of climate change-induced weather changes on electrical grids to enhance reliability and reduce power outages. Cashin, Mohaddes and Raissi (2017) exploit exogenous variation in El Niño weather events over time to demonstrate that climate volatility raises energy prices. Consistent with these findings, several studies estimate that climate change raises energy demand (Jaglom et al. 2014 for the U.S., Davis and Gertler 2015 for Mexico) and energy efficiency among firms (Brucal and Dechezleprêtre 2021; Gray, Linn, and Morgenstern 2019).

Temperature volatility further adds to economic uncertainty which has been found to reduce the willingness of firms to hire, invest, and innovate, and of consumers to spend (Bloom 2009, Bloom 2014, Fernández-Villaverde et al. 2011). Recent evidence suggests that climate risk considerations feature prominently in the investment decisions of listed firms around the world. Alfaro, Bloom, and Lin (2022), for example, using a novel Instrumental Variable (IV) strategy to show that firms' exposure to uncertainty including energy price volatility reduces US firms' investments, especially for financially constrained firms. Similarly, Sautner et al. (2023) use a textual analysis using earnings call transcript data to measure climate risk exposure at the firm level, finding that firms facing higher risk are valued at a discount. Dessaint and Matray (2017) find that CEOs of US firms facing higher climate risk adjust their assets by holding more cash.[4] Makridis and Schloetzer (2022) show that temperatures affect firms by undermining consumer sentiment. They use Gallup's U.S. Daily Poll and local weather data to reveal that extreme local temperatures lead to a decrease in economic sentiment, correlating with declines in the stock returns of local firms.[5]

Our findings are consistent with these economic transmission channels of climate change through labor productivity, energy costs, and investment uncertainty. We further contribute to this literature by testing all these channels (separately) and providing evidence based on detailed geospatial climate data that temperature volatility reduces labor productivity, increases the frequency of power outages, and absenteeism of employees. Moreover, we provide evidence that climate volatility raises the economic uncertainty and environmental and non-political risks firms are facing and thus attenuates their investment.

We also contribute to the literature showing that firms financial constraints amplify the effect of uncertainty shocks on investment (Alfaro, Bloom, and Lin 2022). Consistent with this literature, we find that the effect of temperature volatility is larger for firms that face higher financial constraints such as smaller and younger firms, and those with a higher share of short-term liabilities.

Finally, we contribute to the literature trying to identify exogenous instrumental variables for uncertainty. For example, Baker, Bloom and Terry (2023) use natural disasters, terrorist attacks, and political shocks to identify exogenous variation in uncertainty. Julio and Yook (2012) and Ahir, Bloom and Furceri (2022) use

[4] Downey, Lind, and Shrader (2023) also show that constructions firms adjust to higher rainfall risks.

[5] See also Bertrand and Chabot (2015) for evidence on the impact of retailing in the U.K. Studies also assess the impact of climate change on macroeconomic policy or income distributions (e.g., Pisa, Lucidi and Tancioni 2022 or Hsiang, Oliva and Walker 2019).

exogenous elections—that is, those for which the head of government does not have the power to dissolve a parliament and call new elections—to examine the economic implication of political uncertainty and allow to disentangle some of the endogeneity between economic growth and uncertainty. We show that temperature volatility is strongly correlated with firms' level uncertainty and thus an alternative exogenous variable that could be used as an instrument to identify the causal effects of uncertainty.

III. Data

This section discusses the data used in the various empirical analyses. In what follows, we first present temperature data; then, we describe firm-level data, including our explanatory variables—i.e., investment, sales, (un)employment and labor productivity—as well as those used as controls and to disentangle sources of nonlinearity; finally, we list all other variables employed to analyze the transmission channels.

A. Temperature volatility

We collect temperature data from the EU's Copernicus satellite and ground-based measurement system, which provides daily high granular geospatial temperatures (~27.64km x 27.64km at the equator) for the entire world, and for a long-time span. We focus on the US and the period available for firm-level data, i.e., 1961-2018. First, we aggregate temperatures at the US zip code level and match them with firms' location. Afterwards, for the baseline analysis, we collapse daily temperatures at the quarterly level, by computing the within-quarter temperature volatility for each firm, measured as the standard deviation of daily temperatures. As controls, we also consider average, minimum and maximum temperatures, as well as the number of heat (≥ 35-degree Celsius) and cold (≤ 0-degree Celsius) days, for each firm/quarter. Finally, we compute alternative measures of temperature volatility for robustness checks, i.e., the difference between maximum and minimum temperatures and the log of the standard deviation, all of them assembled at the firm/quarter level. Further, we consider the residuals from regressing daily temperatures on date fixed effects, and collapse them at quarterly frequency by computing within-quarter mean, min, max and standard deviation of temperature residuals. This gives us a measure of unexpected temperature changes.

Note that, when we run the analysis at different temporal aggregations—i.e., monthly or yearly frequency—daily temperatures are collapsed accordingly, e.g., computing the within-year or within-month standard deviation of daily temperatures.

Figures 1 (Panel A) shows the evolution of temperatures in the US in the last 30 years. Two aspects stand out. First, both average temperature and volatility have sharply increased, particularly since mid-1990s, with temperature volatility increasing more than average temperatures. Second, Figure 1 (Panel B) indicates that the evolution of temperature volatility has not been homogeneously distributed across the US, with most notable increases in the east coast, great lakes and southwest, i.e., states with high concentration of economic activity. In addition, temperature volatility *per se* varies significantly across US states and locations (Figure 2).

B. Firms Data

Firm-level data have been retrieved from Compustat, which provides high-quality balance sheet and income statement for a large panel of US listed firms, at the quarterly and annual frequency. In particular, we use quarterly data for the baseline analysis, consisting of approximately 33 thousand firms, over the period 1961Q1-2018Q4, covering all NAICS 2-digit sectors, except agriculture and public administration. We focus on firms' capital expenditure for the baseline analysis. As an alternative dependent variable, we consider firms' sales. Other firms' characteristics are taken into account as controls to verify the robustness of baseline results, and as interaction to estimate nonlinear effects. In detail, we consider: firms' liquidity, age, size, debt maturity, Tobin's Q, as well as the main sector in which the firms operate, using the relevant NAICS code. In addition, at the annual frequency, we also consider firms' employment and labor productivity, computed as sales over employment.[6] To match firm-level data with temperatures, we identify the location of firms by looking at the zip code, available in Compustat. Overall, our final quarterly dataset contains approximately 1.3 million observations at the firm/quarter level, over the period 1961Q1-2018Q4.

C. Other Data

In addition to investigate firm-level behavior, we generalize our results to the US economy using macroeconomic indicators. In particular, we resort to Metropolitan Statistical Area (MSA) employment data from the Bureau of Labor Statistics (BLS). BLS provides monthly data from 1/1990 to 1/2022, for 373 metropolitan areas. We use these monthly MSA figures, capturing employment and unemployment (rate), and merge them to our temperature data, for a total of 143,605 observations. To do so, we use the shapefile that defines the borders of each MSA unit and extract daily temperature values. In order to merge it with monthly MSA statistics, we collapse weather data to the monthly level, computing monthly standard deviation and average daily temperatures.

We also examine some key channels through which temperature volatility affects economic activity. One of these is by increasing the frequency of power outages, thus causing disruptions in the production process and supply chain. To collect information on power outages, we refer to the EAGLE-I Power Outage Data, compiled by Brelsford et al (2024). The dataset provides the number of customers affected by a power outage at the county level on a given day, between 2014 and 2022, and it covers the whole geographical area of the United States and its associated territories, for a total of 3,243 counties. We merge this county-date panel to our raw daily weather data, and collapse data at the monthly level; this results in a new panel dataset at the monthly frequency, including the number of customers affected by a power outage for each county/month, and the monthly average and standard deviation of daily temperatures at the county/month level, for a total of approximately 350 thousand observations.

Next, we also aim to understand whether the economic costs of temperature volatility are due to decline in labor productivity. One measure of changes in labor productivity, or the lack thereof, is the number of sick days of employees. To examine this transmission channel, we focus on teachers, whose jobs are conducted indoors. Note that as we look at an occupation which is not directly exposed to weather-related fluctuation at work, our

[6] Employment firm-level data are available at the yearly frequency.

results are primarily representative for service-related industries, which should, if anything, be less affected by temperature volatility than their peers in the construction and manufacturing sectors. To do so, the Illinois State Board of Education granted us the access to their data on the number of sickness days of each public school's teacher in the State of Illinois from 2013 until 2020. We use the sum of all sickness days in a school district in a given school/year, and merge these figures with the relevant temperature data. To do so, we resort to the school district shapefile of Illinois to extract daily temperature statistics for each school district, which we then collapse it to the school/year level. The final dataset contains approximately 6.8 thousand observations, i.e., 849 school districts by 8 years. The high number of school districts in Illinois enables us to exploit intra-state temperature variation to measure the effect of temperature volatility on sickness days, by accounting for time-invariant unobservable at a very disaggregated geographical level of analysis.

Next, we test the correlation between temperature volatility and firm-level economic uncertainty, the latter being a (potential) key channel through which temperature uncertainty affects firms' investment. We do it by making use of novel data that asses the degree of uncertainty faced by (ca. 10 thousand) US listed firms, in terms of annual growth rate of realized volatility in the stock returns, over the period 1992-2019 (Alfaro et al., 2021). In detail, annual firm realized volatility is estimated as the annualized 12-month standard deviation of daily CRSP returns (typically spanning 252 days of trading return data in a year, 200 minimum). Since firms' uncertainty is measured yearly, we collapse our daily temperature data at the year-level, by computing the yearly average and standard deviation of daily temperatures, for each firm.

The literature also recognizes that firms' exposure to (different sources of) risks may affect their performance (Hassan et al., 2019). To test this additional mechanism potentially channeling the effect of temperature uncertainty on firms' investments, we collect data from Hassan et al. (2019) and Sautner et al. (2023), and link them to our measure of temperature uncertainty. Hassan et al. (2019) use textual analysis of quarterly earnings conference-call transcripts to measure the extent of political and non-political risks—as well as risks associated to specific (political) topics—faced by 7,357 US listed firms, over the period 2002-2016. In this analysis, we focus on environment-related risks and non-political risks. To build the former index, Hassan et al. (2019) rely on a vocabulary compiled by *OnTheIssues.org* to educate voters about the positions of politicians on key topics, including "environment", e.g., clean air and water, climate change, renewables. To define non-political risks, the authors use a selected vocabulary of non-political text—based on both undergraduate textbooks on financial accounting to reflect financial disclosures and accounting information, and selected articles from well-known newspapers like New York Times, USA Today, the Wall Street Journal, and the Washington Post on the subject of "performance," "ownership changes," or "corporate actions". Then, they count the number of instances in which this selected text is used in conjunction with words *uncertainty* or *risk* during conference calls. Sautner et al. (2023) also use transcript of conference calls to measure the market's perception of how firms are affected by climate change, using a sample of over 10,000 firms in 30 countries (including the US), for the period 2002-2020. The authors construct a measure at quarterly frequency of firms' exposure to climate change—relative frequency of bigrams related to climate change in transcripts of conference calls—and firm-level risk due to climate change—relative frequency with which bigrams related to climate change are mentioned together with words *uncertainty* or *risk* in transcripts of conference calls.[7]

IV. Main Empirical Methodology

A. Baseline

We estimate impulse-response functions of firm's economic activity to temperature uncertainty, based on local projections (Jorda 2005). The approach enables us to incorporate the dynamic effect of temperature volatility on firms' performance through its lags. In addition, this procedure does not impose the dynamic restrictions embedded in vector autoregression specifications and is particularly suited to control for a large set of firms fixed effects, as well as to estimate nonlinearities in the dynamic response. Our baseline specification takes the following form:

$$y_{f,t+k} - y_{f,t-1} = \alpha_f^k + \gamma_t^k + \beta^k TeV_{f,t-1} + \delta^k X_{f,t-l} + \varepsilon_{f,t+k}; \qquad (1)$$

where subscripts *f* and *t* indicate firm and time (quarters), respectively; $y_{f,t+k} - y_{f,t-1}$ is the cumulative percent variation of (the log of) firms' capital expenditure, between *t+k* and *t-1*, with k=0,…,20 (quarters); α_f^k are firms fixed effects, included to control for firms time-invariant characteristics, such as location—their inclusion is particularly relevant as temperature volatility drastically changes from one location to another as shown in Figure 2; γ_t^k are quarter fixed effects, which account for all macroeconomic shocks affecting firms at the same time. $TeV_{f,t-1}$ is our measure of temperature volatility at the firm-location/quarter level.

In the baseline specification, the vector of controls $X_{f,t-l}$ includes four lags of the dependent variable, of temperature volatility and of average temperatures at firm/quarter level (with *l=1,…,4*). The inclusion of the latter is key to disentangle the effect of average temperature from volatility. In the robustness checks, we expand the set of controls to include firms' characteristics, as well as min and max temperatures, and the number of heat and cold days. The coefficients β^k indicate the percent variation of firms' capital expenditure, between *t-1* and *t+k,* in response to a 1-degree Celsius increase in temperature volatility at time *t-1*.

The high frequency and the level of granularity of data allow us to identify the causal economic effects of temperature volatility. First, the geographical granularity and the panel structure of the dataset enable us to account for unobserved heterogeneity across firms and locations by including fixed effects at the firm-location levels. Specifically, subnational geography such as proximity to the coast or mountains may influence temperature averages and volatility as well as economic activity since coastal regions, for example, may have more stable temperatures and potentially more economic opportunities (Figure 2). Combining granular geocoded climate data with rich longitudinal firm panel data is thus key to identify the economic impact of climate change

[7] Note that it is possible to match firms in Alfaro et al. (2021), Hassan et al. (2019) and Sautner et al. (2023) with Compustat data, by using firms' identification code; in doing so, we can extrapolate firms' zip code from Compustat, and use it to download daily temperatures at the firm/location level.

because—in contrast to studies using more aggregate data—it allows to focus on performance changes within firms taking out the potential impact of variation in local geographical characteristics within states or counties.

Second, the firm level data allow to control for the year of establishment of the firms and spans 60 years of data, implying that firms' awareness of climate change risks were absent or low for most of the sample period, addressing potential selections effects arising from new firms entering the market in recent years choosing locations less exposed to climate change risks. To further address this issue, we perform an analysis using unexpected changes in temperature volatility computed as described in the data section. Third, while economic activity at more aggregate levels can influence temperature volatility—and therefore invalidate causal inference due to reverse causality—it is unreasonable that this would happen at the zip code level. Finally, the quarterly frequency of our data further addresses endogeneity concerns as economic activity is unlikely to affect temperatures within a quarter, even more so at the zip code level.

Equation (1) is estimated for an unbalanced panel of firms from 1961Q1 to 2018Q4. Impulse response functions are computed using the estimated coefficients β^k, and confidence bands are obtained using robust standard errors clustered at the firm/location level.

V. Results

A. Baseline

Table 1 presents the results obtained estimating Equation (1) for each horizon (quarter) *k*, from 0 to 20. The firm fixed effects are jointly statistically significant, as are the time fixed effects, reflecting the importance of aggregate shocks.

Figure 3 presents the evolution of (log) firms' investment following a 1-degree Celsius increase in temperature volatility. Time (quarter) is indicated on the x-axis; the solid line displays the average estimated response of (log) investment; shaded areas denote 90 percent confidence bands. The results suggest that increases in temperature volatility have sizeable and persistent negative effects on firms' investment.[8] In particular, we find that a 1-degree Celsius increase in temperature volatility causes a reduction in investment of 0.4 percent in the first year and about 1.4 percent 20 quarters after. This effect is not only highly statistically significant but also economically sizeable: the results imply that the increase in temperature volatility observed in the US between 2000 and 2018 (from a standard deviation of 4.39 to 5.55 Celsius) have led to a drop in firms' investment by 1.6 percent in the medium term—that is, about 20USD billion for the entire US economy.

Our framework controls for average temperature at the firm location. An interesting question is whether the estimated economic impact of temperature volatility captures part of the effect of average temperature changes on firms' performance. Our evidence suggests that this is not the case. First, and consistent with Addoum et al. (2020), we find that the effect of average temperature is not statistically different from zero for any of the considered time horizons (Table 1 and Figure A1). Second, excluding average temperature changes as a

[8] A potential explanation of the significant medium-term investment effects of temperature volatility is that this measure is highly persistent: the correlation between temperature volatility and its one(four)-quarter lag is about 0.31 (0.83).

control variable from the estimation does not affect the economic impact of temperature volatility (results are similar and not statistically different from the baseline, see Figure A2).

Several studies in the literature (e.g., Burke et al. 2015; Acevedo et al. 2020) have found that the effect of average temperatures on economic activity tends to be non-linear and increases with the initial level of temperatures. To examine this possibility and check whether our estimates reflect such a non-linear effect, we extend the set of controls to include the square and cube of the average temperature. The effects of temperature volatility remain similar to the baseline estimates (Figure A3), and we find that the square and cube terms of average temperatures tend to have a negligible impact on firms' investment (Figures A4 and A5).

Higher temperature volatility may simply reflect more extreme temperatures, which have been found in the literature to be detrimental to economic activity (e.g., Pisa et al. 2022; Makridis and Schloetzer 2022). To disentangle these two effects, we extend the analysis to alternatively control for the minimum and the maximum temperatures, for each firm/quarter. The results point to three main findings. First, the effect of a 1-degree Celsius increase in temperature uncertainty is attenuated but still statistically significant when controlling for minimum temperatures—about -0.15 percent in the first year and about -0.7 percent 20 quarters after (Figure A6, Panel A)—but hardly changes when controlling for maximum temperatures—about -0.2 percent in the first year and about -1.5 percent 20 quarters after (Figure A6, Panel B).

Second, we find that a decline in minimum temperature has significant and negative effects on firms' investment. In particular, the results suggest that a 1-degree Celsius decline in minimum temperatures is associated with a reduction in investment by 0.1 percent in the first year and about 0.35 percent 20 quarters after (Figure A7, Panel A). The impact of the decline in minimum temperatures is consistent with our finding that lower labor productivity due to more sick days is one of the channels through which temperature volatility affects firms' performance. Third, the effect of rising maximum temperatures is partially negative, but not statistically different from zero for many of the considered time horizons for the estimated impact (Figure A7, Panel B). These results are qualitatively similar if we consider the number of heat and cold days, instead of maximum and minimum temperatures (Figures A8 and A9). Overall, these results suggest that, while periods of extreme cold as reflected in the observed decline in minimum temperatures are a channel through which higher volatility has reduced firms' investment in the US, the adverse economic impact of higher temperature volatility goes beyond the effect of extreme temperatures.

B. **Robustness Checks**

To further validate the robustness of these results, we performed several sensitivity tests across alternative samples and specifications. As a first check, we re-estimate equation (1) using three alternative measure of temperature volatility: (i) the log of the standard deviation of temperature; (ii) the difference between max and min temperatures; and (iii) residuals from regressing temperatures on date fixed effects, i.e., "unexpected" temperature volatility. The results presented in Figure A10 confirm a statistically significant and persistent effect of temperature volatility on firms' investment.

Then, we check whether the estimated impulse functions are sensitive to the lag parametrization used in equation (1), and the way we cluster standard errors. Results show that the impulse response functions obtained with alternative lags (1/2; 1/3; and 0/4) (Figure A11) or standard errors clustered at zip code level (Figure

A12) are similar to, and not statistically different from, those reported in Figure 1. In Figure A13, we exclude lags of the dependent variable in the estimation of equation (1), and confirm the baseline results. We winsorize the dependent variable to range between the 1st and the 99th percent of the distribution, and we show that the results are not affected by changes in investment at the tails of the distribution (Figure A14). Results are also identical to baseline ones if we consider a sub-sample starting in 2000, thus focusing on years of increasing climate concerns (Figure A15).

In an additional robustness check, we expanded the set of controls to include: (i) time-varying firm characteristics (age, size, liquidity, debt maturity and Tobin's Q of firms), both one at the time and together; (ii) firms specific time trends to account for different deterministic paths in firms' investment; (iii) firm-quarter dummies to control for seasonality; and (iv) firm-region dummies and region-specific time trends to control for differences across broad geographic regions as well as regional trends in both temperature and temperature volatility. The results reported in Figures A16 (Panels A-F) and A17 (Panels A-D) confirm our main findings.

Finally, we follow Ciminelli et al. (2022) and modify Equation (1) to include forward periods of the temperature volatility variable ($\sum_{j=1}^{k} TeV_{f,t+k}$). This makes it possible to control for shocks to temperature volatility that may potentially occur during the horizon of the impulse response function and that are not captured by the term $TeV_{f,t-1}$. As shown by Teulings and Zubanov (2014), not doing so could leave the model potentially mis-specified and bias our estimates. The results presented Figure A18 also in this case are similar to, and not statistically different from, those obtained in the baseline.

C. **Alternative economic outcomes**

We extend the analysis to consider alternative firms' economic outcomes. First, we consider the investment ratio as the dependent variable instead of the log of investment. Figure 4 Panel A presents analogue results as in Figure 3. The results suggest that a 1-degree Celsius increase in temperature volatility causes a reduction in the investment ratio of about 1 percentage point after 20 quarters.

In Figure 4 Panel B, we report the response of firms' sales. The results suggest that increases in temperature volatility also have negative and persistent effects on sales. The effects, however, are smaller than for investment—the reduction in sales is about 0.1 percent in the first year and about 0.5 percent 20 quarters after. This result is consistent with much of the literature on economic uncertainty, suggesting that uncertainty and volatility tend to have larger effects on investment than other variables such as output, productivity, and hours worked (Bloom 2008, 2014).

Finally, in Figure 4 Panels C and D, we consider the response of employment and labor productivity (based on annual data available for employment in Compustat).[9] The results suggest that a 1-degree Celsius increase in temperature volatility causes a medium-term reduction in employment (productivity) of about 0.7 (1.2) percent after 5 years.[10]

[9] When using data at yearly frequency as dependent variable, we directly compute the temperature shocks—both volatility and average—at the same level of temporal aggregation, using information on daily temperatures.

[10] For consistency, we also replicated the analysis for investment and sale using annual data. The results are reported in Figure A19. While the shapes of the estimated IRF are similar to those obtained using quarterly data, the magnitude of the results is larger when using annual data (about 5 percent for investment and 2 percent for sales after 5 years).

Our analysis relies on firms' information provided by Compustat. While the main advantaged of the dataset is that provides several economic variables (notably investment) for a long time period and at the quarterly frequency, which is better suited to identify the causal effect of temperature volatility, it has also two important limitations that can potentially give an inaccurate picture of the overall effect of temperature uncertainty for the US economy. The first is that the dataset covers only publicly listed firm. To the extent that small firms—which are not publicly listed—are more affected by temperature uncertainty, as we show in the next section, our results may underestimate the economy-wide effect of temperature volatility. The second is that the dataset provides information about firms' headquarters. This may also imply that our estimates are a lower bound of the true effect of temperature volatility to the extent that what matters more for investment decisions and firms' performance is not the volatility in temperature faced by the headquarters, but rather the volatility faced by corporate offices.

To address both issues, we replicated the analysis using monthly employment and unemployment rate data related to Metropolitan areas.[11] The results reported in Figure 5 (Panels A and B) confirm that temperature volatility has negative, statistically significant, and persistent effects on labor markets. In particular, we find that a 1-degree Celsius increase in temperature volatility causes a medium-term reduction (increase) in the monthly employment (unemployment rate) of about 0.06 percent (0.02 percentage point) after 60 months. To compare the employment results obtained with MSAs with those using Compustat, we also replicated the MSA analysis using annual data. The results presented in Figure A20 point to larger and significant economic effects, with a 1-degree Celsius increase in temperature volatility reducing (increasing) employment (unemployment rate) by about 1.7 percent (0.6 percentage point) after 5 years. Notably, the employment effect is more than double than that obtained with Compustat, confirming that the results obtained with the firms' data are likely to under-estimate the true negative effects of temperature uncertainty.

D. **Potential non-linearities**

In line with the literature suggesting a nonlinear effect of average temperature on the economy, such as a larger effect when average temperature is high, we also consider that the same nonlinear effect can be at work with temperature volatility. Thus, we augment our baseline specification as in Equation (1), by considering the interaction between temperature volatility and four dummies, which are equal to one if temperature volatility in firm *f* at quarter *t* is alternatively: (i) smaller than 25th percentile of the temperature volatility distribution; (ii) between 25th and 50th percentiles of the temperature volatility distribution; (iii) between 50th and 75th percentiles of the temperature volatility distribution; (iv) larger than the 75th percentile of the temperature volatility distribution. The resulting regression equation reads as follows:

$$y_{f,t+k} - y_{f,t-1} = \alpha_f^k + \gamma_t^k + \beta_1^k TeV_{f,t-1} \times TeV_{1,f,t-1} + \beta_2^k TeV_{f,t-1} \times TeV_{2,f,t-1} + \beta_3^k TeV_{f,t-1} \times TeV_{3,f,t-1} + \beta_4^k TeV_{f,t-1} \times TeV_{4,f,t-1} + \delta^k X_{f,t-l} + \varepsilon_{f,t+k}; \quad (2)$$

[11] Ideally, we would like to use firms' census data, but we did not have access to these data.

where TeV_n, with n=1,..,4, indicates the four dummies and n is the quartile of the distribution of temperature volatility. The results of this exercises are reported in Figure A21. While the point estimates are typically higher when temperature volatility is initially high (at the 4th quartile of the distributions), the effects are not statistically different across different quartiles of the distribution.

Figure 1, Panel B, reveals that the increase in temperature volatility in the last 30 years has not been homogeneously distributed across the US. Accordingly, we test if our baseline results are driven by locations where temperature volatility has increased the most. Empirically, we replicate estimation of Equation (2), but we construct the dummy variables on the basis of the evolution of temperature volatility between 1990 and 2018. In detail, we estimate the following equation:

$$y_{f,t+k} - y_{f,t-1} = \alpha_f^k + \gamma_t^k + \beta_1^k TeV_{f,t-1} \times \Delta TeV_{1,f} + \beta_2^k TeV_{f,t-1} \times \Delta TeV_{2,f} + \beta_3^k TeV_f \times \Delta TeV_{3,f,t-1} + \beta_4^k TeV_f \times \Delta TeV_{4,f} + \delta^k X_{f,t-l} + \varepsilon_{f,t+k}; \quad (3)$$

where ΔTeV_n, with n=1,…,4, is equal to one if the increase in temperature volatility between 1990 and 2018 in firm f is equal to first/second/third/fourth quartiles of the evolution of temperature volatility between 1990 and 2018 in our sample. The results, reported in Figure A22, do not point to statistically significant differences across the estimated coefficients.

E. Channels

In this section, we analyze some potential channels through which temperature uncertainty can affect economic outcomes.

A first channel is by increasing firms' economic uncertainty. Indeed, recent evidence suggests that climate risk considerations feature prominently in the investment decisions of listed firms around the world (e.g., Li et al. 2020; Sautner et al. 2020). To check for this possibility, we test the correlation between temperature volatility and firm-level economic uncertainty. We do so by making use of a novel data that assesses the degree of uncertainty faced by US listed firms, in terms of annual growth rate of realized volatility in stock returns, over the period 1992-2019 *(*Alfaro et al. 2023*)*. As described in Section III.C, annual firm realized volatility is estimated as the annualized 12-month standard deviation of daily CRSP returns (typically spanning 252 days of trading return data in a year, 200 minimum). Since firms' uncertainty is measured yearly, we collapse our temperature data at year-level, by computing yearly temperature volatility as the standard deviation of daily temperatures, for each firm/year, and estimate the following regression:

$$y_{f,t} = \alpha_f + \alpha_t + \beta TeV_{f,t-1} + \gamma X_{f,t-1} + \varepsilon_{f,t}; \quad (4)$$

where subscripts f and t refer to firm and year, respectively; $y_{f,t}$ indicates the yearly percent change of firms' uncertainty; $TeV_{f,t}$ is our measure of temperature volatility and $X_{f,t}$ is the average temperature for each firm/year; α_f and α_t are firm and year fixed effects, respectively. Standard errors are clustered at the firm-level. For robustness checks, we consider alternative specifications, without controlling for average temperature and with different batteries of fixed effects: only firm, only year, economic sector at NAICS 2-digit level, and the combination economic sector-year. The results of this analysis are reported in Table 2 (Column I-V) and show a positive and statistically significant effect of temperature volatility on firms' economic uncertainty. In particular, we find that a 1-degree Celsius rise in temperature volatility increases firms' uncertainty by approximately 1.5 percent (Table 2, Column I).

Next, we focus on the impact of temperature uncertainty on firm-level exposure to environmental and non-political risks, by using data at quarterly frequency from Hassan et al. (2019), described in Section III.C. In fact, exposure to (both political and non-political risks) risks have been found by the authors to negatively affect firm-level investments. We use the same empirical model as in equation (4), but using quarterly data and the two indexes from Hassan et al. (2019) as dependent variables (Table 2, Columns VI-XV). Our preferred specification—including firm and quarter fixed effects, and average temperature as control—suggests a positive impact of temperature volatility on firm-level exposure to environmental and non-political risks (+1.3 percent and +1.2 percent, respectively), with the effect that is highly statistically significant (Columns VI and XI). As before, we test the robustness of results to the use of alternative sets of fixed effects and the exclusion of the average temperature as a control, and estimated coefficients associated with temperature uncertainty hardly change.

We also exploit the novel indexes developed by Sautner et al. (2023), who aimed at measuring firm-level exposure to climate change (risks), at the quarterly frequency. In their empirical results, Sautner et al. (2023) find that climate change exposure is significantly priced in the options market. We re-estimate equation (4) using alternatively the degree of firm-level exposure to climate change and the potential risks associated with such exposure, as dependent variables. Estimates—reported in Table 2 Columns XVI-XXV—show a positive effect of temperature uncertainty on both dependent variables, with a magnitude similar to previous exercises. Taken together, this first set of analyses of transmission channels suggests that temperature uncertainty increases firms' riskiness, which in turn have been proved to be negatively correlated with firms' performance, particularly investment.

Temperature volatility can also reduce firms' investments and sales by causing direct damages to infrastructures, with electricity disruption especially in countries relying on overhead power cables, such as the US. To test for this channel, we use daily data on costumers affected by power outages at county level (Brelsford et al 2024). First, we collapse them at monthly frequency by summing up customers by county/month, and match them with monthly temperature data, i.e., average temperature and volatility. Empirically, we rely on a model of the following form:

$$y_{c,t} = \alpha_c + \alpha_t + \beta TeV_{c,t-1} + \gamma X_{c,t-1} + \varepsilon_{c,t}. \tag{5}$$

Subscripts c and t refer to county and month; $y_{c,t}$ indicates the (log) of the number of customers affected by power outages in county c at time t, i.e., the monthly percent increase in power outages; $TeV_{c,t-1}$ is temperature volatility, and $X_{c,t-1}$ includes the average (lagged) temperature, for each county/month. α_c and α_t are county and month fixed effects, respectively. The results in Table 2, Column (VI), confirm the relevance of this channel and suggest that a 1-degree Celsius rise in temperature volatility increases the number of power outages by 9 percent per month.

Another potential channel associated with higher temperature volatility is by increasing workers sickness and absenteeism. To test for this channel, we make use of a novel dataset on the yearly number of sickness days of each public school's teacher, granted by the Illinois State Board of Education, covering the period 2013-2020. First, we collapse teacher-level data at the school-district level at yearly frequency, for a total of 849 school-districts, and match them with yearly temperatures (average and fluctuations) using school-district shapefiles. We estimate the following specification:

$$y_{sd,t-}y_{sd,t-1} = \alpha_{sd} + \alpha_t + \beta TeV_{sd,t-1} + \gamma X_{sd,t-1} + \varepsilon_{sd,t}; \quad (6)$$

where subscripts *sd* and *t* indicate school-district and time (year), respectively; $y_{sd,t-}y_{sd,t-1}$ indicates the percentage point change in the number of sick days, for each school-district/year; $TeV_{sd,t-1}$ is temperature volatility in district *i* at time *t-1*, and $X_{c,t-1}$ includes the average (lagged) temperature, for each school-district-year. Note that we also control for the number of contracted days for each full-time employed teacher, which enters vector $X_{c,t-1}$. α_{sd} and α_t are school-district and year fixed effects, respectively.

The results reported in Table 2 (Column VII) confirm that temperature volatility has sizeable effects on the number of days a given teacher has been absent due to sickness. In particular, we find that a 1-degree Celsius increase in temperature volatility is associated with an increase in the of number of sick days per contracted days of about 8 percentage points.

VI. Heterogenity Across Sectors and Firms

A. Sectoral analysis

Previous findings in the literature suggest that the effects of uncertainty on the economy may vary across economic sectors and being larger in manufacturing than in other sectors (Brouthers et al. 2002; Freel 2005). We test whether the same applies for temperature uncertainty by splitting our sample between firms operating in manufacturing and services.[12] The results reported in Figure 6, Panels A and B show that while temperature uncertainty has statistically insignificant effects for firms in the service sector, it has negative, statistically significant and persistent effects for manufacturing firms.

Next, we follow Addoum et al. (2022) and examine whether firms in heat-sensitive industries (identified by Graff-Zivin and Neidell, 2014) are more affected by temperature volatility.[13] In particular, we create a dummy *HS* equal to one if firms operate in a heat-sensitive sector—with *NHS*=1-*HS* identifying firms in non-heat-sensitive sectors—and we interact them with temperature volatility, i.e., we estimate the following equation:

$$y_{f,t+k} - y_{f,t-1} = \alpha_f^k + \gamma_t^k + \beta^k HS \times TeV_{f,t-1} + \phi^k NHS \times TeV_{f,t-1} + \delta^k X_{f,t-l} + \varepsilon_{f,t+k}; \quad (7)$$

[12] Firms operating in manufacturing and services represent approximately the 30% and the 10% of the sample, respectively.

[13] Heat-sensitive sectors include (corresponding NAICS-code in parenthesis): food and tobacco (311 and 3122), paper manufacturing (322), motor vehicle manufacturing (3361), metal and mining (2122), transport (48), construction (23), utilities (221).

The results presented in Figure 7 show that while temperature volatility has statistically significant effects on firms' investment in both heat-sensitive and non-sensitive sectors, the effect is larger and more precisely estimated for the former.

B. Firm-level analysis.

The literature suggests that financial constraints amplify the effects of uncertainty on economic activity and, in particular, on investment (e.g., Alfaro et al. 2023). In this section, we borrow from this literature and examine whether the response of investment to increases in temperature uncertainty varies across firms according to their degree of financial constraints. Following the macro-financial literature, we consider five firm characteristics proxying financial constrains: the age of the firm; the size of firms; firms characterized by a large share of liabilities in short-term maturities; the share of liquid asset that can be used to finance investment, and the Tobin's Q—that is, the market value of a company divided by its assets' replacement cost (see Table A1 for descriptive statistics). According to the literature, we should expect the effects of temperature volatility to be larger for smaller and younger firms, those with a higher share of short-term liabilities and lower share of liquidity, and those with a lower Tobin's Q.

To check for this possibility, we modify equation (1) to allow the response of firms' performance to temperature volatility to be nonlinear, according to firm-level characteristics. In particular, we extend the baseline specification as follows:

$$y_{f,t+k} - y_{f,t-1} = \alpha_f^k + \gamma_t^k + F(z_{ft})[\beta_L^k TeV_{f,t-1} + \theta_L^k X_{f,t-l}] + \left(1 - F(z_{ft})\right)[\beta_H^k TeV_{\mathrm{f},t-1} + \theta_H^k X_{f,t-l}] + \varepsilon_{f,t+k} \quad (8)$$

with $F(z_f) = \frac{exp^{-\gamma z_f}}{1+exp^{-\gamma z_f}}$, $\gamma = 1.5$

in which ***z*** is alternatively an indicator of firms' characteristics (age, size, liquidity, debt maturity and Tobin's Q of firms) normalized to have zero mean and unit variance by means of a cross-firm variation in the normalization, that is $z_f = \frac{s_f - \bar{s}}{sd(s)}$. We use the average firms' characteristic over the entire sample (s_f) in the normalization to reduce endogeneity due to the potential time-varying response of firms' characteristic to temperature volatility. In the robustness checks, we also consider the initial sample value of the firms' characteristic. $F(z_f)$ is the smooth transition function. The weights assigned to each regime vary between 0 and 1 according to the weighting function $F(z_f)$, so that $F(z_f)$ can be interpreted as the probability of a firm to be in a specific state. The coefficient β_L^k refers to the low regime case (i.e., young, small, low liquidity, low maturity, low Tobin's Q firms)—that is, when $F(z_{it}) \approx 1$ and ***z*** goes to minus infinity. β_H^k is the coefficient of the alternative regime (i.e., old, large, high liquidity, high maturity, high Tobin's Q firms), that is when (1 – $F(z_{it})$) ≈ 1 and ***z*** goes to plus infinity. We set γ=1.5 to give an intermediate degree of intensity to the regime switching. $F(z_{ft})$=0.5 is the cut-off between the weak and strong regimes. The approach is similar to considering a dummy variable that takes value 1 when the variable is about the firm-specific mean—that is, $F(z_{ft})$>=0.5, and zero otherwise—we consider this approach in the robustness check. The difference is that instead of considering two discrete values (0 and 1), the smooth transition approaches allow the regimes to continuously vary between 0 and 1.

This approach to model interactions is equivalent to the smooth transition model developed by Granger and Terävistra (1993). Its advantages are threefold. First, compared with a model in which each dependent variable is interacted with each factor, it permits a direct test of whether the effect of temperature uncertainty varies across different regimes, such as high versus low financial constraints. Second, compared with a linear interaction model, it allows the magnitude of the effect of temperature uncertainty to vary non-linearly as a function of the different factors. Third, compared with estimating structural vector autoregressions for each regime, it allows the effect of temperature uncertainty to change smoothly between regimes by considering a continuum of states to compute the impulse response functions, thus making the response more stable and precise.

Consistent with the literature on economic uncertainty, the results suggest that the effects of temperature volatility on investment is disproportionally (at least two times) larger for firms that face financial constraints. We find that a 1-degree Celsius increase in temperature volatility leads to medium-term investment losses of about 4 percent for firms with a low Tobin's Q, and about 2½ for small and young firms, and those characterized by lower liquidity and with higher share of short-term debt maturity (Figure 8). The difference between the regimes is statistically significant for all considered time horizons.

We test the robustness of our results to alternative specifications. First, we use the initial sample value for each of firms' characteristics in the above normalization to further reduce endogeneity concerns. Second, we construct a series of dummy variables that take the value 1 if firm-level characteristics are larger than sample average, and zero otherwise, and we interact them with temperature volatility. In detail, we estimate the following equation:

$$y_{f,t+k} - y_{f,t-1} = \alpha_f^k + \gamma_t^k + D * \beta_L^k TeV_{f,t-1} + (1-D) * \beta_H^k TeV_{\mathrm{ft}-1}\, F + \theta^k X_{f,t-l} + \varepsilon_{f,t+k;} \quad (9)$$

where the dummy *D* refers to the low regime (i.e., young, small, low liquidity, low maturity, low Tobin's Q firms). The results obtained with these two exercises confirm our previous findings even if the differences between regimes is less clear-cut for some variable/specification (Figure A23-A24).

Finally, we investigate which of firm's characteristics play a larger role in amplifying the effect of temperature volatility on investment. To do so, we consider an alternative specification where we simultaneously include the interaction between the smooth transition functions $F(z_f)$, associated with each firms' characteristic *z*, and temperature volatility. We consider the regime that is expected to amplify the effect of temperature volatility on firms' performance, i.e., low age, low size, low liquidity, low maturity and low Tobin's Q, that is: the effect for younger firms—that is, those corresponding with an age lower than 4 quarters; for smaller firms—that is, those corresponding with a (log of) total assets lower than 2; for low-liquidity firms—that is, those corresponding with liquidity lower than 0.03; for short-term maturity firms—that is, those corresponding with a ratio of current liabilities to total liabilities lower than 0.2; and low Tobin's Q firms—those corresponding with Tobin's Q lower than 1. In detail, we estimate the following equation:

$$y_{f,t+k} - y_{f,t-1} = \alpha_f^k + \gamma_t^k + \delta^k TeV_{f,t-1} + F(z_{ft}) * \beta_L^k TeV_{f,t-1} + \theta_L^k X_{f,t-l} + \varepsilon_{f,t+k}$$

with $F(z_f) = \frac{exp^{-\gamma z_f}}{1+exp^{-\gamma z_f}}$, $\gamma = 1.5.$ (10)

The results of the analysis are reported in Table A2 and suggest that Tobin's Q and size are the firms' characteristics that are the most statistically significant in shaping the investment losses due to temperature volatility.

VII. Conclusions

A growing number of studies analyze the economic costs of changing climate conditions. Existing literature predominantly focuses on the impact of increasing average temperature changes or extreme events using aggregate data. Other channels through which climate change may affect the economy, such as climate variability, have not been fully explored in the literature. As a result, empirical evidence may underestimate the true economic costs of climate change.

In this article, we make two contributions to the literature. First, we illustrate that the negative impact of climate change on firms' economic activity in the US is caused by temperature fluctuations rather than average temperature changes—whose effects may, however, be significant in developing economies. Second, We further show that important channels through which temperature volatility reduces economic activity are by increasing power/energy disruptions, reducing labor productivity, and adding to the riskiness and economic uncertainty that firms face. Consistent with the last mechanism, we find that firms facing financial constraints are more exposed to temperature volatility.

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TABLES

Table 1. The Impact of Temperature Volatility on Firms' Investment

VARIABLES	fcap_0	fcap_2	fcap_4	fcap_6	fcap_8	fcap_10	fcap_12	fcap_14	fcap_16	fcap_18	fcap_20
L1.sdtemp	-0.004***	-0.004**	-0.004**	-0.004*	-0.008***	-0.009***	-0.009***	-0.007**	-0.011***	-0.009***	-0.014***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
L2.sdtemp	-0.001	0.001	-0.000	-0.001	-0.003	-0.009***	-0.008**	-0.007**	-0.007**	-0.009***	-0.011***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
L3.sdtemp	-0.001	-0.003	-0.002	-0.005**	-0.006**	-0.011***	-0.008**	-0.009***	-0.008**	-0.011***	-0.014***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
L4.sdtemp	0.003**	-0.000	0.000	-0.001	-0.005**	-0.006**	-0.005*	-0.005*	-0.007**	-0.007**	-0.012***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
L1.meantemp	-0.000	-0.000	-0.000	-0.001	0.001	0.001	0.002	0.001	0.001	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
L2.meantemp	-0.001	-0.000	-0.001	0.000	0.001	0.001	0.000	0.001	0.000	-0.001	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
L3.meantemp	-0.000	0.001	-0.001	-0.000	0.000	0.002	0.001	0.002	0.001	0.001	-0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
L4.meantemp	0.001	-0.000	0.000	0.001	0.002	0.002	0.001	0.002	0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
L.fcap_0	-0.179***	-0.356***	-0.466***	-0.524***	-0.537***	-0.570***	-0.568***	-0.586***	-0.585***	-0.602***	-0.596***
	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
L2.fcap_0	-0.110***	-0.285***	-0.380***	-0.398***	-0.442***	-0.443***	-0.473***	-0.467***	-0.486***	-0.476***	-0.494***
	(0.002)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
L3.fcap_0	-0.105***	-0.245***	-0.323***	-0.336***	-0.376***	-0.375***	-0.395***	-0.392***	-0.409***	-0.399***	-0.419***
	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
L4.fcap_0	-0.082***	-0.185***	-0.213***	-0.255***	-0.257***	-0.285***	-0.280***	-0.295***	-0.286***	-0.302***	-0.291***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	598,840	562,634	531,098	502,062	475,141	449,958	426,413	404,198	383,528	363,883	345,372
R-squared	0.722	0.578	0.537	0.532	0.525	0.529	0.528	0.536	0.539	0.548	0.550

Note: The table reports the percent variation of firms' capital expenditure in response to a one-degree Celsius increase in temperature volatility, with estimates based on the following equation: $y_{f,t+k} - y_{f,t-1} = \alpha_f^k + \gamma_t^k + \beta^k TeV_{f,t-1} + \delta^k X_{f,t-l} + \varepsilon_{f,t+k}$, with *k*=20 (quarter). $y_{f,t+k} - y_{f,t-1}$ indicates the percent variation of firms' capital expenditure (in log) between *t-1* and *t+k,* while $TeV_{f,t-1}$ is temperature volatility at firm/quarter level. The vector $X_{f,t-l}$ includes four lags of firms' capital expenditure, of temperature volatility, and of average temperature at firm/quarter level. Firm and quarter fixed effects are always included. Standard errors are clustered at firm/location level.

Table 2. The Impact of Temperature Volatility on Firms' Uncertainty

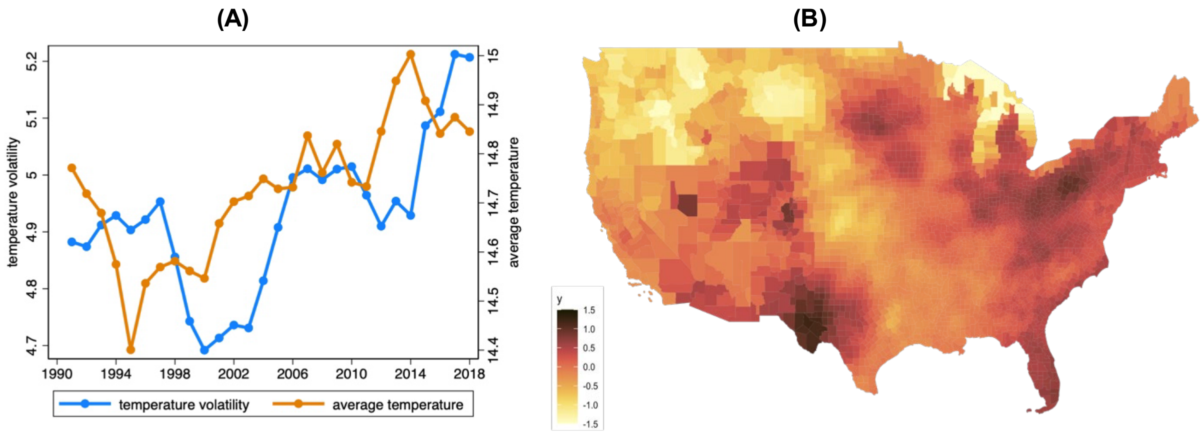
	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII	XIII	XIV	XV
Dep. Var.	**Firm-level uncertainty**					**Firm-level non-political risk**					**Firm-level environmental risk**				
Temp. Volatility	1.47*** (.326)	1.48*** (.321)	0.59*** (.067)	0.03*** (.006)	3.64*** (.280)	1.23*** (.466)	.98** (.388)	.235 (.659)	1.23*** (.466)	1.23*** (.466)	1.33** (.606)	.808 (.515)	2.80*** (.856)	1.36** (.606)	1.36** (.606)
Average Temp.	-0.02 (.13)		0.07*** (.20)	0.06*** (.02)	-0.5*** (.12)	.087 (.096)		.31** (.124)	.087 (.096)	.087 (.096)	.195 (.126)		.77*** (.16)	.195 (.126)	.195 (.126)
Obs.	93,310	93,310	94,605	94,605	93,310	177,116	177,116	177,116	177,116	177,116	177,116	177,116	177,116	177,116	177,116
R2	0.28	0.28	0.00	0.24	0.06	0.23	0.23	0.03	0.23	0.23	0.22	0.22	0.05	0.21	0.21
Sector FE	No	No	Yes	Yes	No	No	No	No	No	No	No	No	No	No	No
Firm FE	Yes	Yes	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes	No	No	Yes
Quarter FE	Yes	Yes	No	Yes	No	Yes	Yes	No	Yes	No	Yes	Yes	No	Yes	No

	XVI	XVII	XVIII	XIX	XX	XXI	XXII	XXIII	XXIV	XXV		XXVI		XXVII
Dep. Var.	**Firm-level climate change exposure**					**Firm-level climate change risk**					**Dep. Var.**	**Power outages**		**Sickness days**
Temp. Volatility	1.42*** (.26)	1.65*** (.217)	5.14*** (.697)	1.42*** (.26)	1.42*** (.26)	1.33*** (.459)	1.147*** (.372)	3.135*** (.63)	1.32*** (.459)	1.33*** (.459)	**Temp. Volatility**	8.91*** (0.61)		8.12** (3.71)
Average Temp.	-.08 (.054)		-.404 (.120)	-.082 (.054)	-.082 (.054)	.065 (.086)		.358*** (.118)	.065 (.086)	.065 (.086)	**Average Temp.**	4.42*** (0.21)		2.01 (3.12)
Obs.	173,176	173,176	173,176	173,176	173,176	173,832	173,832	173,832	173,832	173,832	**Obs.**	346,04		5,577
R2	.49	.49	.003	.49	.49	.21	.20	.001	.20	.20	**R2**	0.72		
Firm FE	Yes	Yes	No	No	Yes	Yes	Yes	No	No	Yes	**County FE**	Yes	**School FE**	Yes
Quarter FE	Yes	Yes	No	Yes	No	Yes	Yes	No	Yes	No	**Month FE**	Yes	**Year FE**	Yes

Note: In columns (I-XXV), estimates are based on equation (4); in Column (XXVI), estimate is based on equation (5); in Column (XVII), estimate is based on equation (6). *** *p<0.01, ** p<0.05*

FIGURES

Figure 1. The Change in Temperature Volatility Between 1990 and 2018



Note: Panel A (left chart) shows the evolution of US temperature volatility and average temperature (smoothed using 5-year centered moving averages) between 1990 and 2018; Panel B (right chart) shows the changes in temperature volatility across US areas between 1990 and 2018.

Figure 2. Temperature volatility in 2018 (i.e., yearly average standard deviation of daily temperatures)

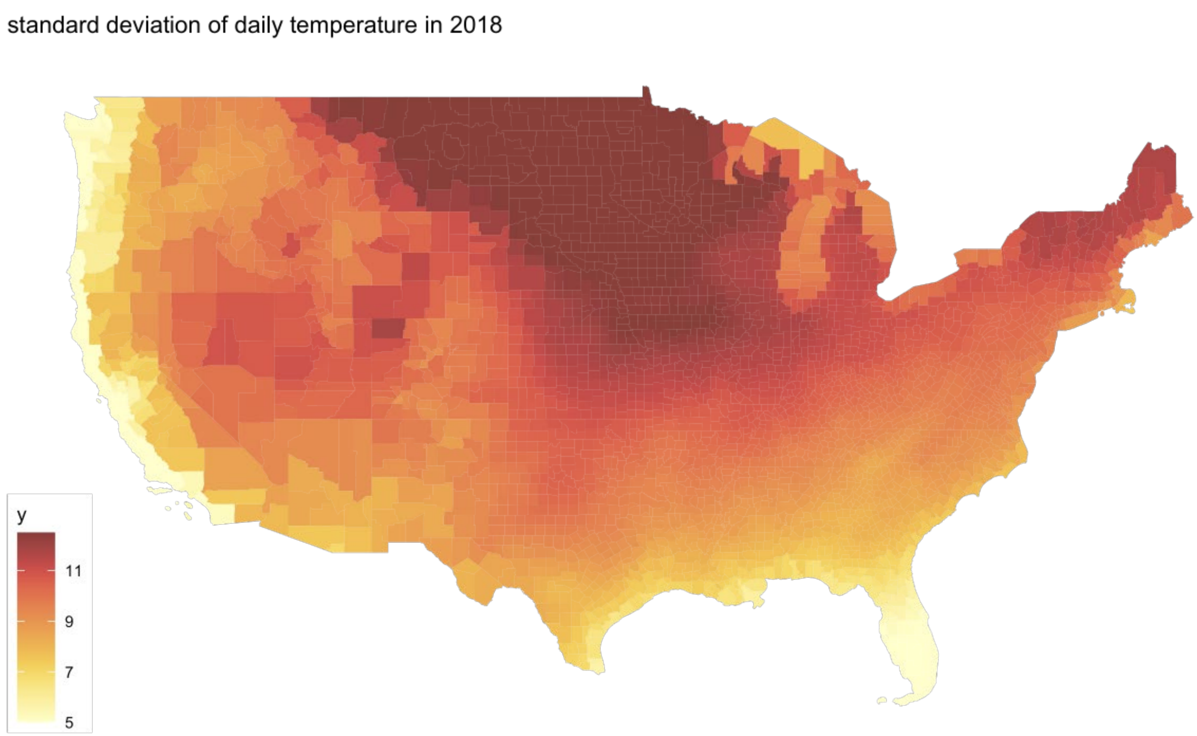
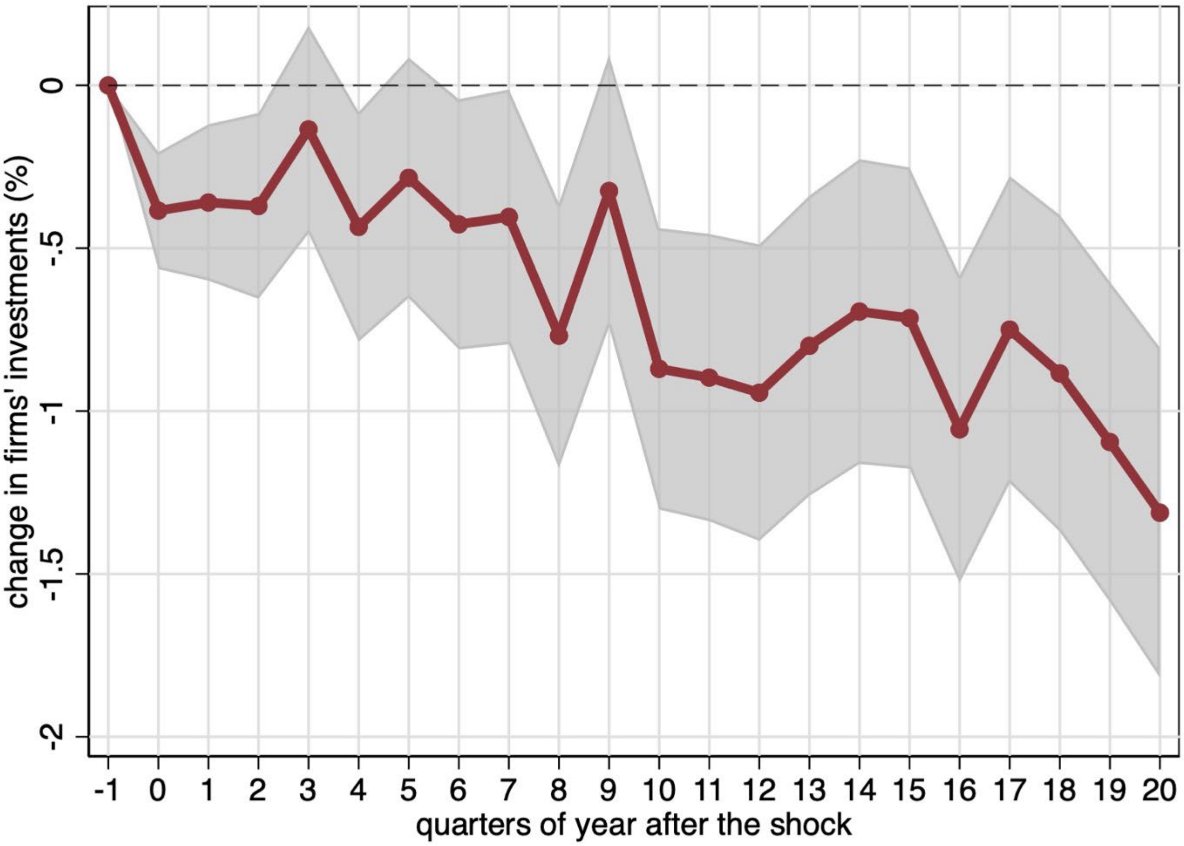
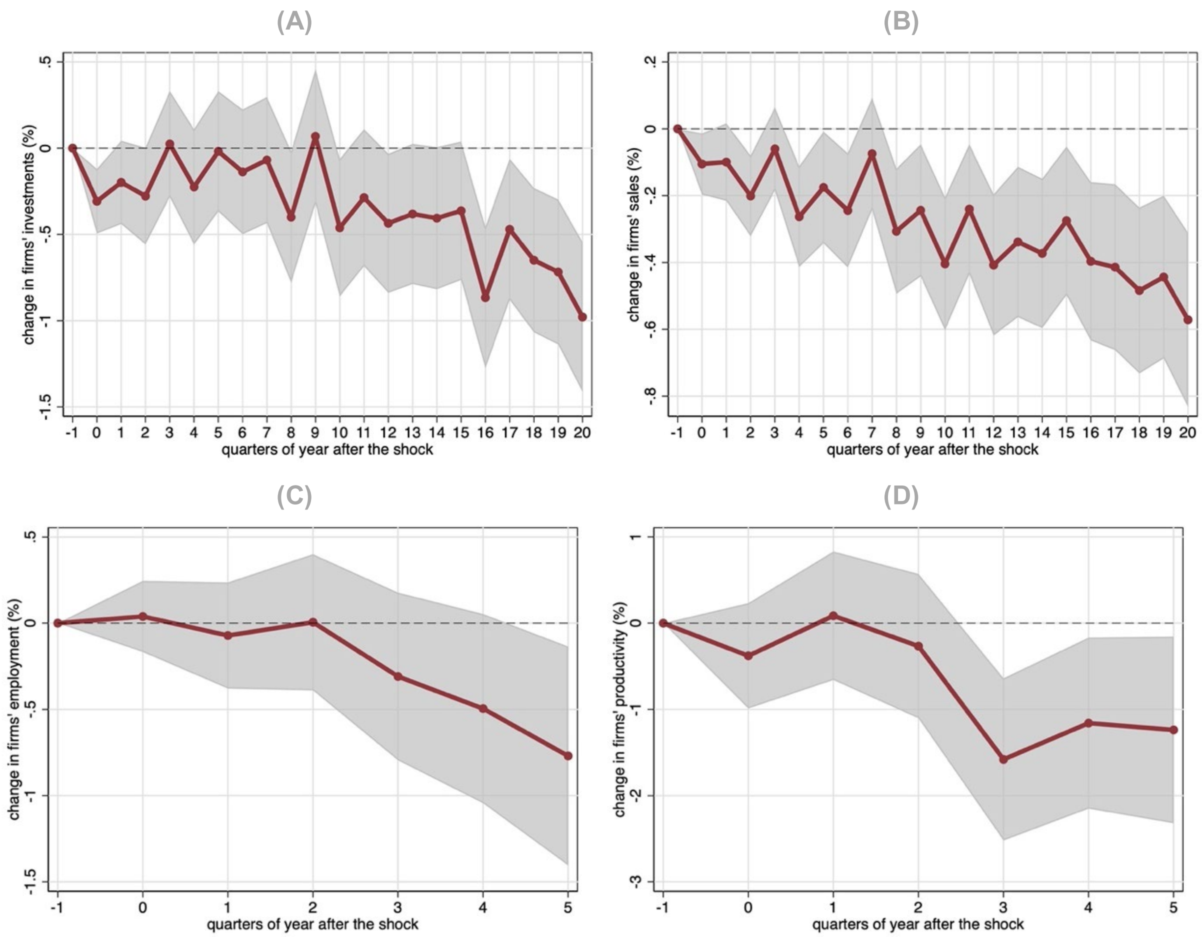


Figure 3. The Impact of Temperature Volatility On Firms' Investment



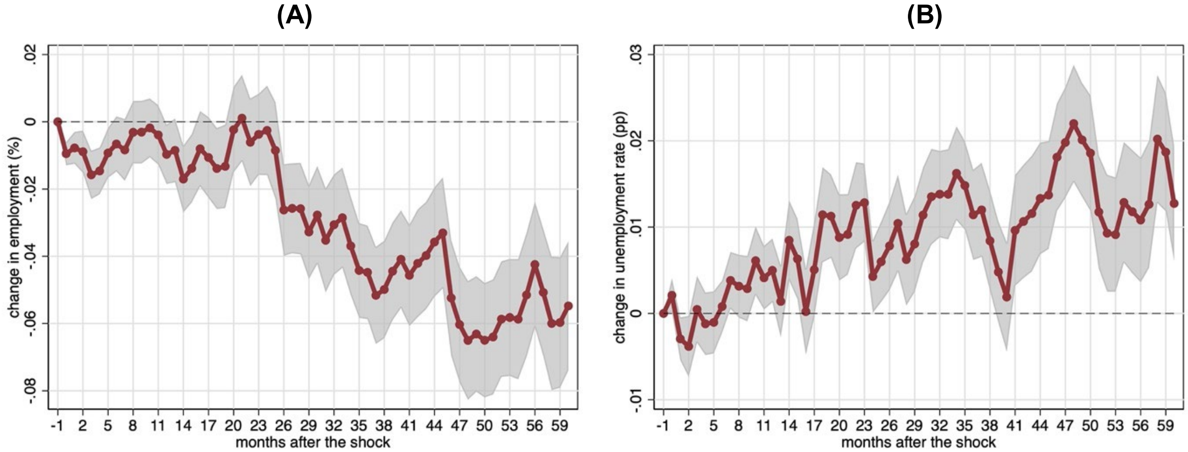
Note: The graph shows the percent variation of firms' capital expenditure in response to a one-degree Celsius increase in temperature volatility (red line), as well as 90 percent confidence bands (shaded area). Impulse response functions are estimated based on the following equation: $y_{f,t+k} - y_{f,t-1} = \alpha_f^k + \gamma_t^k + \beta^k TeV_{f,t-1} + \delta^k X_{f,t-l} + \varepsilon_{f,t+k}$, with *k*=20 (quarter). $y_{f,t+k} - y_{f,t-1}$ indicates the percent variation of firms' capital expenditure (in log) between *t-1* and *t+k,* while $TeV_{f,t-1}$ is temperature volatility at firm/quarter level. The vector $X_{f,t-l}$ includes four lags of firms' capital expenditure of temperature volatility, and of average temperature at firm/quarter level. Firm and quarter fixed effects are always included. The x-axis shows quarters (*k*) after the temperature volatility shock at *t =-1*. The y-axis shows the percent variation of the dependent variable between *t-1* and *t+k,* with *k* (quarter)=20.

Figure 4. The impact of temperature volatility on firms' investment ratio (A), sales (B), employment (C) and labor productivity (D)



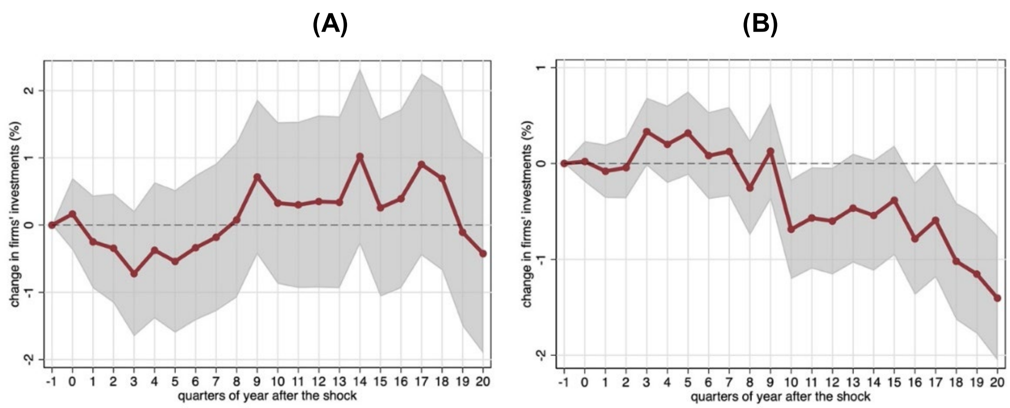
Note: The graphs show the percent variation of firms' investment ratio (panel A)–computed as capital expenditure over the lag of total property, plant and equipment–, (log of) sales (panel B), (log of) employment (panel C), and labor productivity (panel D)—computed as sales over employment—in response to a one-degree Celsius increase in temperature volatility (red line), as well as 90 percent confidence bands (shaded area). Impulse response functions are estimated based on the following equation: $y_{f,t+k} - y_{f,t-1} = \alpha_f^k + \gamma_t^k + \beta^k TeV_{f,t-1} + \delta^k X_{f,t-l} + \varepsilon_{f,t+k}$, with *k*=20 (quarter) for panel A and B, and 5 (years) for panel C and D. $y_{f,t+k} - y_{f,t-1}$indicates the percent variation of firms' investment ratio/sales/employment/labor productivity, between *t-1* and *t+k,* while $TeV_{f,t-1}$ is temperature volatility at firm/quarter level. The vector $X_{f,t-l}$ includes four lags of the dependent variables, of temperature volatility, and of average temperature at firm/quarter level. Firm and quarter fixed effects are always included. The x-axis shows quarters (*k*) after the temperature volatility shock at *t =-1*. The y-axis shows the percent variation of the dependent variable between *t-1* and *t+k,* with *k* (quarter)=20.

Figure 5. The impact of temperature volatility on unemployment (A), and unemployment rate (B), using Metropolitan Statistical Area (MSA) data



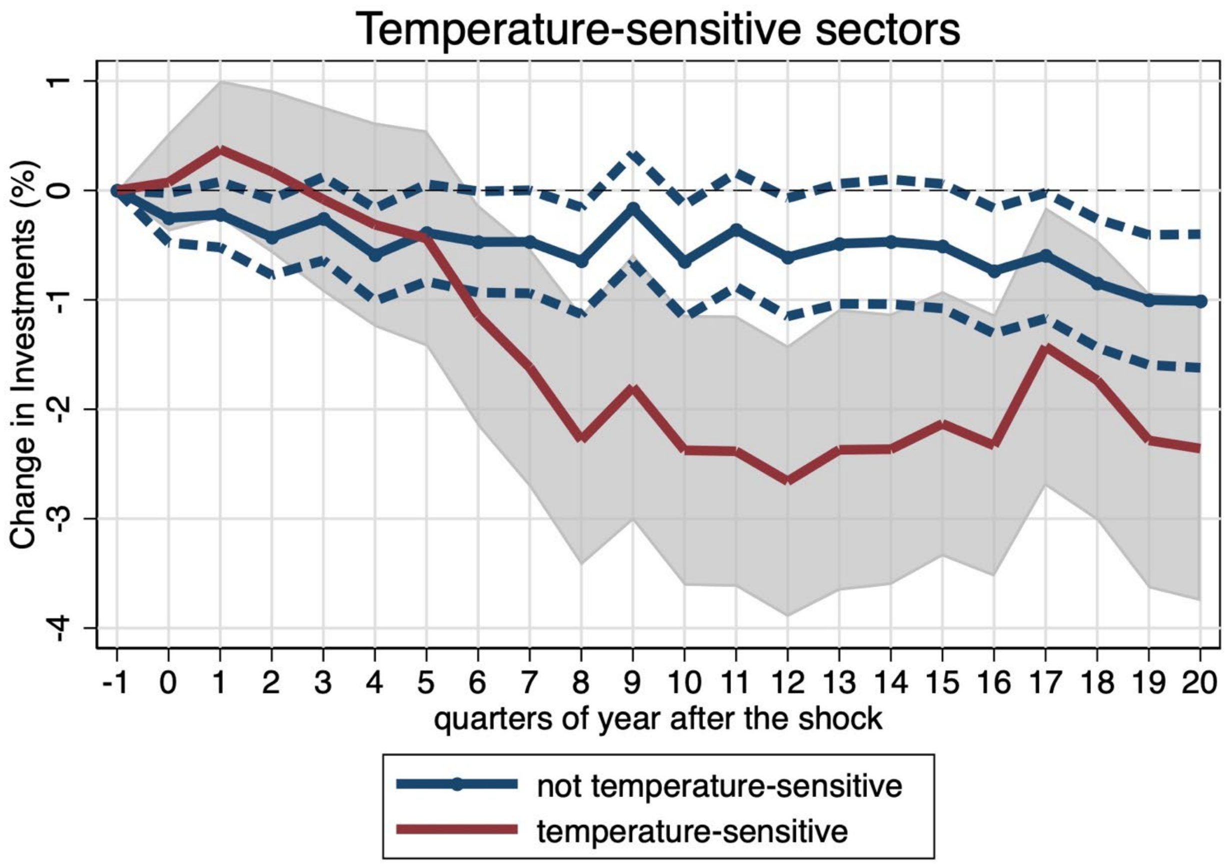
Note: The graphs show the variation of (log of) employment (%) (panel A) and unemployment rate (percentage point) (panel B)—using MSA data—in response to a one-degree Celsius increase in temperature volatility (red line), as well as 90 percent confidence bands (shaded area). Impulse response functions are estimated based on the following equation: $y_{f,t+k} - y_{f,t-1} = \alpha_f^k + \gamma_t^k + \beta^k TeV_{f,t-1} + \delta^k X_{f,t-l} + \varepsilon_{f,t+k}$, with k=60 (months). $y_{f,t+k} - y_{f,t-1}$ indicates the percent variation of MSA's employment (in log) and unemployment rate, between *t-1* and *t+k,* while $TeV_{f,t-1}$ is temperature volatility at firm/quarter level. The vector $X_{f,t-l}$ includes four lags of the dependent variables, of temperature volatility, and of average temperature at firm/quarter level. MSA and month fixed effects are always included. The x-axis shows months (k) after the temperature volatility shock at *t =-1*. The y-axis shows the percent variation of the dependent variable between *t-1* and *t+k,* with *k* (months)=60.

Figure 6. The impact of temperature volatility on firms' investment, depending on firms' economic sector: (A) service, (B) manufacturing



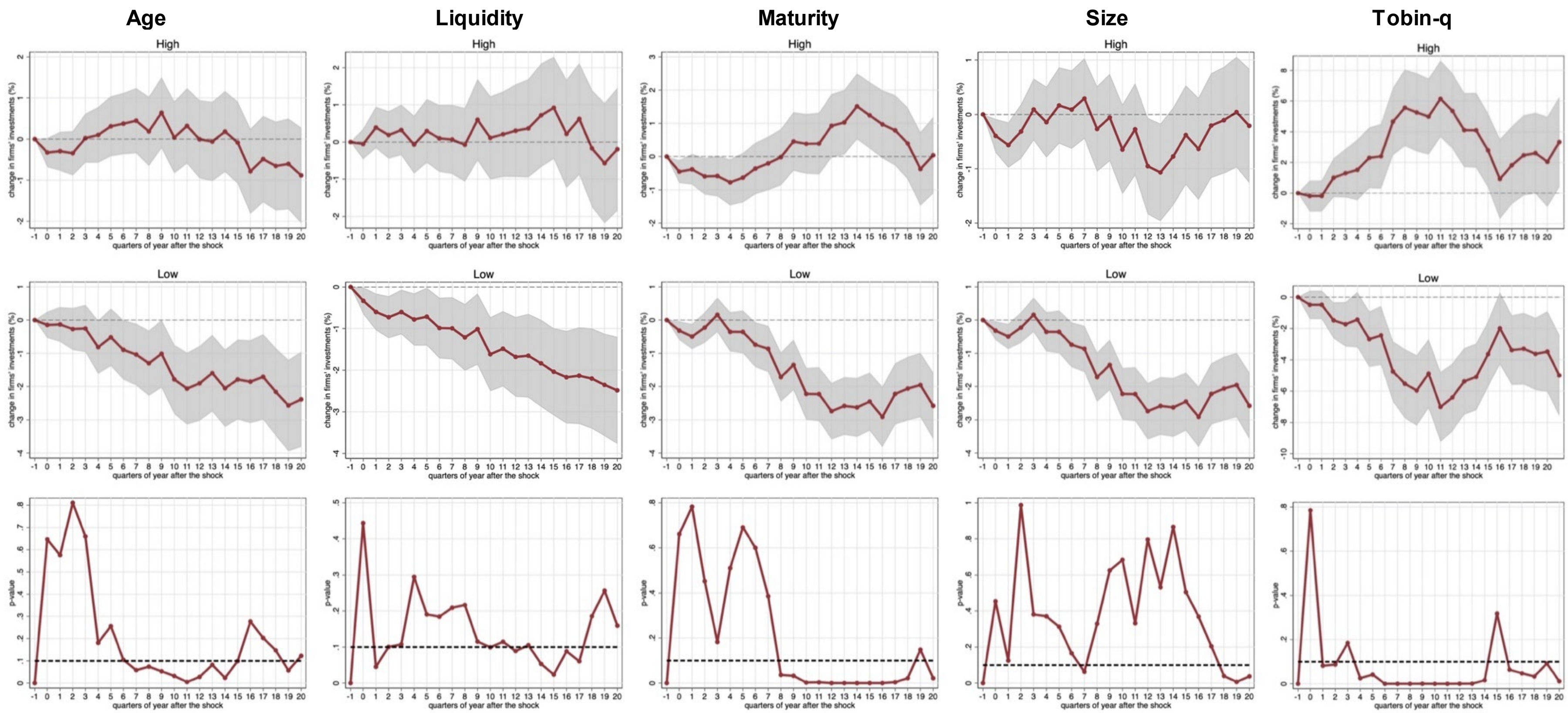
Note: The graphs show the percent variation of firms' capital expenditure in response to a one-degree Celsius increase in temperature volatility (red lines), as well as 90 percent confidence bands (shaded area). Impulse response functions are estimated based on the following equation: $y_{f,t+k} - y_{f,t-1} = \alpha_f^k + \gamma_t^k + \beta^k TeV_{f,t-1} + \delta^k X_{f,t-l} + \varepsilon_{f,t+k}$, with k=20 (quarter). $y_{f,t+k} - y_{f,t-1}$indicates the percent variation of firms' capital expenditure (in log) between *t-1* and *t+k,* while $TeV_{f,t-1}$ is temperature volatility at firm/quarter level. The vector $X_{f,t-l}$ includes four lags of firms' capital expenditure, of temperature volatility, and of average temperature at firm/quarter level. Firm and quarter fixed effects are always included. The x-axis shows quarters (k) after the temperature volatility shock at *t =-1*. The y-axis shows the percent variation of the dependent variable between *t-1* and *t+k,* with *k* (quarter)=20. Right panel only includes firms operating in manufacturing; left panel only includes firms operating in service.

Figure 7. The impact of temperature volatility on firms' investment, depending on firms' economic sector: temperature-sensitive sectors vs. non-temperature-sensitive sectors



Note: The graph shows the percent variation of firms' capital expenditure in response to a one-degree Celsius increase in temperature volatility, in case of temperature-sensitive sectors (red line) and non-temperature-sensitive sectors (blue line), as well as 90 percent confidence bands (shaded area and dotted lines, respectively). Impulse response functions are estimated based on the following equation: $y_{f,t+k} - y_{f,t-1} = \alpha_f^k + \gamma_t^k + \beta^k HS \times TeV_{f,t-1} + \phi^k NHS \times TeV_{f,t-1} + \delta^k X_{f,t-l} + \varepsilon_{f,t+k}$, with *k*=20 (quarter). $y_{f,t+k} - y_{f,t-1}$ indicates the percent variation of firms' capital expenditure (in log) between *t-1* and *t+k,* while $TeV_{f,t-1}$ is temperature volatility at firm/quarter level. *HS* is a dummy equal to one for temperature-sensitive sectors, and *NHS=1-HS.* The vector $X_{f,t-l}$ includes four lags of firms' capital expenditure, of the interaction terms between temperature volatility and *HS/NHS*, and of average temperature at firm/quarter level. Firm and quarter fixed effects are always included. The x-axis shows quarters (*k*) after the temperature volatility shock at *t =-1*. The y-axis shows the percent variation of the dependent variable between *t-1* and *t+k,* with *k* (quarter)=20.

Figure 8. The impact of temperature volatility on firms' investment, depending on firms' characteristics



Note: The graphs show the effect of temperature volatility on firms' capital expenditure, depending on firms' age, size, liquidity, maturity and Tobin's Q. Estimates are based on the following equation: $y_{f,t+k} - y_{f,t-1} = \alpha_f^k + \gamma_t^k + F(z_{ft})[\beta_L^k TeV_{f,t-1} + \theta_L^k X_{f,t-l}] + \left(1 - F(z_{ft})\right)[\beta_H^k TeV_{ft-1} + \theta_H^k X_{f,t-l}] + \varepsilon_{f,t+k}$; with $F(z_{ft}) = \frac{exp^{-\gamma z_{ft}}}{1+exp^{-\gamma z_{ft}}}$, $\gamma = 1.5$. *z* is alternatively an indicator of age, size, liquidity, maturity and Tobin's Q of firms, normalized to have zero mean and unit variance by means of a cross-firm variation in the normalization. $F(z_{ft})$ is the corresponding smooth transition function. Top panels refer to the case of old, large, high liquidity, high maturity, high Tobin's Q firms. Middle panels indicate young, small, low liquidity, low maturity and low Tobin's Q firms. Bottom panels report the F-test on the different of coefficients between regimes. $y_{f,t+k} - y_{f,t-1}$ is the percent variation of firms' capital expenditure (in log) between *t-1* and *t+k,* while $TeV_{f,t-1}$ is temperature volatility at firm/quarter level. The vector $X_{f,t-l}$ includes four lags of firms' capital expenditure, of the interaction between temperature volatility and the smooth transition function, and of average temperature at firm/quarter level. Firm and quarter fixed effects are included. The x-axes show quarters (*k*) after the temperature volatility shock at *t =-1*. The y-axes show the percent variation of the dependent variable between *t-1* and *t+k,* with *k* (quarter)=20.

APPENDIX

TABLES

Table A1. Firms' characteristics, descriptive statistics

Variable	Mean	SD	Min	Max	Construction
Age	23.5	23.7	0	202.25	(Current quarter – Date of incorporation)
Size	5.1	2.4	-6.9	14	log (AT)
Liquidity	0.16	0.19	-1.18	1	$\frac{\text{CHE}}{\text{AT}}$
Maturity	0.59	0.33	-23.4	132.6	$\frac{\text{LCT}}{\text{LT}}$
Tobin's Q	3.74	237.4	-1682	109810	$\frac{\text{AT} + (\text{CSHO} * \text{PRCC\_F}) - \text{CEQ}}{\text{AT}}$

Note: AT: Total Assets; CHE: Cash and Short-Term Investment; LCT: Current Liabilities; LT: Total Liabilities; CSHO: Common Shares Outstanding; PRCC_F: Price Close-Annual-Fiscal; CEQ: Total Common/Ordinary Equity. All variables have been retrieved from Compustat, except age from World scope.

Table A2. The impact of temperature volatility on firms' investment. Interaction with firm-level characteristics

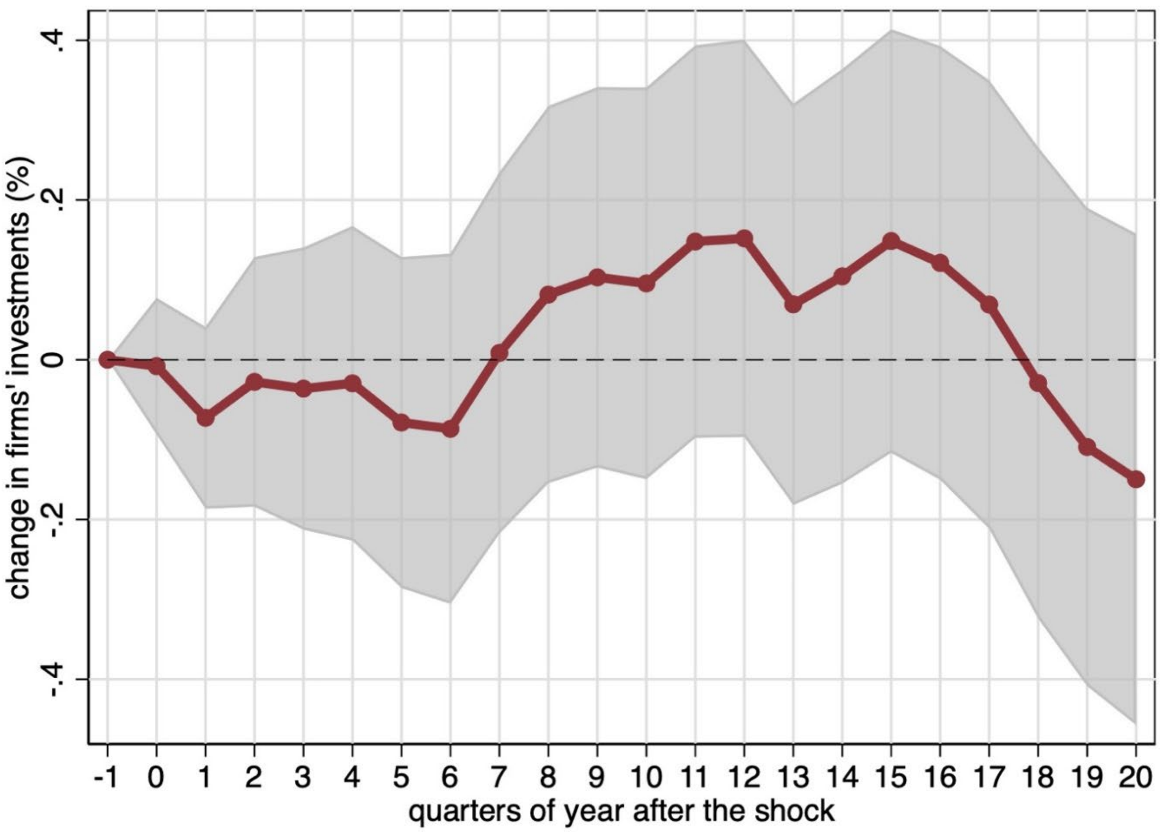
Quarters	(0)	(2)	(4)	(6)	(8)	(10)	(12)	(14)	(16)	(18)	(20)
Age	.002	.001	-.011	-.014	-.015	-.02*	-.02*	-.022*	-.009	-.012	-.012
	(.004)	(.006)	(.008)	(.009)	(.01)	(.011)	(.011)	(.012)	(.013)	(.013)	(.014)
Size	-.007	.006	-.018*	-.017	-.028**	-.029**	-.026*	-.026*	-.039**	-.051***	-.055***
	(.005)	(.008)	(.01)	(.011)	(.013)	(.013)	(.014)	(.015)	(.016)	(.017)	(.018)
Liquidity	-.006	-.015**	-.015*	-.017	-.002	-.012	-.007	-.023	-.017	-.022	-.018
	(.004)	(.007)	(.009)	(.01)	(.012)	(.013)	(.015)	(.017)	(.018)	(.02)	(.021)
Maturity	.002	.026***	.009	.012	-.027**	-.024*	-.045***	-.029*	-.044**	-.026	-.046**
	(.005)	(.008)	(.01)	(.012)	(.013)	(.014)	(.016)	(.017)	(.018)	(.02)	(.021)
Tobin	-.011	-.041	-.075**	-.128***	-.146***	-.171***	-.116***	-.095***	-.082**	-.075**	-.091**
	(.016)	(.027)	(.032)	(.036)	(.041)	(.04)	(.036)	(.035)	(.036)	(.036)	(.042)
Obs	314132	300663	288735	277456	266743	256471	246657	237081	227895	218950	210343
R-squared	.739	.585	.536	.523	.514	.514	.513	.518	.52	.526	.528
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: The table shows the effect of temperature volatility on firms' capital expenditure. Coefficients report the interaction term between temperature volatility and the smooth transition function $F(z_{ft}) = \frac{exp^{-\gamma z_{ft}}}{1+exp^{-\gamma z_{ft}}}$, $\gamma = 1.5$, for the case that we expect to be relevant in mediating the effect of temperature volatility. In detail we estimate the following equation: $y_{f,t+k} - y_{f,t-1} = \alpha_f^k + \gamma_t^k + F(z_{ft})[\beta_L^k TeV_{f,t-1}] + X_{f,t-l} + \varepsilon_{f,t+k}$; where z includes low age, low size, low liquidity, low maturity and low Tobin-Q. $y_{f,t+k} - y_{f,t-1}$ is the percent variation of firms' capital expenditure (in log) between *t-1* and *t+k,* while $TeV_{f,t-1}$ is temperature volatility at firm/quarter level. The vector $X_{f,t-l}$ includes four lags of firms' capital expenditure, of the interaction terms, and of average temperature at firm/quarter level. Firm and quarter fixed effects are included. Standard errors in parentheses are clustered at firm-location level.

**** p<.01, ** p<.05, * p<.1*

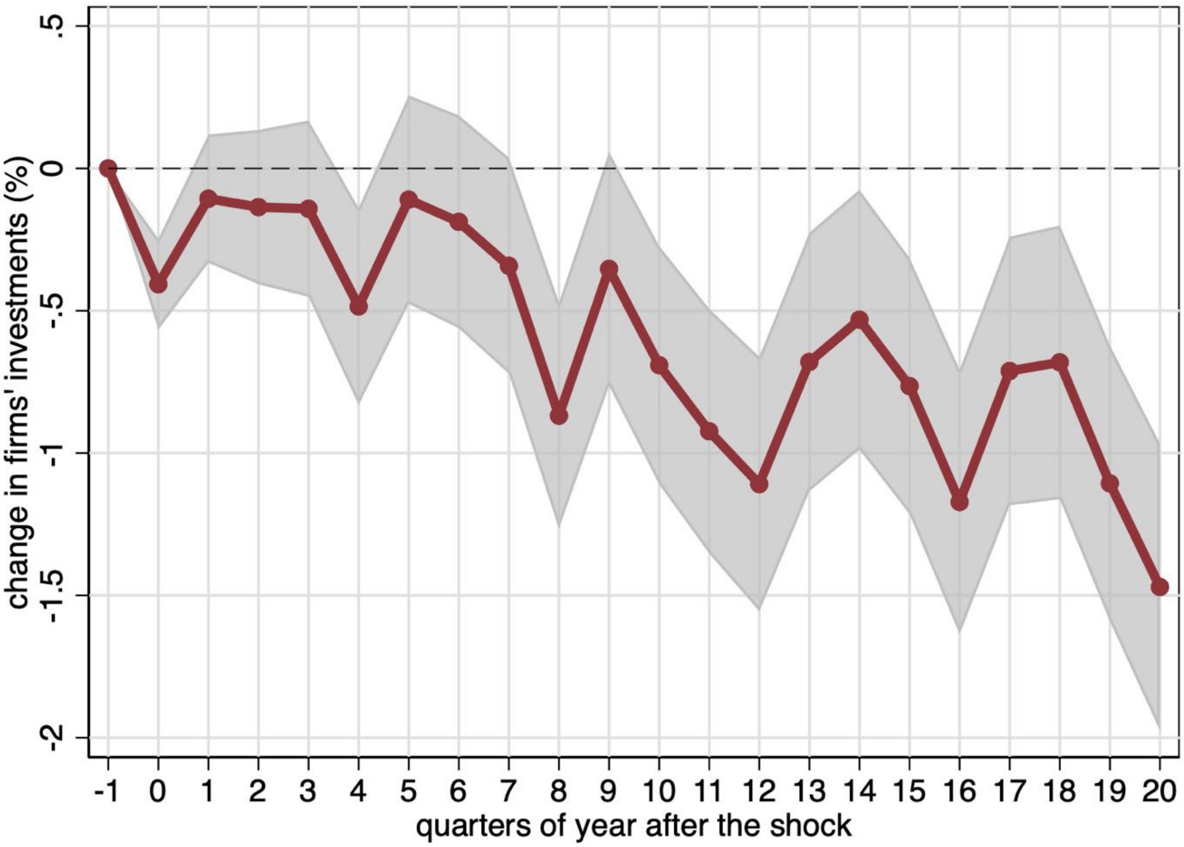
Figures

Figure A1. The impact of average temperatures on firms' investment



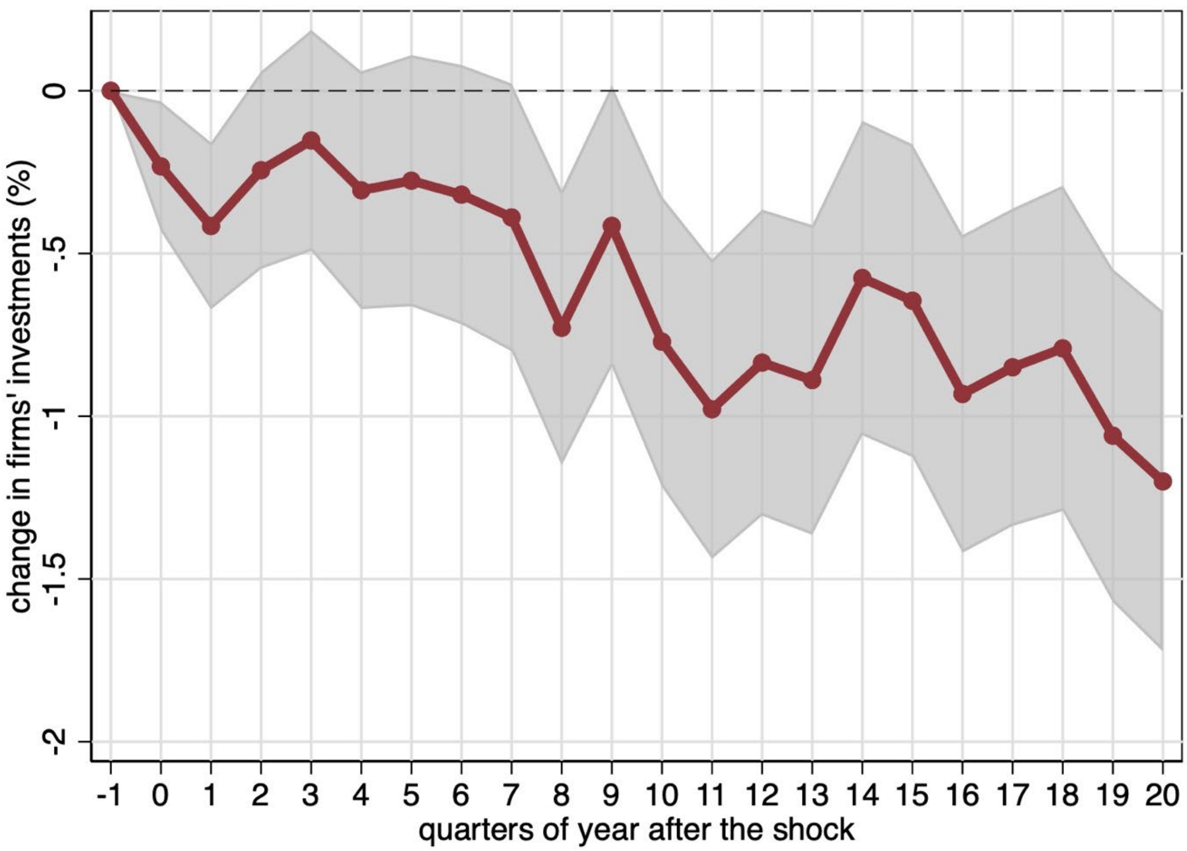
Note: The graph shows the percent variation of firms' capital expenditure in response to a one-degree Celsius increase in average temperature (red line), as well as 90 percent confidence bands (shaded area), based on the following equation: $y_{f,t+k} - y_{f,t-1} = \alpha_f^k + \gamma_t^k + \beta^k TeAvg_{f,t-1} + \delta^k X_{f,t-l} + \varepsilon_{f,t+k}$, with k=20 (quarter). $y_{f,t+k} - y_{f,t-1}$ indicates the percent variation of firms' capital expenditure (in log) between *t-1* and *t+k,* while $TeAvg_{f,t-1}$ is the average temperature at firm/quarter level. The vector $X_{f,t-l}$ includes 4 lags of firms' capital expenditure, and of temperature volatility. Firm and quarter fixed effects are always included. The x-axis shows quarters (*k*) after the average temperature shock at t = -1. The y-axis shows the percent variation of the dependent variable between *t-1* and *t+k,* with *k* (quarter)=20.

Figure A2. The impact of temperature volatility on firms' investment (excluding average temperature as control)



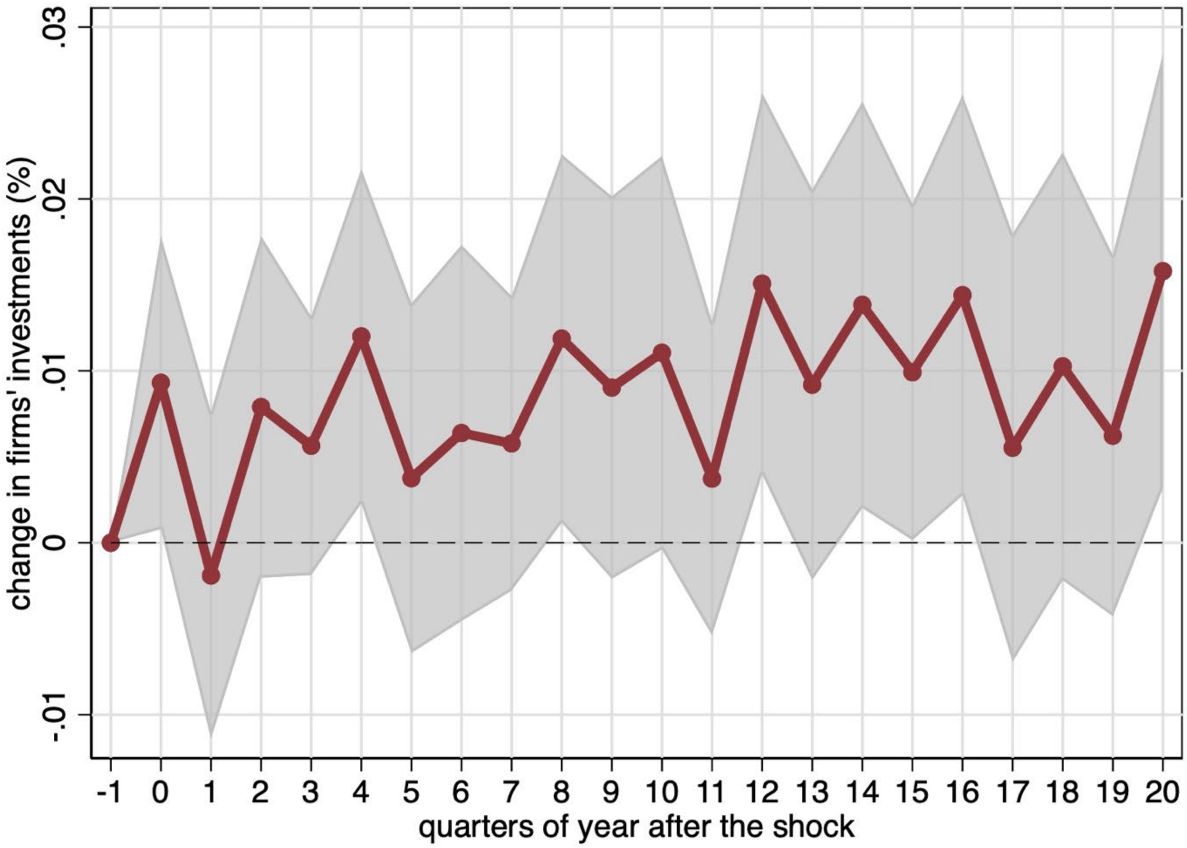
Note: The graph shows the percent variation of firms' capital expenditure in response to a one-degree Celsius increase in temperature volatility (red line), as well as 90 percent confidence bands (shaded area). Impulse response functions are estimated based on the following equation: $y_{f,t+k} - y_{f,t-1} = \alpha_f^k + \gamma_t^k + \beta^k TeV_{f,t-1} + \delta^k X_{f,t-l} + \varepsilon_{f,t+k}$, with *k*=20 (quarter). $y_{f,t+k} - y_{f,t-1}$indicates the percent variation of firms' capital expenditure (in log) between *t-1* and *t+k,* while $TeV_{f,t-1}$ is temperature volatility at firm/quarter level. The vector $X_{f,t-l}$ includes four lags of firms' capital expenditure, of temperature volatility at firm/quarter level. Firm and quarter fixed effects are always included. The x-axis shows quarters (*k*) after the temperature volatility shock at *t =-1*. The y-axis shows the percent variation of the dependent variable between *t-1* and *t+k,* with *k* (quarter)=20.

Figure A3. The impact of temperature volatility on firms' investment (with average temperature square and cube as additional controls)



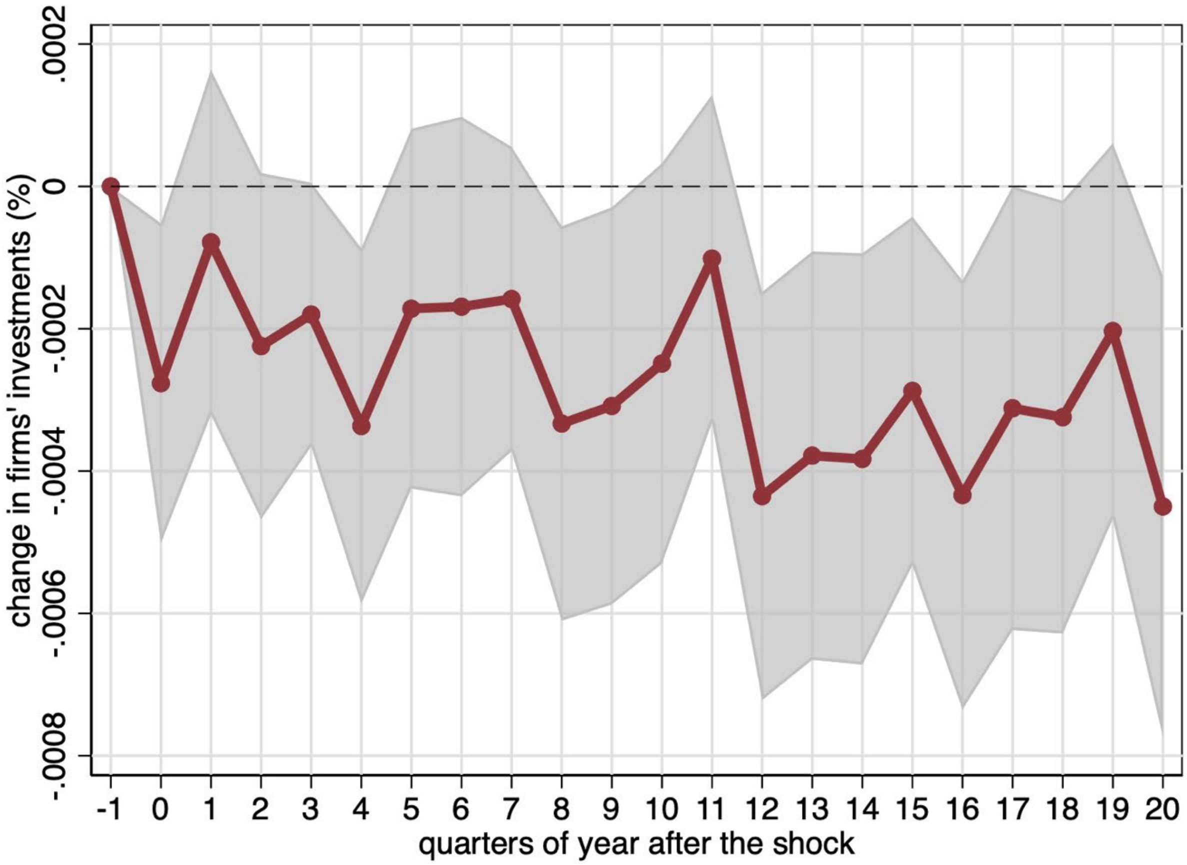
Note: The graph shows the percent variation of firms' capital expenditure in response to a one-degree Celsius increase in temperature volatility (red line), as well as 90 percent confidence bands (shaded area). Impulse response functions are estimated based on the following equation: $y_{f,t+k} - y_{f,t-1} = \alpha_f^k + \gamma_t^k + \beta^k TeV_{f,t-1} + \delta^k X_{f,t-l} + \varepsilon_{f,t+k}$, with *k*=20 (quarter). $y_{f,t+k} - y_{f,t-1}$ indicates the percent variation of firms' capital expenditure (in log) between *t-1* and *t+k,* while $TeV_{f,t-1}$ is temperature volatility at firm/quarter level. The vector $X_{f,t-l}$ includes four lags of firms' capital expenditure, of temperature volatility, and of average temperature at firm/quarter level, as well as the lag of average temperature square and cube. Firm and quarter fixed effects are always included. The x-axis shows quarters (*k*) after the temperature volatility shock at *t =-1*. The y-axis shows the percent variation of the dependent variable between *t-1* and *t+k,* with *k* (quarter)=20.

Figure A4. The impact of average temperature square on firms' investment



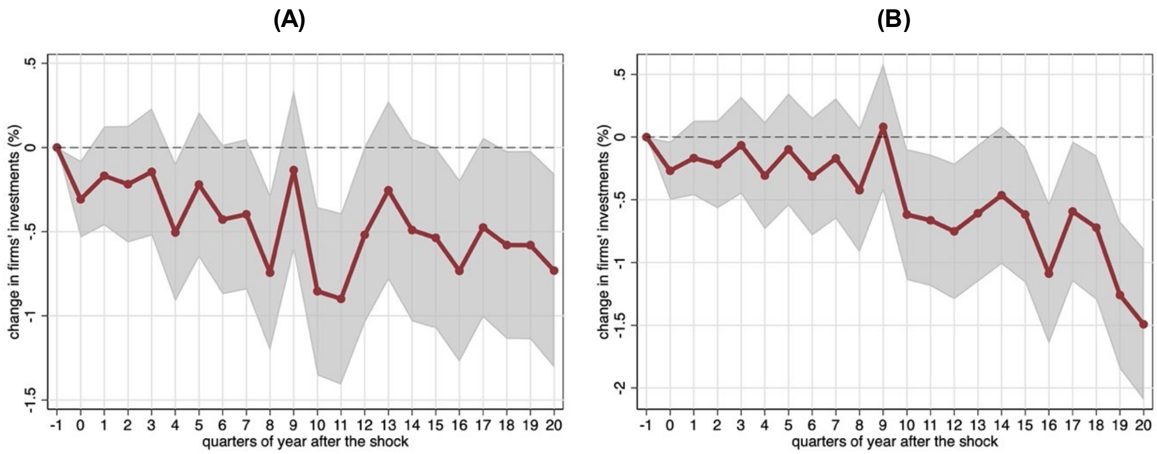
Note: The graph shows the percent variation of firms' capital expenditure in response to a one-degree Celsius increase in average temperature square (red line), as well as 90 percent confidence bands (shaded area), based on the following equation: $y_{f,t+k} - y_{f,t-1} = \alpha_f^k + \gamma_t^k + \beta^k TeAvg\_SQ_{f,t-1} + \delta^k X_{f,t-l} + \varepsilon_{f,t+k}$, with k=20 (quarter). $y_{f,t+k} - y_{f,t-1}$ indicates the percent variation of firms' capital expenditure (in log) between *t-1* and *t+k*, while $TeAvg\_SQ_{f,t-1}$ is the average temperature square at firm/quarter level. The vector $X_{f,t-l}$ includes 4 lags of firms' capital expenditure, of temperature volatility, and of average temperature. Firm and quarter fixed effects are always included. The x-axis shows quarters (k) after the average temperature square shock at *t =-1*. The y-axis shows the percent variation of the dependent variable between *t-1* and *t+k,* with k (quarter)=20.

Figure A5. The impact of average temperatures cube on firms' investment



Note: The graph shows the percent variation of firms' capital expenditure in response to a one-degree Celsius increase in average temperature square (red line), as well as 90 percent confidence bands (shaded area), based on the following equation: $y_{f,t+k} - y_{f,t-1} = \alpha_f^k + \gamma_t^k + \beta^k TeAvg\_CUBE_{f,t-1} + \delta^k X_{f,t-l} + \varepsilon_{f,t+k}$, with k=20 (quarter). $y_{f,t+k} - y_{f,t-1}$ indicates the percent variation of firms' capital expenditure (in log) between t-1 and t+k, while $TeAvg\_CUBE_{f,t-1}$ is the average temperature cube at firm/quarter level. The vector $X_{f,t-l}$ includes 4 lags of firms' capital expenditure, of temperature volatility, and of average temperature, and the lag of average temperature square. Firm and quarter fixed effects are always included. The x-axis shows quarters (k) after the average temperature cube shock at t =-1. The y-axis shows the percent variation of the dependent variable between t-1 and t+k, with k (quarter)=20.

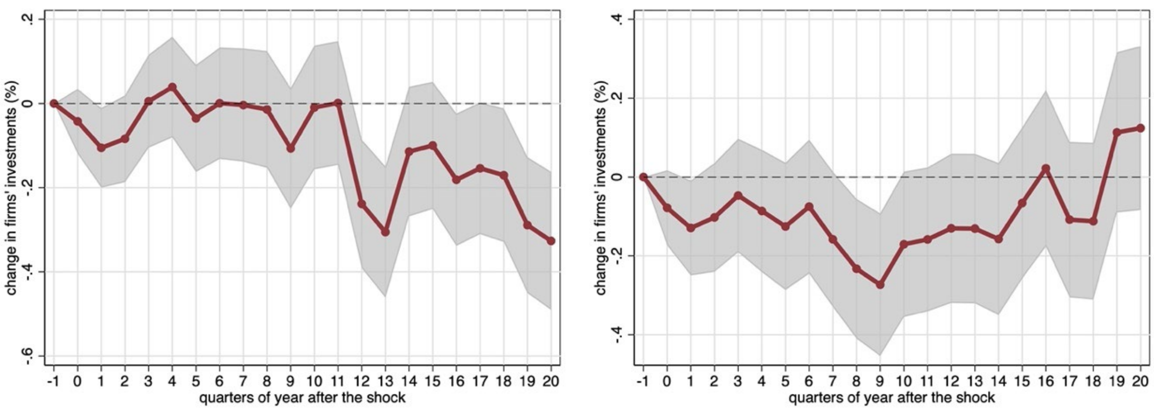
Figure A6. The impact of temperature volatility on firms' investment, with minimum temperature (panel A) or maximum temperature (panel B) as additional controls



Note: The graphs show the percent variation of firms' capital expenditure in response to a one-degree Celsius increase in temperature volatility (red line), as well as 90 percent confidence bands (shaded area). Impulse response functions are estimated based on the following equation: $y_{f,t+k} - y_{f,t-1} = \alpha_f^k + \gamma_t^k + \beta^k TeV_{f,t-1} + \delta^k X_{f,t-l} + \varepsilon_{f,t+k}$, with *k*=20 (quarter). $y_{f,t+k} - y_{f,t-1}$ indicates the percent variation of firms' capital expenditure (in log) between *t-1* and *t+k,* while $TeV_{f,t-1}$ is temperature volatility at firm/quarter level. The vector $X_{f,t-l}$ includes four lags of firms' capital expenditure, of temperature volatility, and of average temperature at firm/quarter level, as well as the lag of minimum temperature (panel A) or maximum temperature (panel B), at firm/quarter level. Firm and quarter fixed effects are always included. The x-axis shows quarters (*k*) after the temperature volatility shock at *t =-1*. The y-axis shows the percent variation of the dependent variable between *t-1* and *t+k,* with *k* (quarter)=20.

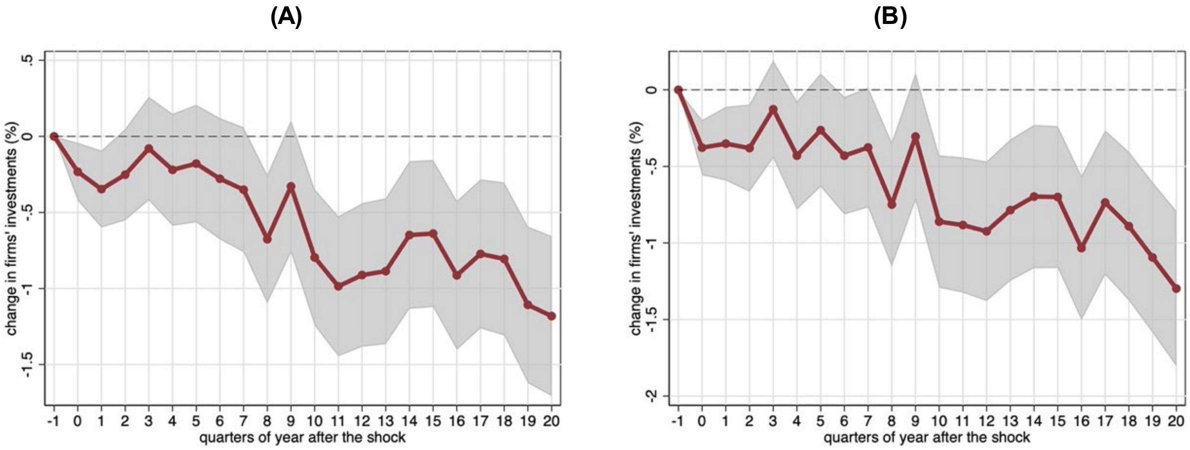
Figure A7. The impact of minimum temperatures (panel A) or maximum temperatures (panel B) on firms' investment

(A) **(B)**



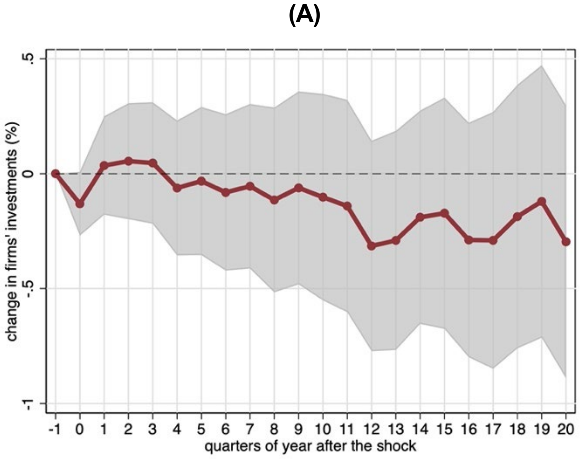
Note: The graphs show the percent variation of firms' capital expenditure in response to a one-degree Celsius reduction in minimum temperature (red line – panel A) or increase in maximum temperature (red line – panel B), as well as 90 percent confidence bands (shaded area). Impulse response functions are estimated based on the following equation: $y_{f,t+k} - y_{f,t-1} = \alpha_f^k + \gamma_t^k + \beta^k Min/MaxTemp_{f,t-1} + \delta^k X_{f,t-l} + \varepsilon_{f,t+k}$, with *k*=20 (quarter). $y_{f,t+k} - y_{f,t-1}$ indicates the percent variation of firms' capital expenditure (in log) between *t-1* and *t+k,* while $Min(Max)Temp_{f,t-1}$ is the lag of minimum (maximum) temperature at firm/quarter level. The vector $X_{f,t-l}$ includes four lags of firms' capital expenditure, of temperature volatility, and of average temperature at firm/quarter level. Firm and quarter fixed effects are always included. The x-axis shows quarters (*k*) after the temperature shock at *t =-1*. The y-axis shows the percent variation of the dependent variable between *t-1* and *t+k,* with *k* (quarter)=20.

Figure A8. The impact of temperature volatility on firms' investment, with the number of cold (panel A) or heat days (panel B) as additional controls



Note: The graphs show the percent variation of firms' capital expenditure in response to a one-degree Celsius increase in temperature volatility (red line), as well as 90 percent confidence bands (shaded area). Impulse response functions are estimated based on the following equation: $y_{f,t+k} - y_{f,t-1} = \alpha_f^k + \gamma_t^k + \beta^k TeV_{f,t-1} + \delta^k X_{f,t-l} + \varepsilon_{f,t+k}$, with k=20 (quarter). $y_{f,t+k} - y_{f,t-1}$indicates the percent variation of firms' capital expenditure (in log) between *t-1* and *t+k,* while $TeV_{f,t-1}$ is temperature volatility at firm/quarter level. The vector $X_{f,t-l}$ includes four lags of firms' capital expenditure, of temperature volatility, and of average temperature at firm/quarter level, as well as the lag of the number of cold (panel A) or heat days (panel B), at firm/quarter level. Firm and quarter fixed effects are always included. The x-axis shows quarters (k) after the temperature volatility shock at t =*-1*. The y-axis shows the percent variation of the dependent variable between *t-1* and *t+k,* with k (quarter)=20.

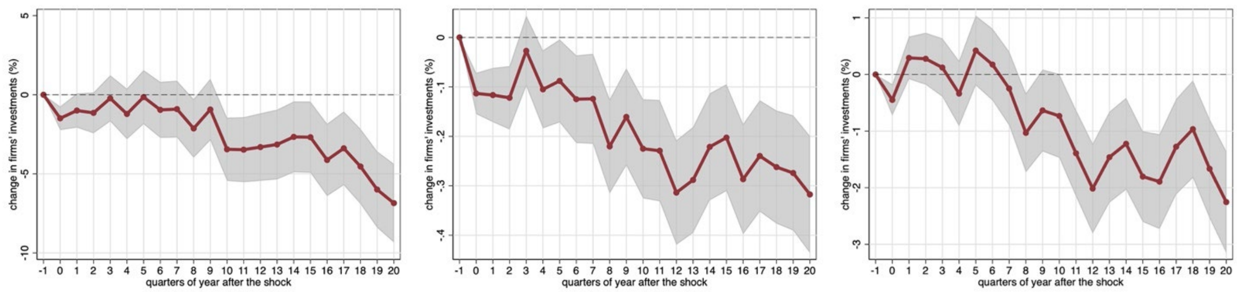
Figure A9. The impact of the number of cold (panel A) or heat days (panel B) on firms' investment



Note: The graphs show the percent variation of firms' capital expenditure in response to one additional cold day (CD)—with temperature ≤ 0-degree Celsius—(red line – panel A) or heat day (HD)—with temperature ≥ 35-degree Celsius—(red line – panel B) per firm/quarter, as well as 90 percent confidence bands (shaded area). Impulse response functions are estimated based on the following equation: $y_{f,t+k} - y_{f,t-1} = \alpha_f^k + \gamma_t^k + \beta^k CD/HD_{f,t-1} + \delta^k X_{f,t-l} + \varepsilon_{f,t+k}$, with k=20 (quarter). $y_{f,t+k} - y_{f,t-1}$indicates the percent variation of firms' capital expenditure (in log) between *t-1* and *t+k,* while $CD(HD)_{f,t-1}$ is the lag of the number of cold/heat days, at firm/quarter level. The vector $X_{f,t-l}$ includes four lags of firms' capital expenditure, of temperature volatility, and of average temperature at firm/quarter level. Firm and quarter fixed effects are always included. The x-axis shows quarters (k) after the temperature shock at t =*-1*. The y-axis shows the percent variation of the dependent variable between *t-1* and *t+k,* with k (quarter)=20.

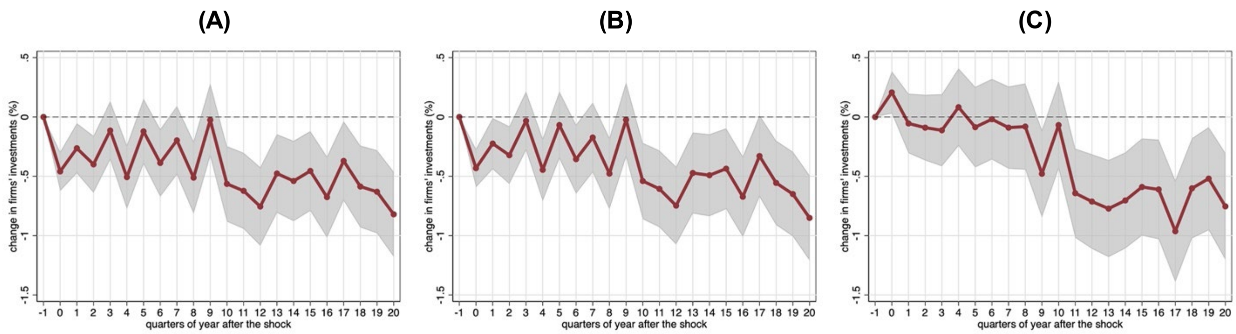
Figure A10. The impact of temperature volatility on firms' investments, with volatility computed as the log of the standard deviation (panel A), the difference between max and min temperatures (panel B), and residuals from regressing temperatures on date fixed effects (panel C)

(A) (B) (C)



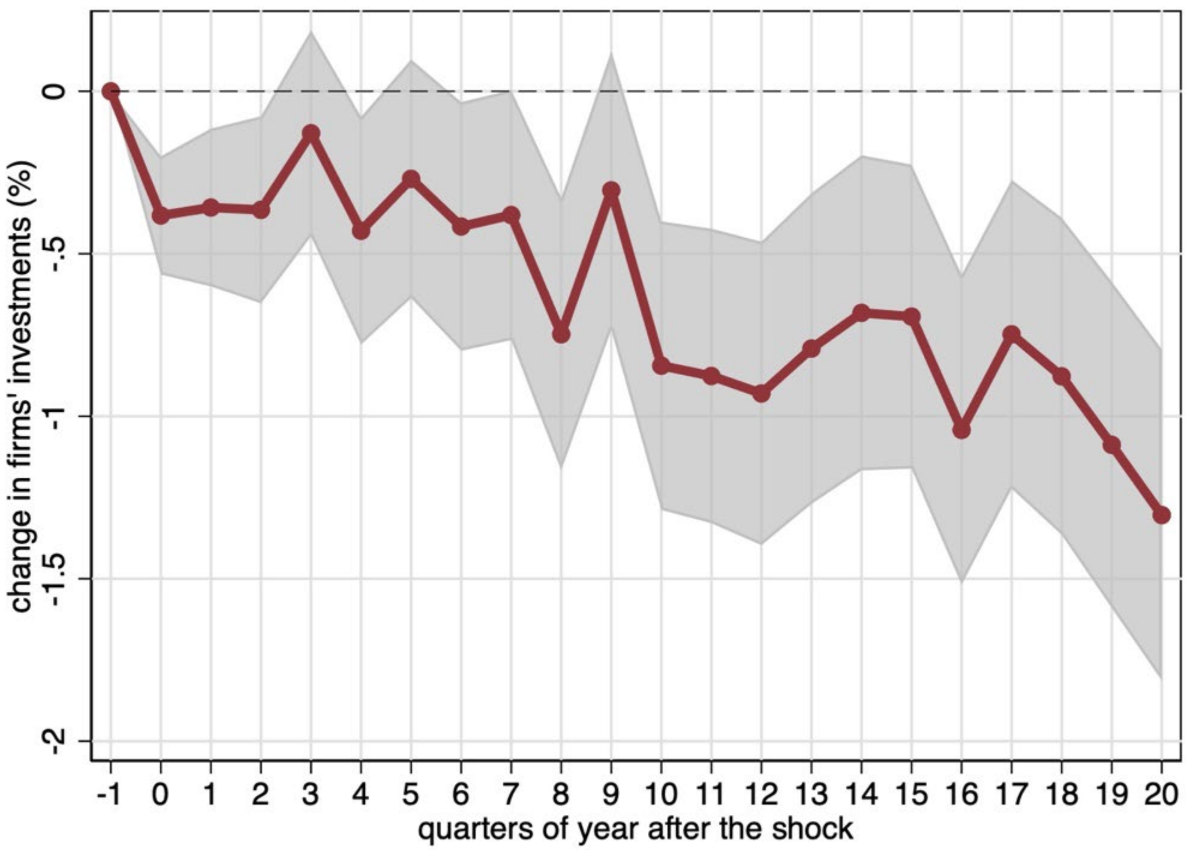
Note: The graphs show the percent variation of firms' capital expenditure in response to a one-degree Celsius increase in the log of the standard deviation of temperatures (red line – panel A), the difference between maximum and minimum temperature (red line – panel B), standard deviation of residuals from regressing daily temperatures on date dummies (red line – panel C), as well as 90 percent confidence bands (shaded area). Impulse response functions are estimated based on the following equation: $y_{f,t+k} - y_{f,t-1} = \alpha_f^k + \gamma_t^k + \beta^k TeV_{f,t-1} + \delta^k X_{f,t-l} + \varepsilon_{f,t+k}$, with k=20 (quarter). $y_{f,t+k} - y_{f,t-1}$indicates the percent variation of firms' capital expenditure (in log) between *t-1* and *t+k,* while $TeV_{f,t-1}$ the temperature shock as defined above, at firm/quarter level. The vector $X_{f,t-l}$ includes four lags of firms' capital expenditure, of the temperature shock, and of average temperature at firm/quarter level. Firm and quarter fixed effects are always included. The x-axis shows quarters (k) after the temperature volatility shock at t =*-1*. The y-axis shows the percent variation of the dependent variable between *t-1* and *t+k,* with k (quarter)=20.

Figure A11. The impact of temperature volatility on firms' investments, with alternative lag structures: 1/2 (panel A), 1/3 (panel B), 0/4 (panel C)



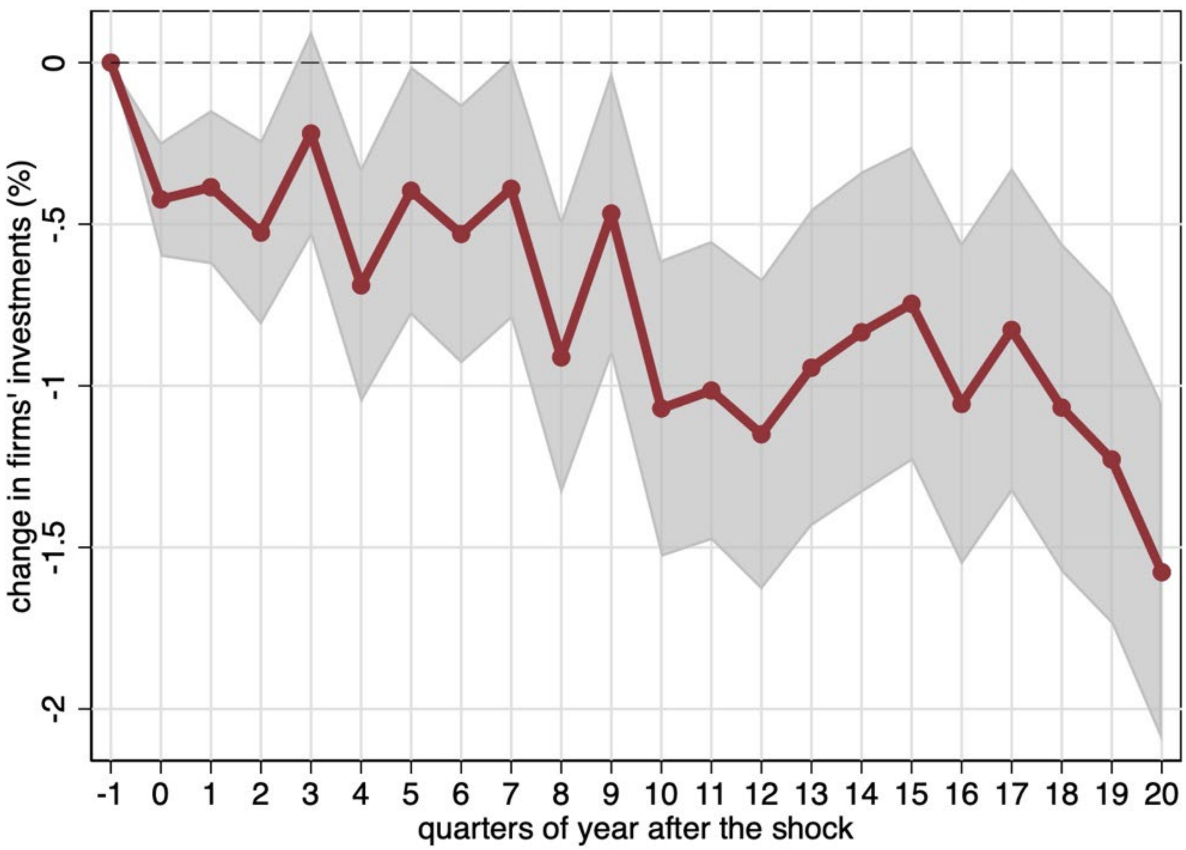
Note: The graphs show the percent variation of firms' capital expenditure in response to a one-degree Celsius increase in temperature volatility (red line), as well as 90 percent confidence bands (shaded area). Impulse response functions are estimated based on the following equation: $y_{f,t+k} - y_{f,t} = \alpha_f^k + \gamma_t^k + \beta^k TeV_{f,t} + \delta^k X_{f,t-l} + \varepsilon_{f,t+k}$, with *k*=20 (quarter). $y_{f,t+k} - y_{f,t-1}$indicates the percent variation of firms' capital expenditure (in log) between *t-1* and *t+k,* while $TeV_{f,t}$ is temperature volatility at firm/quarter level. The vector $X_{f,t-l}$ includes two lags (panel A), three lags (panel B) or contemporaneous plus four lags (panel C) of firms' capital expenditure, of temperature volatility, and of average temperature at firm/quarter level. Firm and quarter fixed effects are always included. The x-axis shows quarters (*k*) after the temperature volatility shock at *t =-1*. The y-axis shows the percent variation of the dependent variable between *t-1* and *t+k,* with *k* (quarter)=20.

Figure A12. The impact of temperature volatility on firms' investments (with standard errors clustered at zip code level)



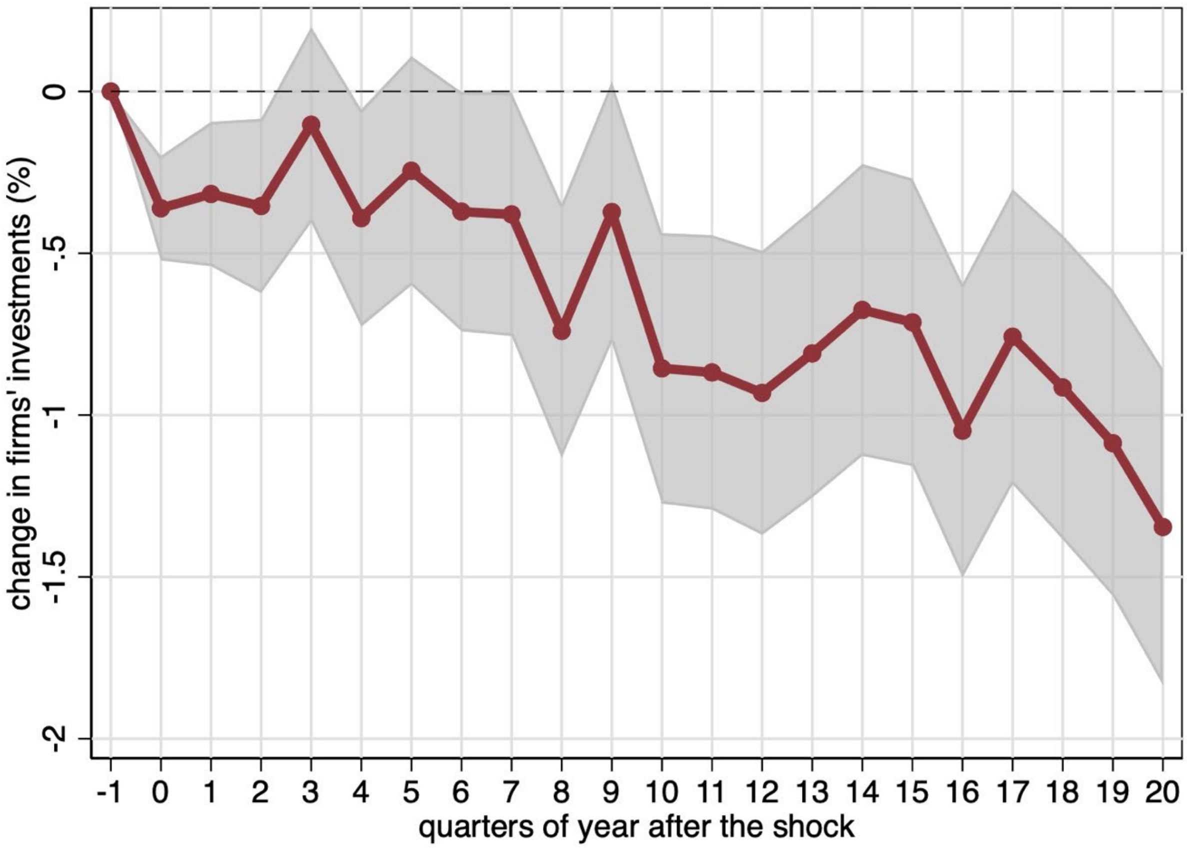
Note: The graph shows the percent variation of firms' capital expenditure in response to a one-degree Celsius increase in temperature volatility (red line), as well as 90 percent confidence bands (shaded area). Impulse response functions are estimated based on the following equation: $y_{f,t+k} - y_{f,t-1} = \alpha_f^k + \gamma_t^k + \beta^k TeV_{f,t-1} + \delta^k X_{f,t-l} + \varepsilon_{f,t+k}$, with k=20 (quarter). $y_{f,t+k} - y_{f,t-1}$ indicates the percent variation of firms' capital expenditure (in log) between *t-1* and *t+k,* while $TeV_{f,t-1}$ is temperature volatility at firm/quarter level. The vector $X_{f,t-l}$ includes four lags of firms' capital expenditure, of temperature volatility, and of average temperature. Firm and quarter fixed effects are always included. The x-axis shows quarters (*k*) after the temperature volatility shock at *t =-1*. Standard errors are clustered at zip code level. The y-axis shows the percent variation of the dependent variable between *t-1* and *t+k,* with *k* (quarter)=20.

Figure A13. The impact of temperature volatility on firms' investments (excluding lags of the dependent variable)



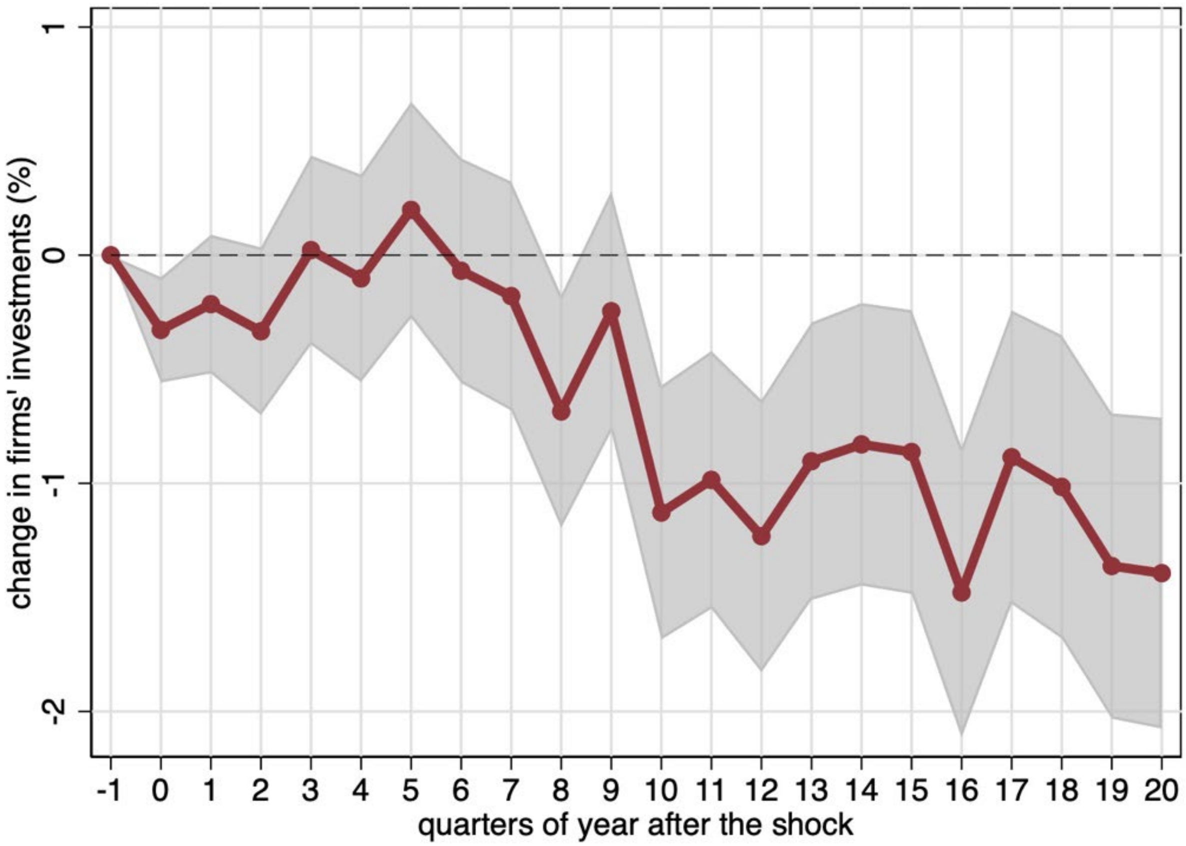
Note: The graph shows the percent variation of firms' capital expenditure in response to a one-degree Celsius increase in temperature volatility (red line), as well as 90 percent confidence bands (shaded area). Impulse response functions are estimated based on the following equation: $y_{f,t+k} - y_{f,t-1} = \alpha_f^k + \gamma_t^k + \beta^k TeV_{f,t-1} + \delta^k X_{f,t-l} + \varepsilon_{f,t+k}$, with *k*=20 (quarter). $y_{f,t+k} - y_{f,t-1}$ indicates the percent variation of firms' capital expenditure (in log) between *t-1* and *t+k,* while $TeV_{f,t-1}$ is temperature volatility at firm/quarter level. The vector $X_{f,t-l}$ includes four lags of temperature volatility, and of average temperature. Firm and quarter fixed effects are always included. The x-axis shows quarters (*k*) after the temperature volatility shock at *t =-1*. The y-axis shows the percent variation of the dependent variable between *t-1* and *t+k,* with *k* (quarter)=20.

Figure A14. The impact of temperature volatility on firms' investments (excluding outliers)



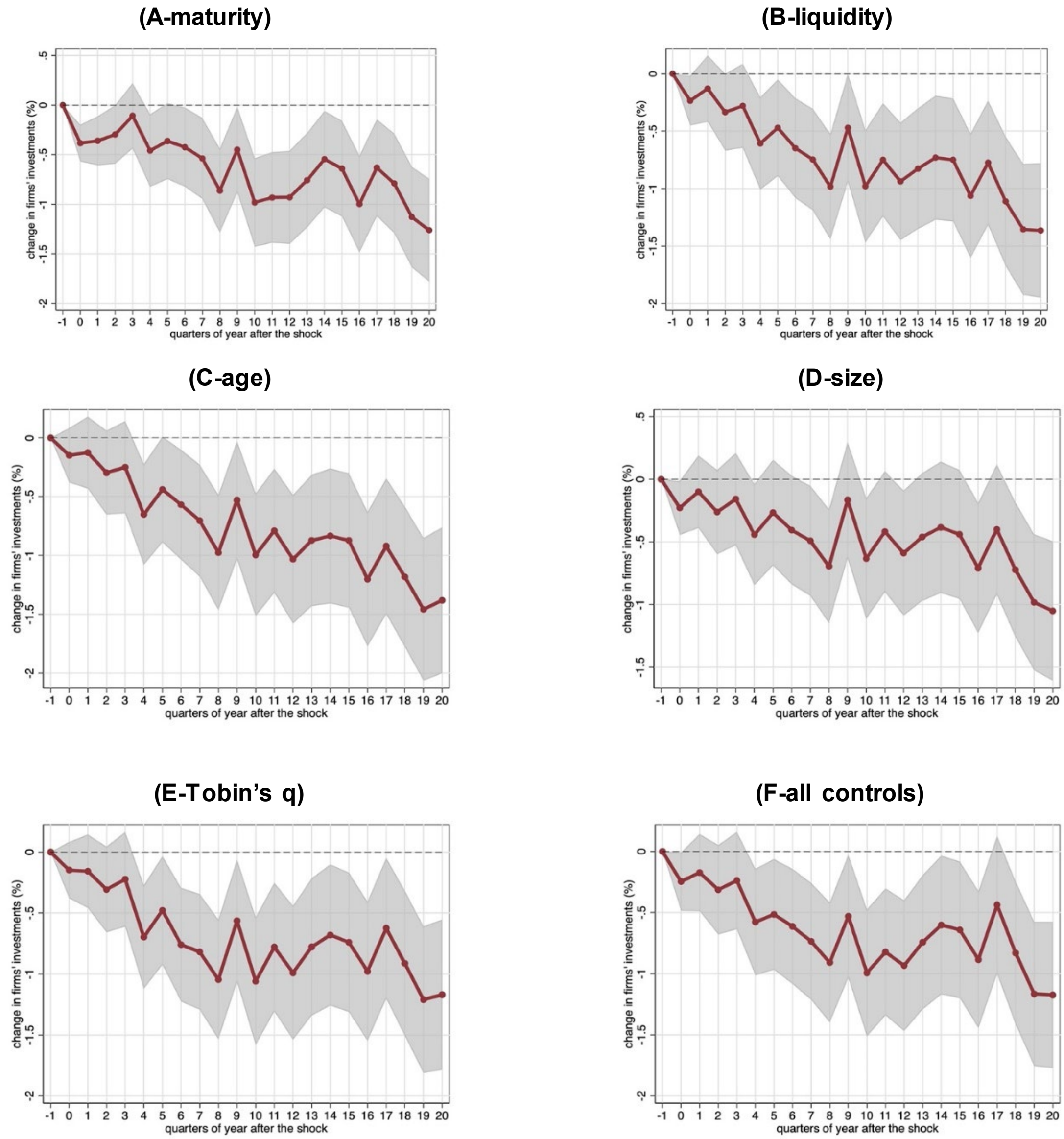
Note: The graph shows the percent variation of firms' capital expenditure in response to a one-degree Celsius increase in temperature volatility (red line), as well as 90 percent confidence bands (shaded area). Impulse response functions are estimated based on the following equation: $y_{f,t+k} - y_{f,t-1} = \alpha_f^k + \gamma_t^k + \beta^k TeV_{f,t-1} + \delta^k X_{f,t-l} + \varepsilon_{f,t+k}$, with *k*=20 (quarter). $y_{f,t+k} - y_{f,t-1}$ indicates the percent variation of firms' capital expenditure (in log) between *t-1* and *t+k,* while $TeV_{f,t-1}$ is temperature volatility at firm/quarter level. The vector $X_{f,t-l}$ includes four lags of firms' capital expenditure, of temperature volatility, and of average temperature. Firm and quarter fixed effects are always included. The x-axis shows quarters (*k*) after the temperature volatility shock at *t =-1*. The graph excludes the top and bottom 1% of the distribution of the dependent variable. The y-axis shows the percent variation of the dependent variable between *t-1* and *t+k,* with *k* (quarter)=20.

Figure A15. The impact of temperature volatility on firms' investments (excluding years before 2000)



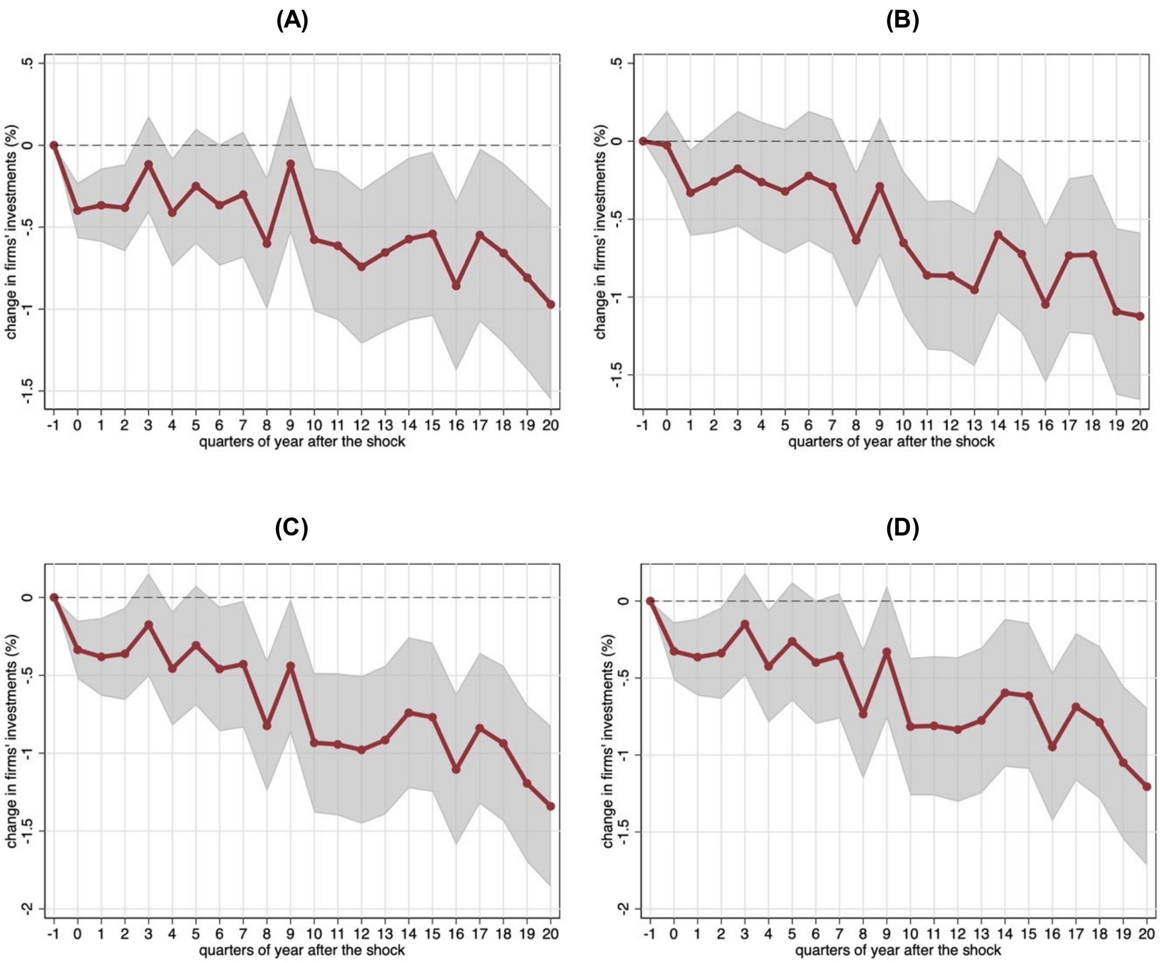
Note: The graph shows the percent variation of firms' capital expenditure in response to a one-degree Celsius increase in temperature volatility (red line), as well as 90 percent confidence bands (shaded area). Impulse response functions are estimated based on the following equation: $y_{f,t+k} - y_{f,t-1} = \alpha_f^k + \gamma_t^k + \beta^k TeV_{f,t-1} + \delta^k X_{f,t-l} + \varepsilon_{f,t+k}$, with *k*=20 (quarter). $y_{f,t+k} - y_{f,t-1}$indicates the percent variation of firms' capital expenditure (in log) between *t-1* and *t+k,* while $TeV_{f,t-1}$ is temperature volatility at firm/quarter level. The vector $X_{f,t-l}$ includes four lags of firms' capital expenditure, of temperature volatility, and of average temperature. Firm and quarter fixed effects are always included. The graph excludes year before 2000. The x-axis shows quarters (*k*) after the temperature volatility shock at *t =-1*. The y-axis shows the percent variation of the dependent variable between *t-1* and *t+k,* with *k* (quarter)=20.

Figure A16. The impact of temperature volatility on firms' investments, with additional control



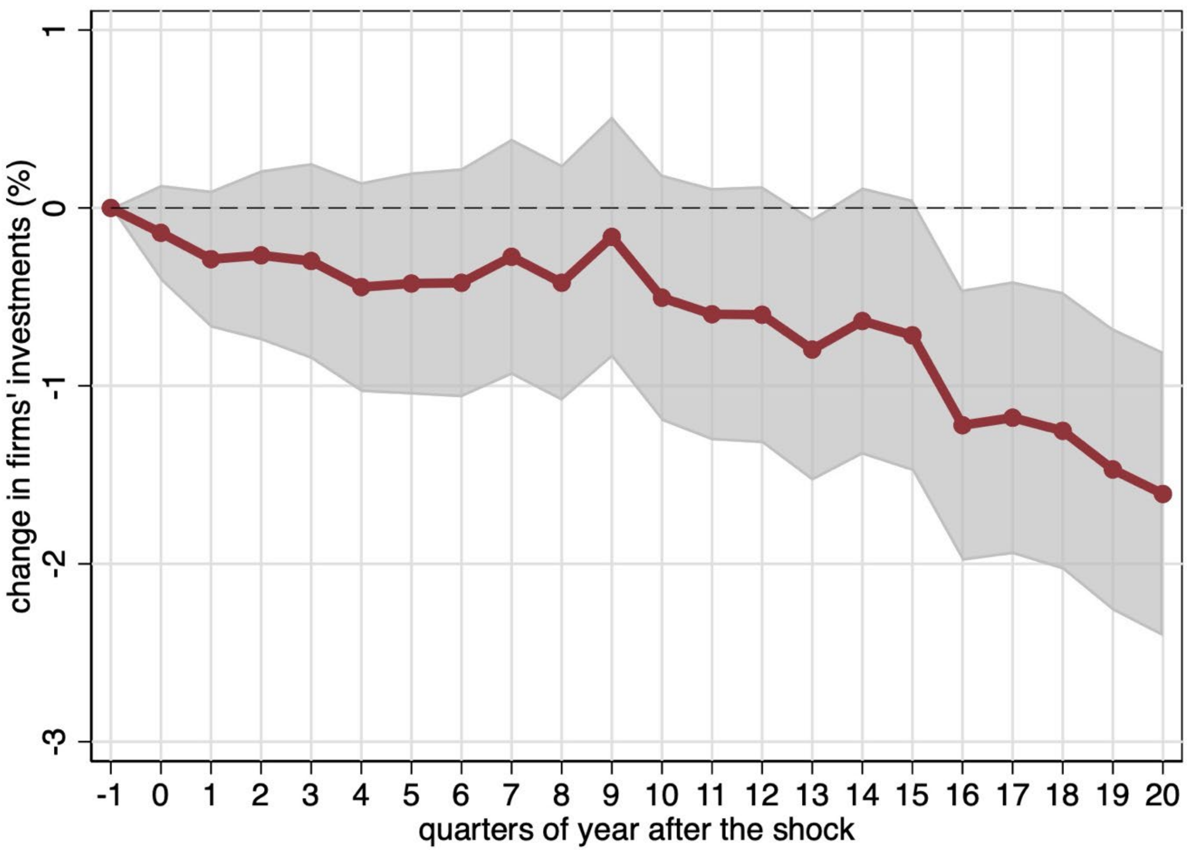
Note: The graphs show the percent variation of firms' capital expenditure in response to a one-degree Celsius increase in temperature volatility (red line), as well as 90 percent confidence bands (shaded area). Impulse response functions are estimated based on the following equation: $y_{f,t+k} - y_{f,t-1} = \alpha_f^k + \gamma_t^k + \beta^k TeV_{f,t-1} + \delta^k X_{f,t-l} + \varepsilon_{f,t+k}$, with *k*=20 (quarter). $y_{f,t+k} - y_{f,t-1}$ indicates the percent variation of firms' capital expenditure (in log) between *t-1* and *t+k,* while $TeV_{f,t-1}$ is temperature volatility at firm/quarter level. The vector $X_{f,t-l}$ includes four lags of firms' capital expenditure, of temperature volatility, and of average temperature, as well as the lag of firms' characteristics, at firm/quarter level. Firm and quarter fixed effects are always included. The x-axis shows quarters (*k*) after the temperature volatility shock at *t =-1*. The y-axis shows the percent variation of the dependent variable between *t-1* and *t+k,* with *k* (quarter)=20.

Fig. A17. The impact of temperature volatility on firms' investment, including firm-specific time trend (panel A), or firm-quarter dummies (panel B), or firm-region dummies (panel C), or region-specific time trend (panel D).



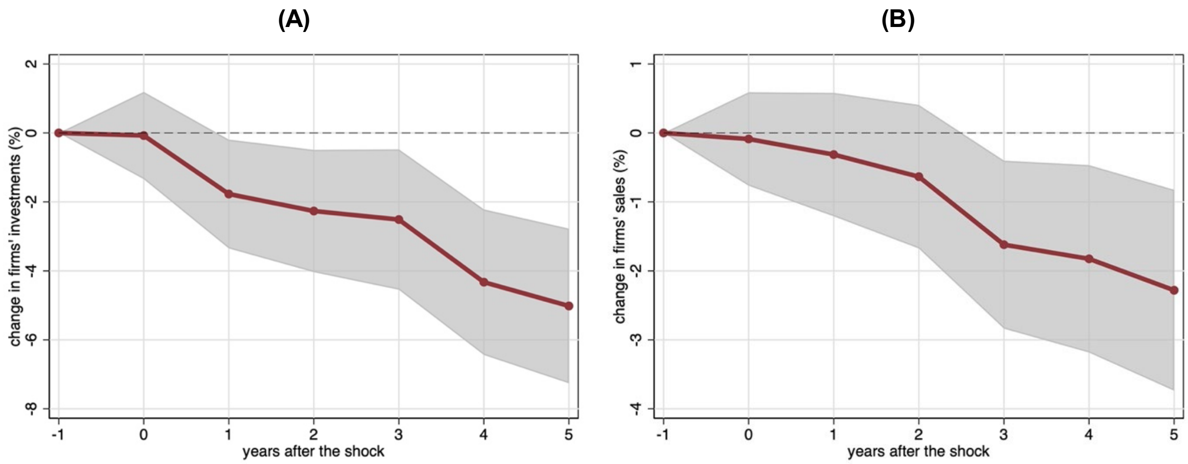
Note: The graphs show the percent variation of firms' capital expenditure in response to a one-degree Celsius increase in temperature volatility (red line), as well as 90 percent confidence bands (shaded area). Impulse response functions are estimated based on the following equation: $y_{f,t+k} - y_{f,t-1} = \alpha_{ft}^{k} + \gamma_{t}^{k} + \beta^{k} TeV_{f,t-1} + \delta^{k} X_{f,t-l} + \varepsilon_{f,t+k}$, with k=20 (quarter). $y_{f,t+k} - y_{f,t-1}$indicates the percent variation of firms' capital expenditure (in log) between *t-1* and *t+k,* while $TeV_{f,t-1}$ is temperature volatility at firm/quarter level. The vector $X_{f,t-l}$ includes four lags of firms' capital expenditure, of temperature volatility, and of average temperature at firm/quarter level. Quarter fixed effects are always included. Firm-specific time trend (panel A) or firm-quarter dummies (panel B) or region-firm dummies (panel C) or region-specific time trend (panel D) are also included. The x-axis shows quarters (k) after the temperature volatility shock at t =*-1*. The y-axis shows the percent variation of the dependent variable between *t-1* and *t+k,* with k (quarter)=20.

Figure A18. The impact of temperature volatility on firms' investments, including forward periods of the temperature shock



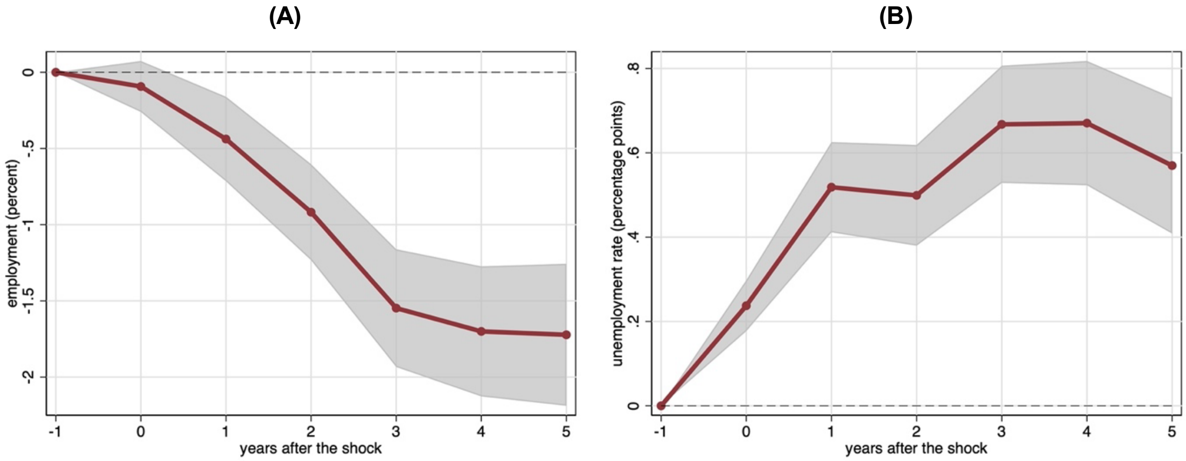
Note: The graph shows the percent variation of firms' capital expenditure in response to a one-degree Celsius increase in temperature volatility (red line), as well as 90 percent confidence bands (shaded area). Impulse response functions are estimated based on the following equation: $y_{f,t+k} - y_{f,t-1} = \alpha_f^k + \gamma_t^k + \beta^k TeV_{f,t-1} + \theta^k TeV_{f,t+k} + \delta^k X_{f,t-l} + \varepsilon_{f,t+k}$, with k=20 (quarter). $y_{f,t+k} - y_{f,t-1}$indicates the percent variation of firms' capital expenditure (in log) between *t-1* and *t+k,* while $TeV_{f,t-1}$ is temperature volatility at *t-1* at firm/quarter level, and $TeV_{f,t+k}$ is temperature volatility at time *t* and *t+k,* with *k*=20 (quarter). The vector $X_{f,t-l}$ includes four lags of firms' capital expenditure, of temperature volatility, and of average temperature at firm/quarter level. Firm and quarter fixed effects are always included. The x-axis shows quarters (*k*) after the temperature volatility shock at *t =-1*. The y-axis shows the percent variation of the dependent variable between *t-1* and *t+k,* with *k* (quarter)=20.

Figure A19. The impact of temperature volatility on firms' investments (A) and sales (B), using annual firm-level data



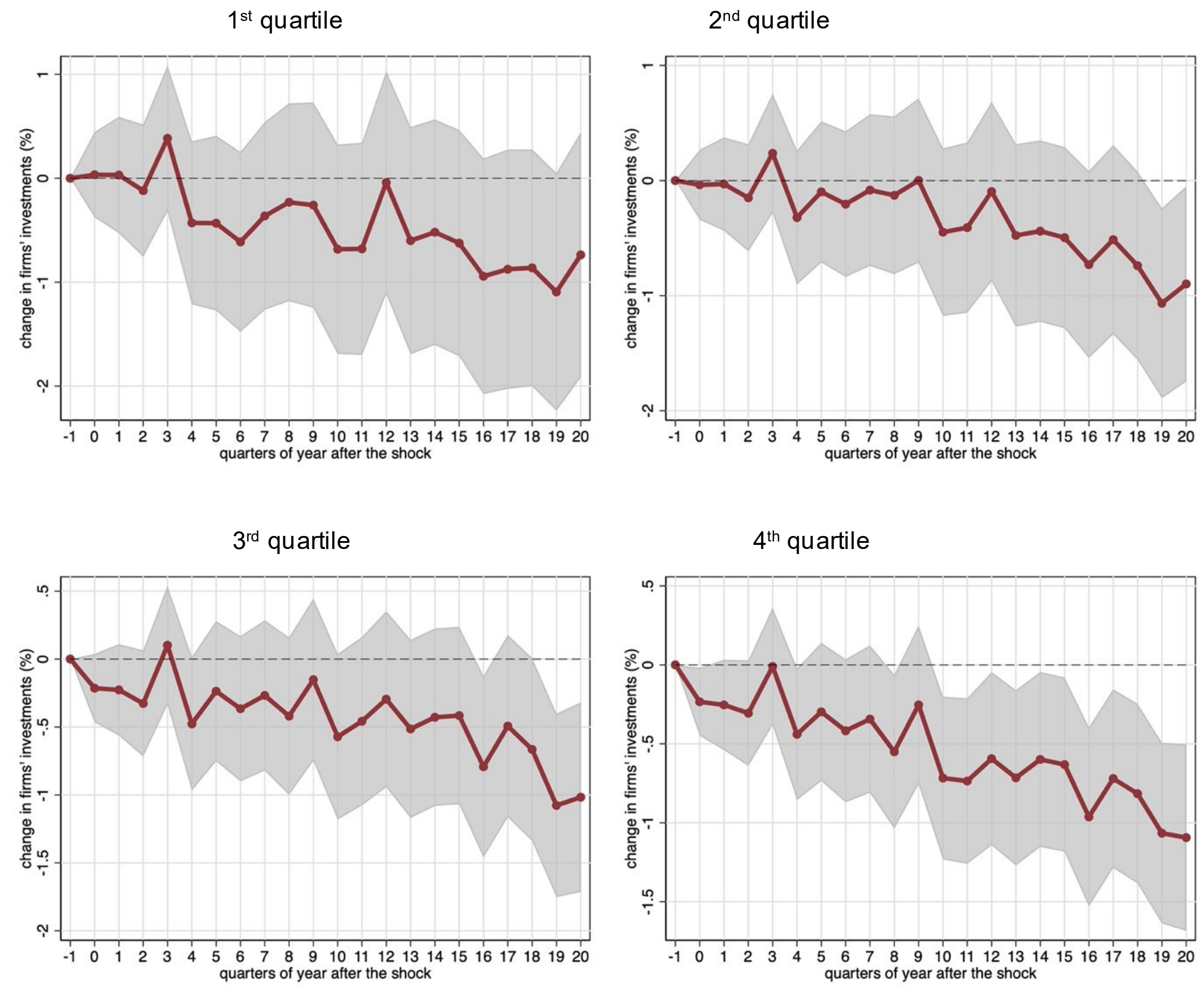
Note: The graphs show the percent variation of firms' capital expenditure (panel A) and sales (panel B), in response to a one-degree Celsius increase in temperature volatility (red line), as well as 90 percent confidence bands (shaded area). Impulse response functions are estimated based on the following equation: $y_{f,t+k} - y_{f,t-1} = \alpha_f^k + \gamma_t^k + \beta^k TeV_{f,t-1} + \delta^k X_{f,t-l} + \varepsilon_{f,t+k}$, with *k*=5 (years). $y_{f,t+k} - y_{f,t-1}$ indicates the percent variation of firms' capital expenditure or sales (in log) between *t-1* and *t+k,* while $TeV_{f,t-1}$ is temperature volatility at firm/year level. The vector $X_{f,t-l}$ includes four lags of firms' capital expenditure or sale, of temperature volatility, and of average temperature, at firm/year level. Firm and year fixed effects are always included. The x-axis shows years (*k*) after the temperature volatility shock at *t =-1*. The y-axis shows the percent variation of the dependent variable between *t-1* and *t+k,* with *k* (years)=5.

Figure A20. The impact of temperature volatility on employment (A) and unemployment rate (B), using annual MSA-level data



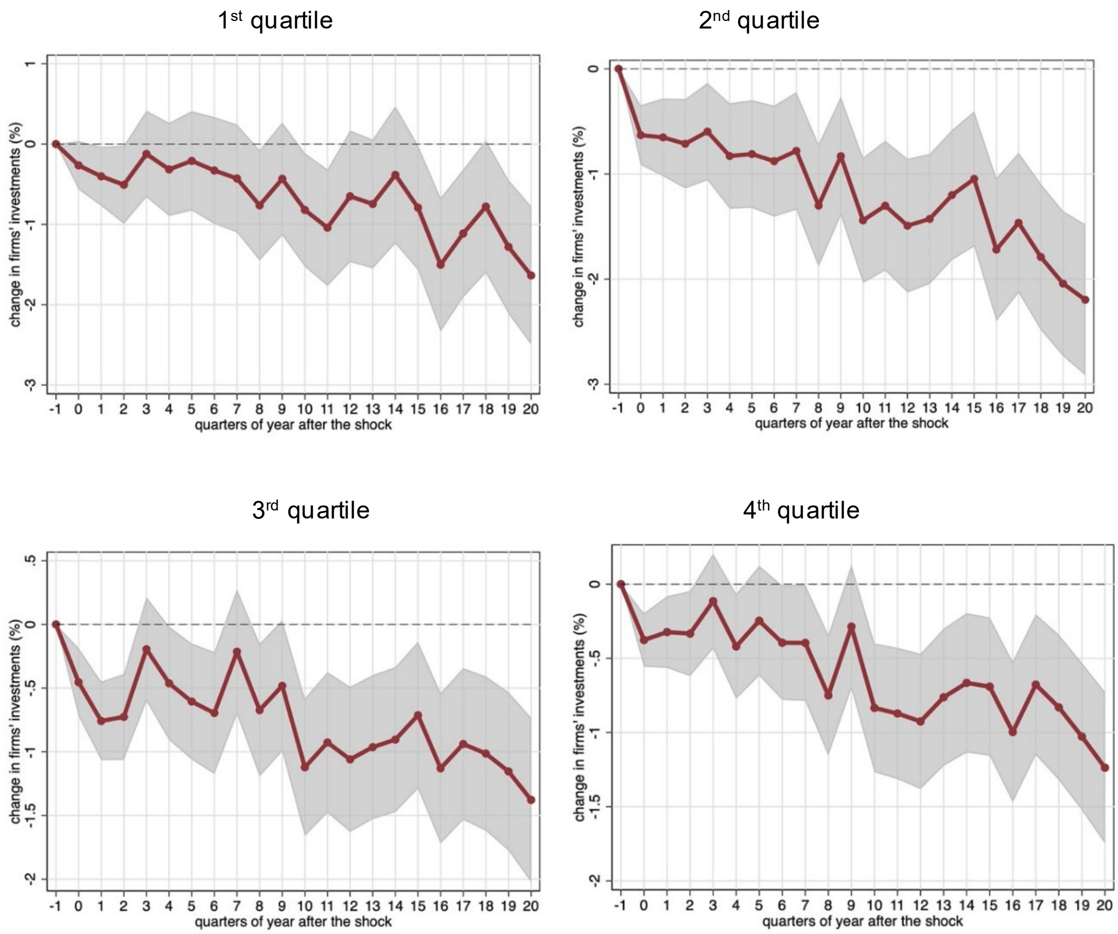
Note: The graphs show the variation of (log of) employment (%) (panel A) and unemployment rate (percentage points) (panel B) using MSA-level data, in response to a one-degree Celsius increase in temperature volatility (red line), as well as 90 percent confidence bands (shaded area). Impulse response functions are estimated based on the following equation: $y_{f,t+k} - y_{f,t-1} = \alpha_f^k + \gamma_t^k + \beta^k TeV_{f,t-1} + \delta^k X_{f,t-l} + \varepsilon_{f,t+k}$, with *k*=5 (years). $y_{f,t+k} - y_{f,t-1}$indicates the percent variation of MSAs' employment (%) and unemployment rate (pp), between *t-1* and *t+k,* while $TeV_{f,t-1}$ is temperature volatility at firm/year level. The vector $X_{f,t-l}$ includes four lags of the dependent variables, of temperature volatility, and of average temperature, at firm/year level. Firm and year fixed effects are always included. The x-axis shows years (*k*) after the temperature volatility shock at *t =-1*. The y-axis shows the percent variation of the dependent variable between *t-1* and *t+k,* with *k* (years)=5.

Figure A21. The impact of temperature volatility on firms' investments: nonlinearities based on quartiles of temperature volatility.



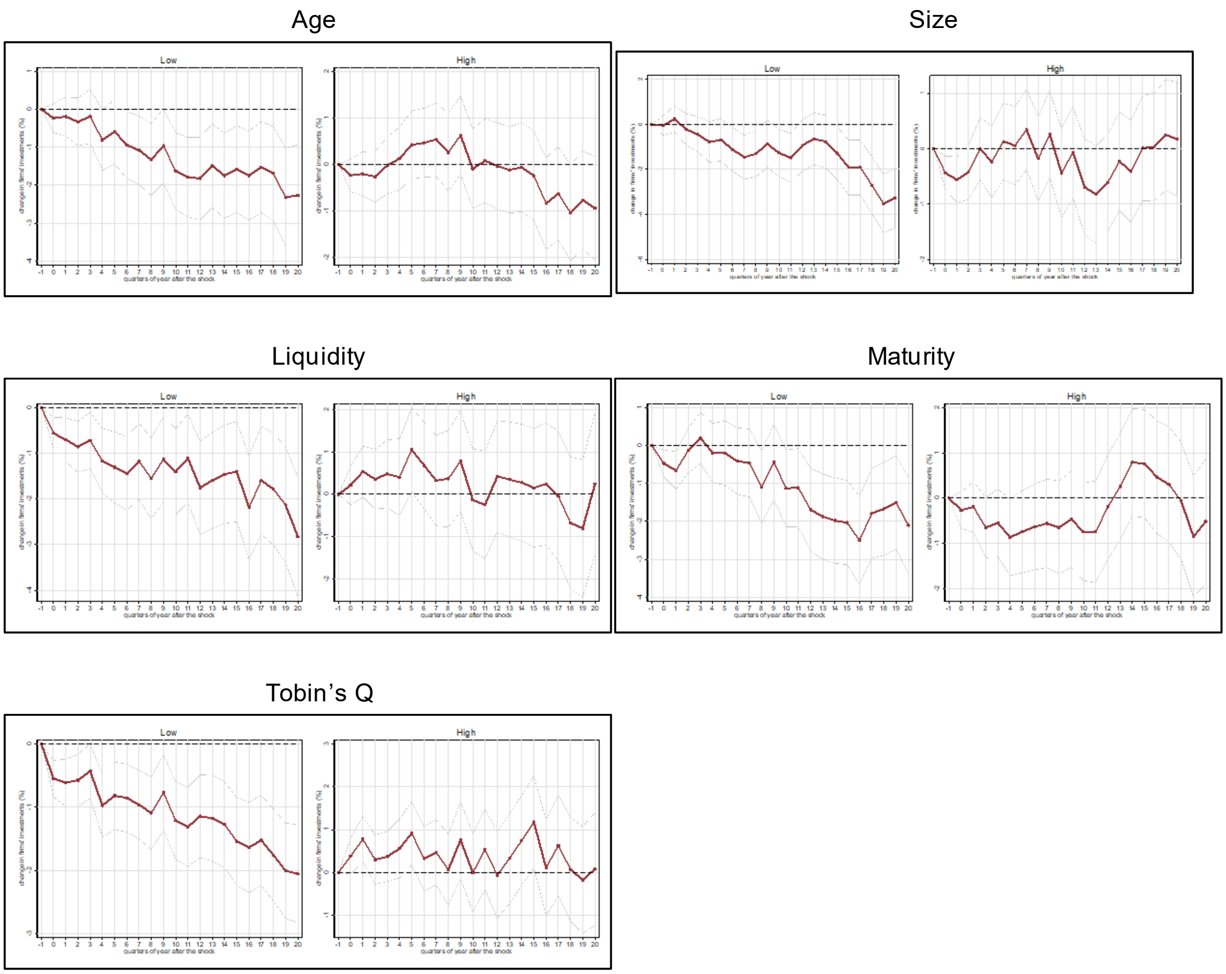
Note: The graphs show the percent variation of firms' capital expenditure in response to a one-degree Celsius increase in temperature volatility (red lines), based on quartiles of the distribution of temperature volatility, as well as 90 percent confidence bands (shaded area). Impulse response functions are estimated based on the following equation: $y_{f,t+k} - y_{f,t-1} = \alpha_f^k + \gamma_t^k + \beta_1^k TeV_{f,t-1} * TeV_{1,f,t-1} + \beta_2^k TeV_{f,t-1} * TeV_{2,f,t-1} + +\beta_3^k TeV_{f,t-1} * TeV_{3,f,t-1} + \beta_4^k TeV_{f,t-1} * TeV_{4,f,t-1} + \delta^k X_{f,t-l} + \varepsilon_{f,t+k}$, with *k*=20 (quarter). *TeVn* are dummies equal to one if temperature volatility in firm *f* at quarter *t* is equal to first/second/third/fourth quartiles of the distribution of temperature volatility in our sample. Each chart reports the impulse response function associated with a different quartile. $y_{f,t+k} - y_{f,t-1}$ indicates the percent variation of firms' capital expenditure (in log) between *t-1* and *t+k,* while $TeV_{f,t-1}$ is temperature volatility at firm/quarter level. The vector $X_{f,t-l}$ includes four lags of firms' capital expenditure, of the interaction between temperature volatility and *TeVn* dummies, and of average temperature at firm/quarter level. Firm and quarter fixed effects are always included. The x-axis shows quarters (*k*) after the temperature volatility shock at *t =-1*. The y-axis shows the percent variation of the dependent variable between *t-1* and *t+k,* with *k* (quarter)=20.

Figure A22. The impact of temperature volatility on firms' investments: nonlinearities based on quartiles of the increase of temperature volatility between 1990 and 2018



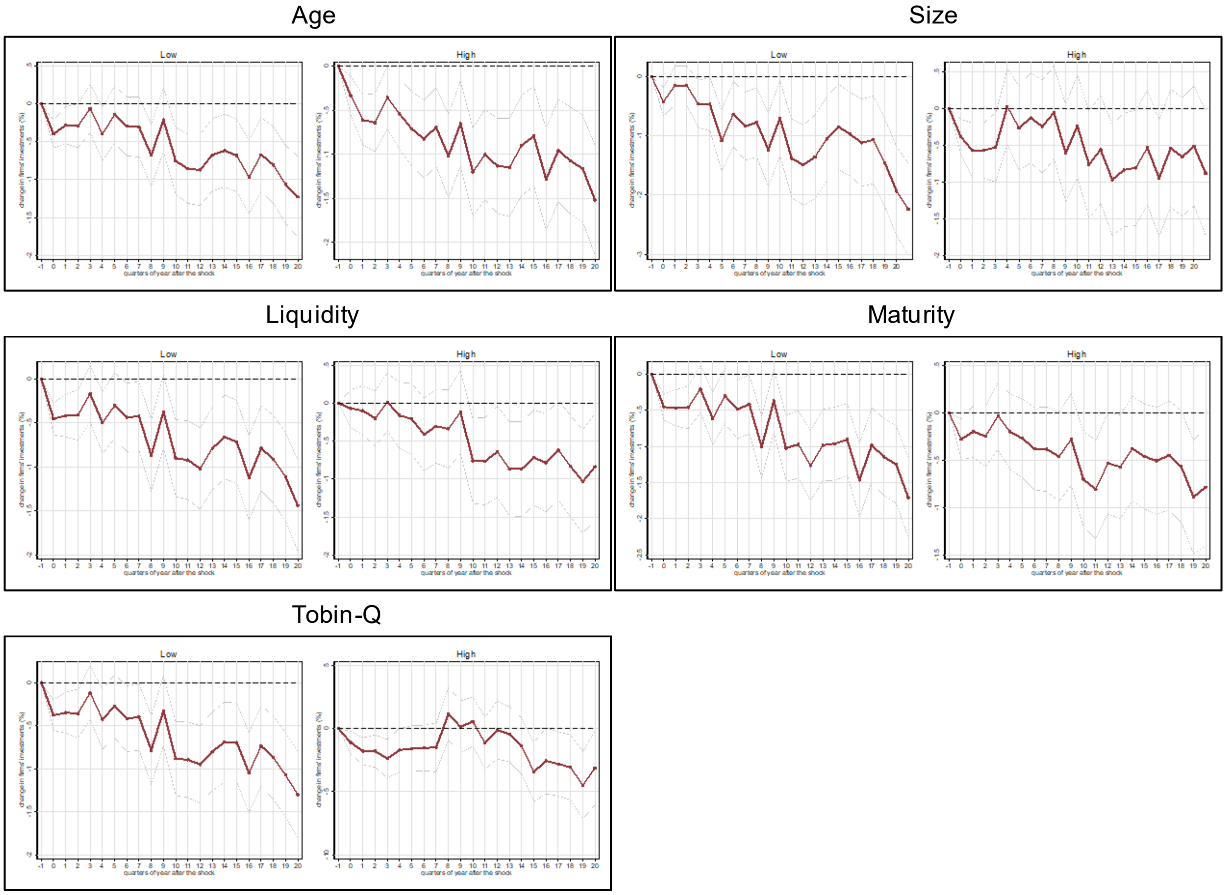
Note: The graphs show the percent variation of firms' capital expenditure in response to a one-degree Celsius increase in temperature volatility (red lines), based on quartiles of the distribution of the evolution of temperature volatility between 1990 and 2018, as well as 90 percent confidence bands (shaded area). Impulse response functions are estimated based on the following equation: $y_{f,t+k} - y_{f,t-1} = \alpha_f^k + \gamma_t^k + \beta_1^k TeV_{f,t-1} * \Delta TeV_{1,f} + \beta_2^k TeV_{f,t-1} * \Delta TeV_{2,f} + +\beta_3^k TeV_{f,t-1} * \Delta TeV_{3,f} + \beta_4^k TeV_{f,t-1} * \Delta TeV_{4,f} + \delta^k X_{f,t-l} + \varepsilon_{f,t+k}$, with *k*=20 (quarter). ΔTeV_n are dummies equal to one if the evolution of temperature volatility between 1990 and 2018 in firm *f* is equal to first/second/third/fourth quartiles of the evolution of temperature volatility between 1990 and 2018 in our sample. Each chart reports the impulse response function associated with a different quartile. $y_{f,t+k} - y_{f,t-1}$ indicates the percent variation of firms' capital expenditure (in log) between *t-1* and *t+k,* while $TeV_{f,t-1}$ is temperature volatility at firm/quarter level. The vector $X_{f,t-l}$ includes four lags of firms' capital expenditure, of the interaction between temperature volatility and ΔTeV_n dummies, and of average temperature at firm/quarter level. Firm and quarter fixed effects are always included. The x-axis shows quarters (*k*) after the temperature volatility shock at *t =-1*. The y-axis shows the percent variation of the dependent variable between *t-1* and *t+k,* with *k* (quarter)=20.

Figure A23. The impact of temperature volatility on firms' investment, depending on firms' characteristics



Note: The graphs show the effect of temperature volatility on firms' capital expenditure, depending on firms' age, size, liquidity, maturity and Tobin-Q. Estimates are based on the following equation: $y_{f,t+k} - y_{f,t-1} = \alpha_f^k + \gamma_t^k + F(z_{ft})[\beta_L^k TeV_{f,t-1} + \theta_L^k X_{f,t-l}] + \left(1 - F(z_{ft})\right)[\beta_H^k TeV_{ft-1} + \theta_H^k X_{f,t-l}] + \varepsilon_{f,t+k}$; with $F(z_{ft}) = \frac{exp^{-\gamma z_{ft}}}{1+exp^{-\gamma z_{ft}}}$, $\gamma = 1.5$. ***z*** is alternatively an indicator of age, size, liquidity, maturity and Tobin-Q of firms, normalized to have zero mean and unit variance by means of a cross-firm variation in the normalization, where we consider the start of period value available for each firm. $F(z_{ft})$ is the corresponding smooth transition function. Left panels refer to the case of young, small, low liquidity, low maturity and low Tobin-Q firms. Right panels indicate old, large, high liquidity, high maturity, high Tobin-Q firms. $y_{f,t+k} - y_{f,t-1}$ is the percent variation of firms' capital expenditure (in log) between *t-1* and *t+k,* while $TeV_{f,t-1}$ is temperature volatility at firm/quarter level. The vector $X_{f,t-l}$ includes four lags of firms' capital expenditure, of the interaction between temperature volatility and the smooth transition function, and of average temperature at firm/quarter level. Firm and quarter fixed effects are included. The x-axes show quarters (*k*) after the temperature volatility shock at *t =-1*. The y-axes show the percent variation of the dependent variable between *t-1* and *t+k,* with *k* (quarter)=20.

Figure A24. The impact of temperature volatility on firms' investment, depending on firms' characteristics



Note: The graphs show the effect of temperature volatility on firms' capital expenditure, depending on firms' age, size, liquidity, maturity and Tobin-Q. Estimates are based on the following equation: $y_{f,t+k} - y_{f,t-1} = \alpha_f^k + \gamma_t^k + \beta^k TeV_{f,t-1} * D1 + \beta^k TeV_{f,t-1} * D2 + \theta_H^k X_{f,t-l} + \varepsilon_{f,t+k}$; where D1 is a dummy equal to 1 if average firms' characteristics, i.e. age, size, liquidity, maturity and Tobin-Q of firms, are lower than the average of the sample, and zero otherwise (left panel). D2 is a dummy equal to 1 if average firms' characteristics, i.e., age, size, liquidity, maturity and Tobin-Q of firms, are larger than the average of the sample, and zero otherwise (right panel). Graphs report coefficients of the interaction terms. $y_{f,t+k} - y_{f,t-1}$ is the percent variation of firms' capital expenditure (in log) between *t-1* and *t+k,* while $TeV_{f,t-1}$ is temperature volatility at firm/quarter level. The vector $X_{f,t-l}$ includes four lags of firms' capital expenditure, of the interaction term between temperature volatility and firms' characteristics, and of average temperature at firm/quarter level. Firm and quarter fixed effects are included. The x-axes show quarters (*k*) after the temperature volatility shock at *t =-1.* The y-axes show the percent variation of the dependent variable between *t-1* and *t+k,* with *k* (quarter)=20.

PUBLICATIONS