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Hotter Planet, Hotter Factories

Uneven Impacts of Climate Change on Productivity

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Abstract

This study documents the impacts of climate change on firm-level productivity by matching a globally comparable and standardized survey of nonagricultural firms covering 154 countries with climate data. The findings show that the overall effects of rising temperatures on productivity are negative but nonlinear and uneven across climate zones. Firms in hotter zones experience steeper losses with increases in temperature. A 1 degree Celsius increase from the typical wet-bulb temperature levels in the hottest climate zone (25.7 degrees Celsius and above) results in a productivity decline of about 20.8 percent compared to firms in the coldest climate zone. The effects vary not only based on the temperature zones within which firms are located, but also on other factors such as firm size, industry classification, income group, and region. Large firms, firms in manufacturing, and those in low-income countries and hotter climate zones tend to experience the biggest productivity losses. The uneven impacts, with firms in already hotter regions and low-income countries experiencing steeper losses in productivity, suggest that climate change is reinforcing global income inequality. If the trends in global warming are not reversed over the coming decades, there is a heightened risk of widening inequality across countries. The implications are especially dire for the poorest countries in the hottest regions.

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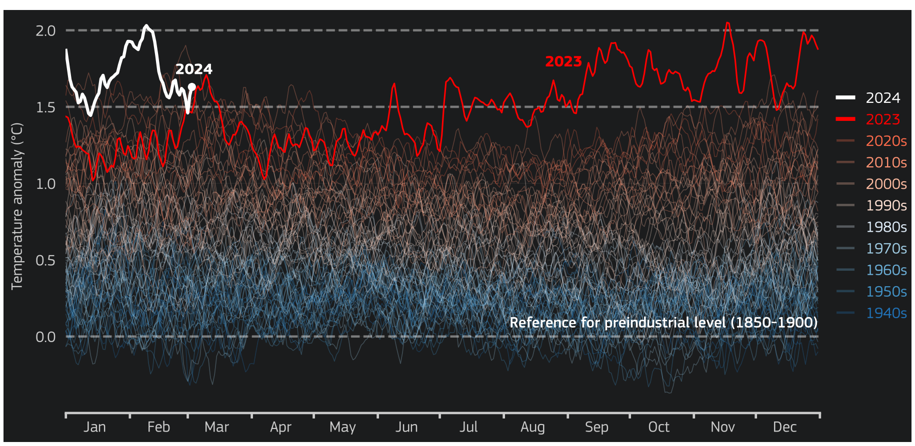
I. Introduction

There is overwhelming scientific evidence that climate change poses possibly the biggest risk to the world and demands an urgent global response. Greenhouse gas emissions trap heat and lead to global warming, contributing to a rise in temperature (Stern, 2008). According to the Intergovernmental Panel on Climate Change, a temperature rise of 1.0 degree Celsius (^0C) above pre-industrial levels (1850–1900) has already materialized, and global warming of 1.5^0C and 2^0C will be exceeded during the $21st$ century unless deep reductions in carbon dioxide (CO_2) and other greenhouse gas emissions occur in the coming decades (see Figure 1).(Masson-Delmotte et al., 2021)[1]. Understanding the mechanisms through which climate change affects economies and estimating its impacts in various sectors are essential to implement mitigation and adaptation policies and actions at national and global scales. These mechanisms include climate finance and the implementation of the historic agreement at the 2022 United Nations Climate Change Conference to establish "loss and damage" funds for vulnerable countries.

Figure 1. : Global Surface Temperature Anomalies



Source: Copernicus Climate Change Services (C3S) Data Store.

This study examines the uneven effects of exposure to temperature anomalies on firm-level productivity.[2] We use data from the World Bank Enterprise Survey (WBES), which has more than 190,000 observations covering 154 countries

[1]Some estimates put the increase in temperatures between 4^0C, and 6^0C (Houghton, 2004; World Bank, 2013)

[2]The US National Aeronautics and Space Administration defines temperature anomaly as "the difference in temperature from an average or baseline." The baseline temperature is typically computed by averaging 30 or more years of temperature data.

between 2006 and 2021. Using geomasked coordinates, we merge the WBES firm-level data with gridded historical monthly temperatures and relative humidity data between 1980 and 2021 obtained from the European Union's Copernicus Climate Change Services (C3S). The gridded climate data have $0.25^0 \times 0.25^0$ horizontal resolution, which is a grid of approximately 27.5×27.5 kilometers (km). Climate change in this study refers to variations in climate patterns captured by temperature anomalies. We use both near-surface temperatures and relative humidity to calculate the wet-bulb temperature (WBT), which is used to calculate the heat index. The heat index is considered a good measure of heat stress conditions that can affect the human body.[3] Our main source of identification is the exogenous variation in area-level deviation of the WBT from the long-term average.[4] The area-level WBT is measured within a radius of 30 km around the establishment, and the area-level long-term average is the mean of the WBTs for each month between 1980 and 2021. We estimate a nonlinear regression model of log sales per worker—a good proxy for firm productivity—on WBT deviation, controlling for firm- and location-specific characteristics and country, subnational, region, and year fixed effects. We also perform heterogeneity analysis by firm size and industry classification, thus contributing to the rapidly growing literature that evaluates the impact of climate change on various aspects of the economy.

The economic impacts of climate change, particularly rising temperature, on agriculture and related sectors are now better understood and well documented in the literature (Mendelsohn et al., 1994; Schlenker et al., 2006; Deschênes and Greenstone, 2007; Cline, 2007; Fisher et al., 2012; Carter et al., 2018; Aragón et al., 2021). Most other studies provide estimates and predictions of aggregate impacts on output and economic growth. Studies on the micro-level impacts of climate change on firm productivity often focus on a few individual countries. This restricts our understanding of the possibly uneven and heterogeneous impacts of climate change across various climate zones and across countries in these zones.

Early studies that estimated or predicted the macroeconomic impacts of changes in temperature on production, investment, health, and agriculture showed that increasing temperatures have large and uneven negative effects on economic growth and output, particularly in poorer countries (Dell et al., 2012; Burke et al., 2015). Acevedo et al. (2020) shows that the negative effect of temperature on aggregate output in countries with hot climates—mostly low-income countries—runs through reduced investment, depressed labor productivity, poorer human health, and lower agricultural and industrial output. Heal and Park (2013) find a strong association between temperature deviations from average and per capita income.

[3]The US National Aeronautics and Space Administration considers the heat index as the "apparent temperature" or the temperature that the human body "feels".

[4]In the literature, deviation from the long-term average or reference year is typically referred to as a temperature anomaly.

They find that hotter years are associated with lower or higher output per capita ranging between 3 and 4 percent for hot or cold climate zones, respectively. In most cases, labor productivity may be the key link between climate shocks and economic outcomes at the macro level (Heal and Park, 2013). Yet, there are few studies on the direct links between labor productivity and temperature changes. Tol (2009) labels the labor productivity impacts of climate change as *unknown unknowns* in a review of studies on the economic effects of climate change, noting the wide gap in the literature, although there has been significant progress since then.

More recent studies have examined the impacts of rising temperatures on various aspects of labor productivity at the micro level (see Lai et al. (2023) for a review). However, many such studies provide average estimates of the impact of climate change or temperature deviations from the average, without accounting for the potentially uneven impacts across climate zones, regions, or countries. Neglecting the uneven impacts will have significant implications for understanding how climate change shapes the future distribution of economic outcomes across these categories. Using detailed production data from half a million manufacturing firms in China, Zou and Zhong (2022) find a relatively large negative impact of excess temperatures—a day with average temperature above 90 degrees Fahrenheit (^{0}F) is associated with a total factor productivity (TFP) loss of 0.56 percent, relative to a day with average temperature between 50^{0}F and 60^{0}F. A study of a census of manufacturing firms in India shows that annual plant output falls by about 2 percent per 1^{0}C increase in temperature (Somanathan et al., 2021). In a U.S. study, Deryugina and Hsiang (2014) show that productivity on an individual day declines by 1.7 percent for each 1^{0}C (1.8^{0}F) increase in daily average temperature above 15^{0}C (59^{0}F). Many of these studies that examine the productivity impacts of temperature focus on a few individual countries, hence providing only limited variations in terms of both the impact of temperature changes on productivity and variations across countries by income and geography.

LoPalo (2023) addresses this challenge in an innovative study that extends the analysis to 46 countries, examining the effects of WBT on the productivity of Demographic and Health Survey interviewers. She finds that hot and humid temperatures significantly impact worker productivity. Data quality problems, such as missing responses and flags for poor data quality, become more frequent on hotter days and interviewers become less productive. The number of interviews completed per hour worked declines by 13.6 percent on the hottest days. However, interviews and data collection make up a unique context. LoPalo (2023) provides interesting evidence on the link between temperature and survey workers' productivity from a broad set of countries and regions, allowing for heterogeneous impacts across countries. However, the findings cannot be generalized to enterprises since data collection is a small share of economic activity, and the usually outdoor workplace setting of data collection is different from most production activities in non-agriculture sectors. Our study builds on and contributes to this literature.

This paper makes two main contributions to the literature. First, it employs data from a global, standardized, and comparable survey of firms rather than an individual country. This presents opportunities to understand the potentially heterogeneous impacts of temperature change on firm productivity and allows the estimation of impacts across regions, climate zones, industries, and country income groups. To account for the potentially heterogeneous impacts of changes in temperature in colder and hotter climate zones, we estimate a nonlinear model using a binning approach in which we group together firms located in the same categories of temperatures. This may be the only study that estimates the impact of temperature change on productivity using a representative sample of firms in more than 150 countries, providing the most comprehensive study in the literature. The large sample allows for additional heterogeneity analysis by firm characteristics, including firm size and industry classification, country income group, and region of the world. This analysis can be used in the determination and distribution of costs and investments associated with actions to mitigate and adapt to climate change in global negotiations.

Second, this study uses high-resolution climate data capturing localized climate hazard impacts, which are the most relevant because the nature and extent of exposure and damage vary within a few thousand meters.[5] The study combines gridded historical climate data with WBES firm-level data, allowing better identification of impact within a relatively highly geographically specified location. Thus, we can estimate important heterogeneity, controlling for both within-country and cross-country variations, going beyond cross-country to the level of subnational variations. In addition, the study contributes to the relatively scarce literature on the impacts of climate change on the non-agriculture sectors, especially at the firm level. Despite the relatively rich literature on the impacts of climate change on agriculture, studies on the impacts on the non-agriculture sectors are relatively scarce.

We document that the effects of rising temperatures are nonlinear and uneven across climate zones, where firms in hotter zones experience steeper losses in productivity with increases in temperature, compared to firms in relatively colder zones, which tend to register productivity gains. Specifically, a one unit (1^0C) increase in WBT deviation in the hottest WBT quantile 25.7^0C and above results

[5]The matched data on climate change and enterprises is another key contribution, since it can also be used by other researchers.

in decline in annual sales per worker by about 20.8 percent compared to firms in areas with the coldest WBT, where WBT ranges between 14.5^0C and 23.7^0C. We find positive impacts on productivity for firms located in the lower temperature zones, which reinforces the finding that the impacts of changes in temperature deviations are nonlinear across temperature zones. There is a change in the direction of impact or sign of the coefficient, suggesting a potential inflection point beyond which an increase in temperature has a detrimental impact on firm productivity, which is estimated to be 25.7^0C in our sample.

In addition, the effects vary not only based on the temperature categories within which firms are located, but also other factors, such as firm size, industry classification, income group, and region. For example, large firms, firms in manufacturing, and those in low-income countries and hotter climate zones tend to experience the biggest productivity losses due to climate change. Given that many low-income countries are in hotter climate zones, the climate change impacts due to higher temperatures are further exacerbated by the limited capabilities to invest in adaptation. Poorer regions experience the highest losses due to climate change, especially in the hottest WBT categories. This adds to what we know about climate change reinforcing existing vulnerabilities in the regions of the world that are least capable of responding to the effects of climate change. By providing more granular evidence from 154 countries, the findings of this study have essential implications for current national and global policy debates on the costs of carbon, the distribution of gains and losses, and the distribution of responsibilities and contributions to mitigate climate change.

The remainder of the paper proceeds as follows. Section II briefly discusses the mechanisms through which the rise in temperature affects firm productivity. Section (III) describes the data and provides summary statistics of the outcome and control variables. Section (IV) lays out the empirical model and discusses our identification strategies. We present and discuss the key findings in Section (V), we conclude in Section (VI).

II. Potential Mechanisms

There are at least two channels through which exposure to heatwaves or high temperatures affects labor productivity—directly by impacting labor's capacity to execute tasks and indirectly by impacting capital reallocation and causing disruptions in the supply of key infrastructure, including power, and subsequent changes in energy prices due to climate change.

In the first channel, exposure to temperatures above a certain threshold is associated with an array of adverse impacts on human physiology, capacity to work, and cognitive performance. It poses a series of health risks, reducing labor productivity at workplaces. Many of the adverse impacts, including reduced work capacity, heat stress, heat exhaustion, and dehydration, tend to materialize when the temperature exceeds the range of $25^0C - 26^0$C (Kjellstrom et al., 2009a; Hsiang, 2010). About 30 percent of the global population currently lives in places where climatic conditions exceed the threshold for at least 20 days a year (Mora et al., 2017). Above this threshold, workers suffer *heat stress*[6] which is associated with reduced human performance and capacity. The workers must slow down to reduce their internal body heat and the risk of heat stroke. Elevated core temperature leads to physical fatigue, irritability, lethargy, impaired judgment, reduced vigilance, and loss of dexterity, coordination, and concentration (Kjellstrom et al., 2009a; **?**; International Labour Organization, 2019). These adverse impacts of exposure to high temperatures could be worse in work environments in which the machinery also contributes to heat stress, particularly in a non-air-conditioned indoor workplace. Severe temperature changes could have catastrophic impacts. If body temperature rises above 38^0C ("heat exhaustion"), physical and cognitive functions are impaired; above 40.6^0C ("heat stroke"), the risks of organ damage, loss of consciousness, and death increase sharply (Klein et al., 2014). In addition, there are labor supply losses due to absenteeism (Somanathan et al., 2021), particularly in the absence of indoor cooling technologies (Gupta and Somanathan, 2022), further reinforcing the productivity losses associated with higher temperatures. However, these impacts are not indiscriminate as they depend on the ambient temperature, humidity, wind speed, and adoption of cooling technologies.

The second channel through which exposure to hotter temperatures affects productivity is the higher costs of adaptation in response to the adverse effects of higher temperatures. Businesses could be forced to redirect resources from other productive investments, such as purchases of new machinery and research and development, to investments in adaptation, such as purchasing climate control technologies. Severe heat could also lead to power outages, which introduce additional costs in the form of disruptions to business activity or investments in generators and other alternative sources of energy. In addition, extreme weather has a direct impact on the energy infrastructure itself as energy demand for cooling increases, overloading power grids and leading to outages. The rise in demand for power during hotter days could also contribute to rising energy prices, which in turn increases costs for businesses. In most instances, extended drought conditions adversely affect the level of hydropower generation, potentially resulting in power outages. All or one of these factors could force firms to invest in alternative and potentially more expensive sources of power, such as solar or gasoline

[6] *Heat stress* refers to the heat received in excess of that which the body can tolerate without suffering physiological impairment (Kjellstrom et al., 2009b; International Labour Organization, 2019).

backup generators. Finally, extreme temperature changes could compromise the effective functioning of critical infrastructure, communications, and transportation systems, imposing additional disruptions to business activities.

III. Data

To estimate the impacts of temperature deviations from the long-term average on firm productivity, we match two sets of data. The first data set is global firm-level data from the WBES.[7] This a nationally representative survey covering nonagricultural firms with five or more full-time permanent employees in low-, middle-, and high-income economies. The coverage is comprehensive, with more than 190,000 observations from 154 countries and spanning 2006–22 .[8] The data are collected using a standardized questionnaire, allowing comparability across countries. The WBES collects information on several firm-level variables, including annual sales, number of workers, various firm-level characteristics, and self-reported obstacles to business, such as licensing and power outages. The WBES data include estimates of TFP for a subset of the sample for which detailed data on labor, capital, and material inputs are available. The WBES also contains confidential geomasked information on firms' longitude and latitude coordinates that allows us to match the WBES data with area-level climate data. Geomasked coordinates are available for 143,047 observations. Map 1 shows the countries covered by the WBES for which geomasked locations of the firms are available, where the dots represent the specific locations of firms in the sample.

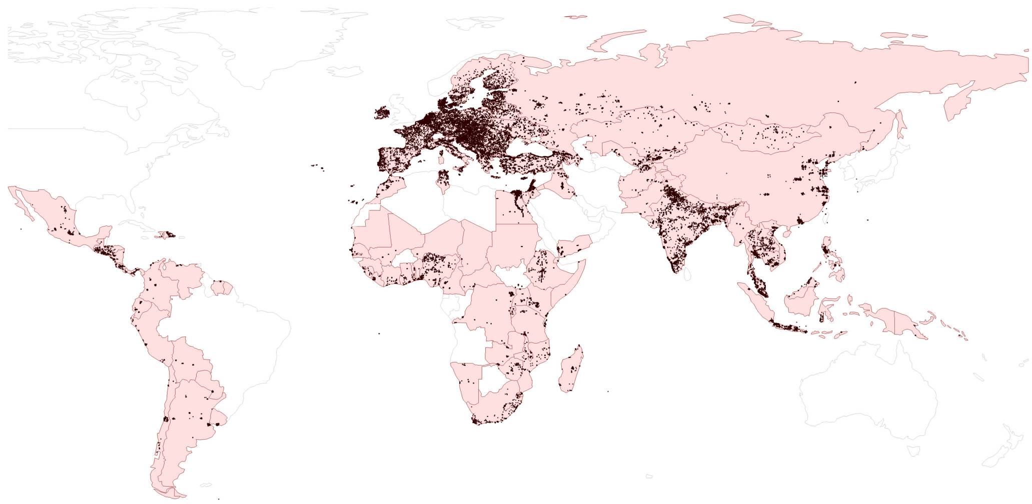
The key outcome variable of interest is annual sales per worker, measured in 2009 US dollars, which is considered in the literature as a reasonable proxy for firm productivity. A limitation of this measure is that the price variation in sales may reflect both supply and demand factors including differences in market power, demand and quality (Cusolito and Maloney, 2018). Its attraction, however it its simplicity and direct interpretation compared to other relatively complicated productivity measures. We also use other measures of firm productivity, such as value added per worker and TFP. However, the latter two measures have a large number of missing observations, which we suspect are systematic. Another key firm performance indicator we examined, which is not reported here, is employment growth, which also proxies for firm growth or lack thereof. We dropped observations from the sample with outliers in sales per worker, which represented a very small proportion of the total sample size.[9]

[7] The WBES can be accessed at: http://www.enterprisesurveys.org We thank the Enterprise Analysis Unit of the Development Economics Global Indicators Department for making the data available.

[8] Some firms appear more than once in countries with repeat surveys.

[9] The criterion used to identify outliers is $Outlier = |\frac{x_i - \hat{x}}{SD} > 3|$, where $\hat{x}$ is the median value and SD is the standard deviation.

Figure 2. : The World Bank Enterprise Survey Coverage and Firms Location



Source: Original map for this paper, based data from the World Bank Enterprise Survey Data.
Note: Darkred dots represent the location of the firms.

Table 1 presents summary statistics of the key variables, including the dependent variable, sales per worker, and selected control variables, including firm-level characteristics such as firm size, age, broad industry classification, ownership structure, export status, and business obstacles reported by firms. Only about 15 percent of the firms are exporters, and 10 percent are considered foreign. There is a fairly even distribution of firm sizes: 47 percent are small (employing 5-19 workers), and the rest are medium-sized (20-99 workers) or large (100+ workers). About 55 percent of the firms are in the manufacturing sector, and the remaining 45 percent are in services. All regions are well represented in the sample: Sub-Saharan Africa accounts for 20 percent of the firms; East Asia and the Pacific and South Asia together, 20 percent; Europe and Central Asia, 31 percent; Latin America and the Caribbean, 20 percent; and the Middle East and North Africa, 10 percent. Further, we control for local socioeconomic factors that are likely to be correlated with firm-level productivity. These include population density from SADEC, road infrastructure density from Global Roads Inventory Project - GRIP - version 4, and pollution using ground-level fine particulate matter of 2.5 micrometers or smaller from NASA/Socioeconomic Data and Applications Center (SADEC)

The second data set we use contains information on gridded historical temperatures and relative humidity from the European Union's C3S Climate Data Store

Table 1—: Summary Statistics

Variable	**Mean (SD)**
Annual average dry-bulb temperature (^{0}C)	29.11 (0.72)
Annual average WBT (^{0}C)	24.62 (1.84)
Annual average WBT (^{0}F)	75.28 (3.55)
Deviation in average dry-bulb temperature (^{0}C)	0.04 (0.06)
Deviation in average WBT (^{0}C)	0.62 (0.47)
Deviation in average WBT (^{0}F)	33.10 (0.85)
Sales per worker (US$, 2009)	71,730 (240,491)
Ownership status	
Domestic (%)	90
Foreign (%)	10
Firm size: categorical	
Small(<20) (%)	47
Medium(20-99) (%)	34
Large(100 and over) (%)	19
Firm size: continuous	74.44 (179.01)
Permanent workers (%)	95.30 (11.68)
Temporary workers (%)	4.70 (11.68)
Skilled workers (%)	71.16 (30.72)
Unskilled workers (%)	28.84 (30.72)
Firm age (year)	18.76 (15.72)
Exporter status	
Non-exporter (%)	85
Exporter (%)	15
Road infrastructure (within 25km radius)	
Highways (km)	66.18 (114.58)
Primary roads (km)	291.52 (365.83)
Secondary roads (km)	325.94 (372.01)
Tertiary roads (km)	426.39 (446.90)
Population density	5,248.32 (6,889.85)
PM2.5: diff between 1998 and 2019	-2.72 (13.15)
Broad sector	
Manufacturing (%)	55
Services (%)	45
Region	
Africa (%)	20
East Asia and Pacific (%)	11
Europe and Central Asia (%)	31
Latin America and the Caribbean (%)	20
Middle East and North Africa (%)	10.0
South Asia (%)	9.2
Number of observations = 141,815	

(Sabater, 2019).[10] The C3S provides a comprehensive reanalysis dataset of var-

[10]Historical temperatures and relative humidity can be obtained from the European Union's C3S Climate Data Store. We downloaded the data on November 25, 2022.

ious climate variables at high resolution and global scale. The data have global coverage that is gridded to a regular latitude-longitude grid of $0.25^0 \times 0.25^0$ or $\approx 27.5 \times 27.5$km grid spacing, covering 1980 to the present. We use the ERA5-Land data set of monthly temperatures and relative humidity measured within a range of 289 centimeters of soil depth to 2 meters above the surface level.

Using these sets of climate data, we perform two computations. First, we compute the WBT[11] in degrees Celsius to account for the effects of humidity on the human body when combined with high temperatures. It is a common practice in the literature to use WBT rather than dry-bulb or air temperature since the effect of changes in temperature varies at different levels of humidity (Kjellstrom et al., 2009c,a; Lemke and Kjellstrom, 2012; Adhvaryu et al., 2020; LoPalo, 2023). WBT provides a better measure for assessing the risks to the human body and health of both temperature and humidity, compared with using only air temperature. WBT is a nonlinear function of temperature and relative humidity, and it is often lower than (dry-bulb) temperature measures. We follow Chen and Chen (2022) and use the following formula to calculate the WBT:

$$WBT = T \cdot tan^{-1}[0.152 \cdot (rh + 8.314)^{(\frac{1}{2})}] + tan^{-1}(T + rh) - tan^{-1}(rh - 1.676) + 0.004(rh)^{(\frac{3}{2})} \tan^{-1}(0.0231rh) - 4.686 \tag{1}$$

where WBT is the wet-bulb temperature (degree Celsius), T is the near-surface dry-bulb temperature (degree Celsius), and rh is relative humidity (percent).

Second, for each geographic area j within a radius of 30km around the establishment, we calculate the WBT deviations from the long-term average for each month of the year as follows:

$$\Delta WBT_{j,t} = \sum_{m=1}^{m=12} \frac{(WBT_{j,mt} - \overline{WBT_{j,m}})}{12}, \tag{2}$$

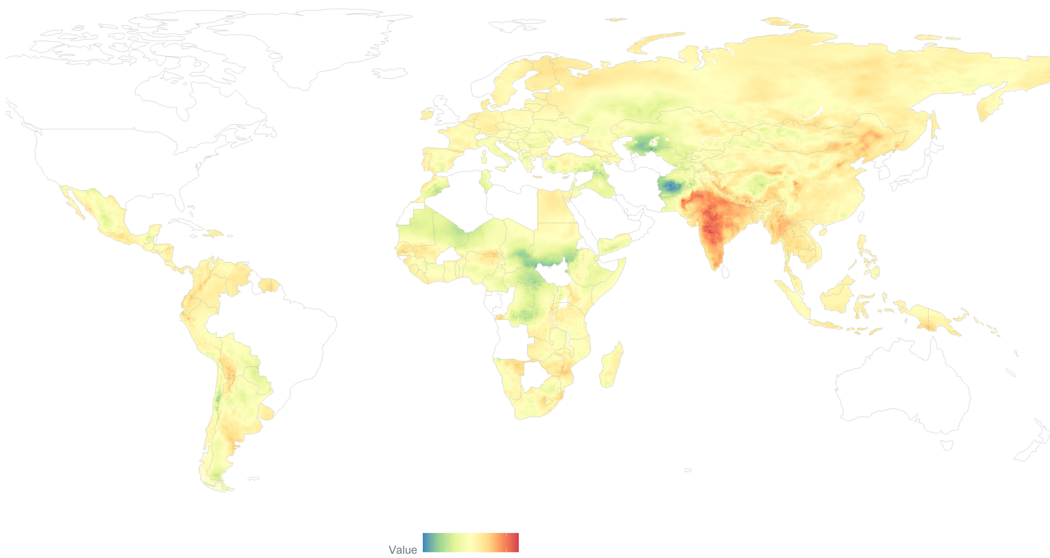
where $\Delta WBT_{j,t}$ denotes the average deviation in WBT in location j and year t, $WBT_{j,mt}$ is WBT in location j for the month of m, and year t, $\overline{WBT_{j,m}}$ is the long-term average (typical) WBT for the month of m in location j.

A key contribution of this study is the estimation of the potentially non-linear effects of climate change on firm-level productivity. To achieve this, we group firms into four quartiles of WBTs: quartile 1: $\leq 23.7^0C$ (the minimum WBT in

[11] All temperature measures are in degrees Celsius unless otherwise specified.

our sample is 14.5^0C), quartile 2: $(23.7^0C, 24.9^0C]$, quartile 3: $(24.9^0C, 25.7^0C]$, and quartile 4: $\geq 25.7^0C$ (the maximum WBT in our sample is 28.22^0C). The first quartile is the coldest climate zone, and the fourth quartile is the hottest with WBT above the threshold beyond which the human body starts to experience heat stress. Various studies adopt a similar binning strategy to estimate the non-linear effects of climate change including Deschênes and Greenstone (2007); Deryugina and Hsiang (2014); Somanathan et al. (2021) and (Chen and Chen, 2022). Identifying the impacts of changes in temperature is particularly important above certain key thresholds, which we attempt to capture in our categories. Identifying the impacts of changes in temperature is particularly important above certain key thresholds, which we attempt to capture in these WBT categories.

Figure 3. : The difference in average monthly WBT between 1980 and 2021

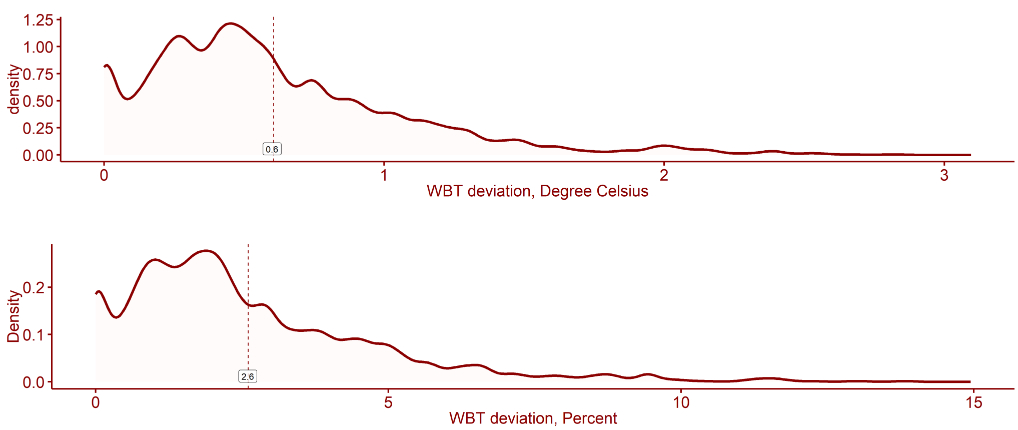


Source: Original map for this paper, using the ERA5-Land data set from the Copernicus Climate Change Service Climate Data Store

Figure 3 presents the difference in WBT between 1980 and 2021 for countries for which WBES data are available. The planet has been getting hotter in recent decades compared to the average WBT in 1980. The average annual deviation in WBT from the long-term average between 1980 and 2021 is 0.62^0C in our sample. Although the rise in temperature over the past 41 years seems universal, there is considerable heterogeneity across geographic locations, with some areas experiencing WBT increases as high as 3.10^0C. Countries such as India, Bangladesh, Myanmar, Thailand, and other countries in the Southeast Asia region experienced much higher increases in WBT compared to other regions of the world. We assess the extent to which such variation drives the observed variation in firm-level productivity.

We match the WBT data with firms' geomasked coordinates. Given the minimum resolution of $\approx 27.5 \times 27.5$km for the temperature and relative humidity data, we extract historical WBT values within a radius of 30km.[12] The average annual dry-bulb temperature for our pooled observation is about 29^0C ($\approx$75.28^{0}F) with the corresponding annual average WBT of 24.6^{0}C (Table 1). Table 1 also shows the average WBT deviation from the long-term average, which is 0.62^{0}C ($\approx$33.1^0F). The deviations are positive in all locations showing that increae in WBT is universal. In addition, the extent of increase in WBT is heterogeneous across locations with some places experiencing a much higher increase of up to 3.1^{0}C or about 15 percent hotter than the typical WBT. Figure 4 presents the distribution of WBT in degree Celsius (top panel) and percent increase (bottom panel).

Figure 4. : Density of deviation in WBT



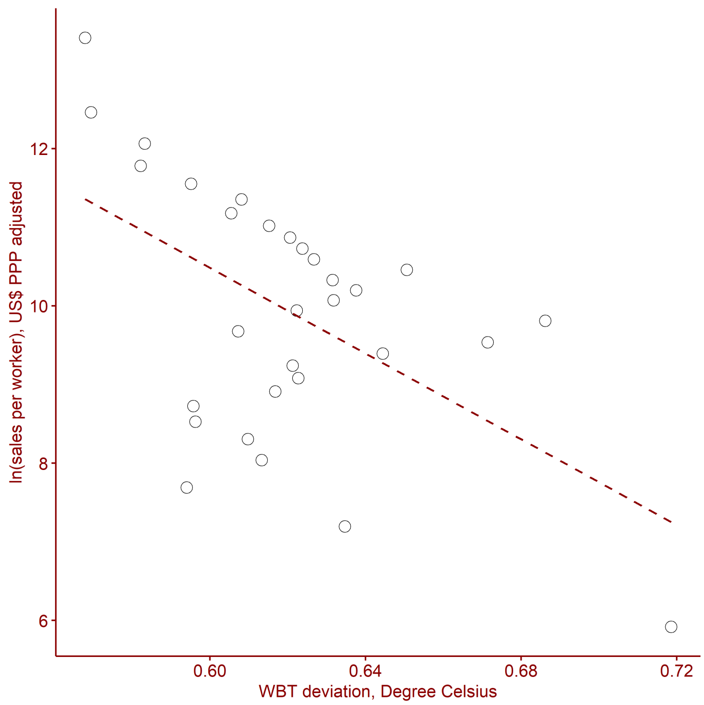
Source: Original figure for this paper based on data from the World Bank Enterprise Surveys and the Copernicus Climate Change Service .
Note: WBT = wet-bulb temperature.

Figure 5 presents a binscatter plot of the WBT deviations from the long-term average and the logarithm of sales per worker. The WBT bins are indicated by the number of dots on the scatter. The grouping of temperature observations by bins suggests that observations within the same bin tend to experience similar

[12]We use an arbitrary radius of 30 kilometers around the establishment, assuming a reasonable commuting distance between the workplace and home. This takes into account the case that exposure to higher temperatures is not only at the firm's premises but also en route to workplaces, residential areas, and other places. In a robustness exercise, we vary the radius to see if the estimates hold.

effects, while those across different categories or bins tend to experience distinctly different impacts as shown by the strong negative correlation. In the next section, we estimate formal regression models to quantify the negative correlation between WBT and firm productivity.

Figure 5. : Correlation between Sales per Worker and WBT Deviation



Source: Original figure for this paper, based on data from the World Bank Enterprise Surveys and the Copernicus Climate Change Service.
Note: WBT deviations are the difference between WBT in month m and year t and the long-term average within a radius of $30km$ around the establishment. PPP = purchasing power parity; WBT = wet-bulb temperature.

IV. Empirical Strategy

We estimate a non-linear regression of the log of sales per worker and other measures of firm performance on area-level deviations in temperatures. Our identification strategy exploits the variation in area-level temperatures near the establishment. In a robustness exercise, we narrow the 30km radius of our main mode, to ≈27.5km, which is the minimum grid size for both the temperatures and relative humidity data. The variation in area-level temperatures is plausibly exogenous as they are not the result of the firms' activities. However, there are various sources of bias that we need to address, the main source arising from potentially omitted variables. In such cases, the deviations in area-level temperatures could be picking up variations in other observed and unobserved area-level factors, which are likely to be correlated with both temperatures and firm productivity. These include area-level sub-national patterns in economic activities, transportation activities, population growth, environmental degradation or restoration such as deforestation or afforestation, and so forth. Some of these factors are time-varying and potentially correlated with temperatures. The variation in these factors could also differ by administrative levels in that some could vary at the city level, while others may vary at the sub-national, country, or continental level. We control for these factors using country, sub-national, and World Bank global region-level fixed effects. We also interact the geographic fixed effects with year-fixed effects.

The basic linear regression model that estimates log sales per worker on deviation in WBT controlling for firm-level characteristics and sub-national, country, and regional factors is given by:

$$ln(y_{ijkc,t}) = \beta\Delta^{WBT}_{jkc,t} + \gamma X_{ijkc,t} + \theta_{kc} + \rho_t + \theta_{kc} \cdot \rho_t + \epsilon_{ijkc,t}, \tag{3}$$

where $y_{ijkc,t}$ denotes firm-level productivity measured by the log of sales per worker of firm i in area j of sub-national region k, country c, and year t. $\Delta^{WBT}_{jk,t}$ is the deviation in average annual near-surface WBT from the long-term average within a radius of 30km around the establishment (that is, area j) and sub-national region k, country c and year t. $X_{ijkc,t}$ is a vector of firm-level characteristics, θ_{kc} is the sub-national region fixed effect, ρ_t is year fixed effect, $\theta_{kc} \cdot \rho_t$ is the interaction term for sub-national and year fixed effects, $\epsilon_{ijkc,t}$ is the independent and identically distributed error term, and β and γ are vectors of the coefficients to be estimated. All regressions are weighted using WBES weights.

The specification in Equation 3 assumes that the effects on productivity are linear. However, depending on the climate zone, and WBT categories, temperature increases could have heterogeneous effects on firm productivity. Kolstad and

Moore (2020) note that since the marginal effect of warming varies as a function of climate, a linear response function is often inappropriate for modeling the effect of climate change. For instance, in colder climate zones, a temperature increase could be beneficial to a firm's productivity, whereas in hotter climate zones a slight increase in WBT could be detrimental to human health, negatively affecting firm productivity. We capture such non-linearity by interacting the deviation in WBT from the long-term average across four WBT categories. This allows for estimating nonlinear temperature effects across the different WBT groupings. The specification with non-linear effects of temperatures on productivity can be written as:

$$\begin{aligned} ln(y_{ijkc,t}) = \beta\Delta^{WBT}_{jkc,t} + {} & \widetilde{\beta_{Q_2}}\Delta^{WBT}_{jkc,t} \times Zone^{Q_2}_{jkc} + \\ & \widetilde{\beta_{Q_3}}\Delta^{WBT}_{jkc,t} \times Zone^{Q_3}_{jkc} + \\ & \widetilde{\beta_{Q_4}}\Delta^{WBT}_{jkc,t} \times Zone^{Q_4}_{jkc} + \\ & Zone^{Q_2}_{jkc} + Zone^{Q_3}_{jkc} + Zone^{Q_4}_{jkc} + \\ & \gamma X_{ijkc,t} + \theta_{kc} + \rho_t + \theta_{kc} \cdot \rho_t + \epsilon_{ijkc,t}, \end{aligned} \tag{4}$$

where $Zone^{Q_2}_{jkc}$, $Zone^{Q_3}_{jkc}$, and $Zone^{Q_4}_{jkc}$ are dummy variables indicating the climate zones based on the quartiles of WBT. All the other notation is defined as for Equation 3. The reference category that is omitted from the regression is the bottom quartile or the coldest WBT zone: $Zone^{Q_1}_{jkc}$. The coefficients of interest are $\widetilde{\beta_{Q_2}}$, $\widetilde{\beta_{Q_3}}$, $\widetilde{\beta_{Q_4}}$, which can be interpreted as the marginal effect of a unit deviation in WBT from the long-term average on firm productivity in the respective WBT category, compared to the reference group. The only assumptions required here are that the temperature shocks are exogenous to each firm and the impact on productivity of the temperature deviation from the long-term average remains constant within each category. There are two fundamental sources of variations that are important for interpreting the impacts and central for estimating the non-linear impact of climate change. These are the variation in the temperature anomalies across climate zones, which provides the shock to our empirical model, and the variation in the baseline temperatures or climate zones, which underpins the nonlinearity of the impact of climate change on productivity.

V. Results and Discussion

We examine the effect of temperature deviations from the long-term average on labor productivity by estimating a non-linear model of our productivity indicator on deviations of WBT from the long-term average, across four WBT categories

Table 2—: Pooled OLS estimation on sales per worker: Whole Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
WBT Deviation×Zone$^{Q_2}_{(23.7^0C,24.9^0C]}$	0.526***	0.520***	0.199***	0.210***	0.234***	0.231***	0.224***	0.224***
	(0.028)	(0.028)	(0.026)	(0.026)	(0.027)	(0.027)	(0.027)	(0.027)
WBT Deviation×Zone$^{Q_3}_{(24.9^0C,25.7^0C]}$	-0.136***	0.103***	-0.075**	-0.060*	-0.073**	-0.031	-0.040	-0.041
	(0.036)	(0.036)	(0.036)	(0.036)	(0.037)	(0.037)	(0.037)	(0.037)
WBT Deviation×Zone$^{Q_4}_{(25.7^0C,max)}$	-1.330***	-1.060***	-0.205***	-0.169***	-0.225***	-0.222***	-0.228***	-0.234***
	(0.059)	(0.058)	(0.059)	(0.059)	(0.059)	(0.059)	(0.059)	(0.059)
Sector dummy	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	Yes	Yes	Yes	Yes	Yes
Country x year FE	No	No	No	No	No	Yes	Yes	Yes
Population (25km radius)	No	No	No	No	No	Yes	Yes	Yes
Road infrastructure (25km radius)	No	No	No	No	No	No	Yes	Yes
Pollution (25km radius)	No	No	No	No	No	No	No	Yes
Observations	88,876	86,467	86,467	86,467	86,467	86,467	86,467	86,467
R^2	0.057	0.146	0.357	0.359	0.370	0.371	0.373	0.373

Note: Standard errors are in parentheses. All models control for firm age, ownership, export status, firm size (employment), proportion of permanent workers, proportion of skilled workers, 55 dummy variables indicating a narrow industry classification, and dummies indicating World Bank regions. All WBT categories are included separately in the model, in addition to the interaction terms. The reference category for climate zone is the bottom quartile in the distribution of WBT which is less than or equal to 23.7^0C. The minimum WBT in our sample is 14.5^0C. FE = fixed effect; km = kilometers; OLS = ordinary least squares; WBT = wet-bulb temperature.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

representing different climate zones. Following Equation 4[13] the coefficients on the interaction term between the climate zones and the deviations in temperature capture the nonlinear impacts of temperatures that vary across the climate zones. The marginal effects are obtained by taking the partial derivatives of log sales per worker with respect to climate zone ($Zone^{Q_q}$) and WBT, where $q = \{1, 2, 3, 4\}$ represents the quartile. The coefficient estimates (β_{Q_q}) can then be interpreted as the impact on productivity of a unit (1^0C) deviation in WBT from the long-term average compared to firms in the coldest zone.[14] Table 2 presents the main results. Table 8 in the appendix presents the complete results.

Specification (1) presents the results for the baseline model with no controls or essential fixed effects, and hence they are less reliable. The specification ignores many factors, both observable and unobservable, that could bias our estimates, which could be captured by a set of controls and fixed effects. To address this, we estimate a series of models by including key controls that potentially explain

[13]We also estimate the basic model specified in Equation 3 and including the squared value of WBT deviation. The results are shown in Table 7, in the appendix.

[14]The marginal effects are obtained by taking the partial derivatives of log sales per worker with respect to climate zone ($Zone^{Q_q}$) and WBT i.e., $\frac{\partial(ln(y_{ijkc,t}))}{\partial(Zone^{Q_q}_{jkc})} \cdot \frac{\partial(Zone^{Q_q}_{jkc})}{\partial(\Delta^{WBT}_{jkc,t})}$.