# CLIMATE AND PRODUCTIVITY IN DEVELOPING COUNTRIES– A FIRM LEVEL APPROACH

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## Abstract

In this paper I investigate the impact of climate on the manufacturing sector in low- to medium-income countries. My approach brings together economic data from the World Bank Economic Survey and temperature data from Berkeley Earth to investigate the impact of unseasonable temperatures on three measures of input productivity for the manufacturing sector: labor, capital, and total factor productivity (TFP). Results suggest that unseasonably hot days reduce value-added labor while unseasonably cold days reduce value-added capital. Moreover, both very high daily peak temperatures and large variations in daily average temperatures in either direction, a plausible outcome from climate change, negatively affect all three types of input productivity but to different extents.

In a 2°C climate change scenario, my results suggest that a less stable climate that produces large variations in daily temperatures will reduce value-added labor, capital, and TFP by about 3.04, 6.75, and 3.65 percent, respectively, all other factors held constant.

**Keywords:** Macroeconomics, Productivity, Economic Development, Climate Change

**JEL Codes:** O11, O44, Q56

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# 1 Introduction

In recent times society has become increasingly focused on climate change risk and abatement. One particular concern for climate change is its potential to increase global inequality and slow poverty eradication efforts in less developed countries (Hallegatte et al., 2016). If climate change were to undermine economic growth and productivity in poorer regions, the ability for less developed countries to bridge the inequality gap will only grow. One way to understand these risks is to consider how variations in temperature act as exogenous shocks to different factors of production – labor, capital, and total factor productivity (see Noy and Nualsri (2008) for a discussion). While research on the topic in the developing world shows a negative effect on aggregate output from increases in average annual temperature anomalies (Dell et al., 2012), whether this translates into differential effects between labor, capital, and TFP is still uncertain. A wide-reaching study of manufacturers in China found evidence that very hot days affect TFP, but the effect on labor and capital was less conclusive (Zhang et al., 2018). Meanwhile, other researchers found that hot weather could actually reduce the availability of labor over the long term by reducing country-wide birth rates (Barreca et al., 2015), while a link between climate change and agricultural productivity has also been found (Fisher et al., 2012). Climate change is also predicted to increase instances of climate related natural disasters (IPCC, 2007), which have been shown to have at least short-term negative effects on the macro economy (Noy, 2009).

An important limitation of research between climate change and productivity to date is that the vast majority of this research represents micro-level studies of specific regions (Sudarshan et al., 2015; Zhang et al., 2018), facilities (Chang et al., 2016), or markets (Anenberg et al., 2017). With the possible exception of Dell et al. (2012), Burke et al. (2015) and Kalkuhl & Wenz (2020), I am not aware of any studies which consider the effect of climate change on aggregate productivity across large parts of the world, no studies which consider climate change on the different types of firm-level input productivity across the developing world, and no studies which look at the effect of climate on value-added productivity in a large-scale macroeconomic context.

In this paper I address these gaps in the literature by being the first to examine the effect of increasing variation in daily temperature averages on three types of firm-level input productivity - labor, capital and total factor productivity (TFP) – across low and medium income countries. I accomplish this by combining longitudinal temperature data from Berkeley Earth (2019) with cross-sectional firm level productivity data from the World Bank Enterprise Survey (WBES) (The World Bank, 2020) to create a pooled cross-sectional dataset of about 29,000 firms from 114 countries. In order to account for possible correlation in the error terms between productivity measures, I estimate a system of equations using Seemingly Unrelated Regression (Zellner, 1962). To address potential endogeneity bias in the data, the empirical strategy includes year and industry fixed effects by ISIC code together with a series of firm level controls. I also include a set of regional dummies based on World Bank regions, controls for longitude, and a region by longitude control to account for geographic heterogeneity. Therefore, the identification comes from within industry variation and within a geographic cross-section instead of between different regions and industries. Finally, as the WBES uses a stratified random sample in their survey design, this paper uses related strata information in constructing standard errors.

Results from my empirical analysis proceed along several dimensions. First, I consider productivity in both sales/output and value-added terms. Value-added productivity is given emphasis in my results as it is a better measure of local climatic and pollution conditions and their effect on firm productivity. Second, while climate change is predicted to produce warmer weather, it is also predicted to produce a less stable climate (Melillo et al., 2014). Thus, my empirical strategy includes different models with different independent weather variables to account for both possibilities. For my model focused on unstable weather, each additional day per fiscal year at least 4°C above or below long-term average monthly temperature trends reduces value-added labor by 0.11 percent ($p<0.05$), value-added capital by 0.23 percent ($p<0.05$) and TFP by 0.13 percent ($p<0.05$). To investigate the effect of warmer weather on productivity, I make use of two separate but similar models. The first uses two key independent variables: one for the count of days with an average daily temperature at least 4°C above long term trends and another for the count of days at least 4°C below long term trends. Compared to the base category of a day within 2°C of the average, this model predicts that each additional unseasonably warm day per fiscal year adversely effects value-added labor (-0.16 percent, $p<0.05$), while each additional day of unseasonable cold reduces value-added capital (-0.59 percent, $p<0.01$). My final model considers the effect of daily maximum temperatures on productivity. Here the independent variable is the count of days per fiscal year where the daily maximum temperature is at least 4°C above long-term trend. Results from this model suggest that each day with an unusually high peak temperature reduces annual value-added labor by 0.13 percent ($p<0.05$), capital by 0.19 percent ($p=.128$), and TFP by 0.18 percent ($p<0.05$). These results are summarized in Table 1.

One way of understanding the economic costs of climate change is to consider how a firm with average productivity would be effected if global temperatures increased by 2°C. I use 2°C as it represents the upper bound goal for climate change from the Paris Agreement (United Nations, 2015). Under this 2°C scenario, an increased frequency of very warm days is predicted to reduce value-added labor productivity by 8.43 percent. This is in line with estimates by the IPCC (1996), which predict that the frequency of very warm days will double as temperatures increase by 2-3°C. I also consider the effect of large variations in temperature due to a less stable climate. Here, the prediction is that under a 2°C climate change scenario, climate change induced instability in weather will reduce value-added labor, capital, and TFP by 3.04, 6.75, and 3.65 percent, respectively.

Losses of this scale have several important implications for the developing world. First, if climate change primarily manifests as warmer weather, firms will have an incentive to prefer capital inputs. In contrast, if climate change primarily leads to more extreme temperature days, including heat waves and severe winter storms (Melillo et al., 2014), all forms of productivity will suffer, but capital most of all. This would lead to a greater preference for labor inputs. Regardless of which effect dominates the relationship between climate change and productivity, overall manufacturing efficiency in low-to-medium income economies will be adversely affected by climate change. The result will be lower economic output for a given level of inputs.

## 2 Background

Research on the impact of temperature on workplaces has only recently gained attention, potentially due to rising concerns around climate change and long-term economic growth. Early research in this field tended to concentrate on agricultural settings and generally found an economically significant negative effect between increased temperature and farm productivity (Deschênes & Greenstone, 2012; Fisher et al., 2012; Schlenker & Roberts, 2009). However, a growing body of recent literature shows that extreme temperature and severe weather patterns negatively impact aggregate productivity, and the productivity of specific sectors. For example, using data from 12 countries, Dell et al. (2009) found that variation in temperature can partially explain both cross-country and within-country variation in income, with about half the short-term negative effects offset with long-term adaptation. Likewise, research on manufacturing productivity in China indicates that an increase in days above 90°F reduces total factor productivity among Chinese firms. Here, the authors suggest that unfettered climate change could reduce Chinese manufacturing by 12 percent by the middle of this century (Zhang et al., 2018). Finally, data from the auto industry in the United States suggests that an increases in the count of days above 90°F reduced auto production by about 1.5 percent (Cachon et al., 2012). Despite the evidence suggesting extreme temperatures negatively affect labor productivity, the level of heat required to induce declines in labor productivity is less clear, as is why those declines occur. For example, while Niemala et al. (2002) found that increasing temperature by 2.5°C reduced call center productivity by 5-7 percent, Lan et al. (2011) showed an increase of 8°C was required to reduce worker neurological test scores designed to proxy worker productivity. Relatedly, Cai et al. (2016) documented that worker productivity displayed an inverted U-shape with temperature: piece-rate productivity among workers at the factory they investigated was highest when outside temperatures were between 76-79°F, decreasing by 11 percent when temperatures were below 60°F and by 6.7 percent when temperatures were above 95°F. This effect was limited to non-local laborers, with long term residents near the factory unaffected by temperature. This accords with the conclusions drawn by Zhang et al. (2018), who similarly found an inverted U-shape in TFP. Overall, their key argument is that absenteeism did not explain drops in output, but rather it was thermal stress inducing production losses. Meanwhile, Graff Zivin et al. (2018) support a link between weather and human capital productivity. Here, using NLSY79 data, they found that high ambient temperature (above 78.8°F) reduced results on math test scores in a statistically significant manner. This suggested that the mechanism for temperature affecting labor productivity is likely through reductions in cognitive performance. However, they argue this effect largely dissipates over time due to long run compensatory factors.

Conversely, the effect of adverse temperatures on capital productivity is less well known. There is reason to believe thermal stress increases breakdowns and the maintenance needs of machinery (Mortier et al., 1992). Plausibly, extreme weather will also increase energy and cooling costs making capital more expensive to operate. Power outages caused by extreme weather events, a particularly insidious issue in the developing world (Gaylord & Hancock, 2013), would also reduce capital productivity. Within a conceptual framework of productivity and output, Cole et al. (2005) suggest that if pollution affects labor productivity, then firms would switch to greater automation. The same could be said for temperature and labor, where reductions in labor productivity lead to greater capital investment in automation. The extent firms automate labor tasks would likely vary by industrial sector, as the impact of extreme weather and climate change may vary by sector. This is also true for firm-level substitutions between capital and human capital, where the investment in one may increase if the other is impaired by pollution (or persistent, extreme temperature) (Bovenberg & Smulders, 1995).

## 3 Data

To investigate the effect of temperature on firm-level productivity, I combine data from several sources. Enterprise data is from the World Bank Enterprise Survey (The World Bank, 2020), which includes harmonized estimates of capital, labor, and total factor productivity for firms across 114 different low- and middle-income countries. To simplify total factor productivity, I take it to represent the contribution to output not explained by capital or labor. At the firm level, this is roughly equivalent to technical progress (The World Bank, 2000). Temperature data is from Berkeley Earth’s gridded daily temperature anomaly dataset (Berkeley Earth, 2019). This data was only recently made available and is classed as experimental. The following sections discuss each data source in detail.

**World Bank Enterprise Survey**

I use firm level data from the World Bank Enterprise Survey (WBES) for surveys conducted between 2006 and 2017 for my productivity and economic indicators. This represents the earliest period from when the World Bank's Enterprise Analysis Unit first employed their "Global Methodology" to the survey, which makes survey observations directly comparable over time (Francis & Karalashvili, 2017). To conduct its survey, the World Bank selects a representative sample of firms based on a stratified random sampling methodology that groups firms by size, geographic location, and industry. The survey has a different set of questions depending on whether a firm is a manufacturer or service provider. As a complete set of questions on productivity are only asked in the manufacturing module, I limit my analysis to firms who are in the manufacturing sector as defined by ISIC codes 15-37.

The most important economic indicator derived from the World Bank survey is an estimate of total factor productivity. While a full methodological description is available from the World Bank website[1] (2017), for this paper, it is important to recognize that the World Bank uses two methods for calculating TFP: an output-based model (VKLM), and a value-added model (VAKL). Together with these estimates of TFP, I also use the WBES to derive both output and value-added versions of labor (L) and capital (K) productivity. In output-based terms labor productivity represents sales per total cost of labor. This can be expressed as:

$$L(out)_i = \frac{Sales_i}{LaborCosts_i} \tag{1}$$

Meanwhile, capital productivity represents sales per replacement cost of machinery, vehicles and equipment and can be expressed as:

[1] Specifically, see: https://login.enterprisesurveys.org/content/sites/financeandprivatesector/en/library/combineddata.html Note: requires (free) login credentials

$$K(out)_i = \frac{Sales_i}{Capital_i} \tag{2}$$

where all values are in 2009 USD terms. The key difference between this output-based model and the value-added (VA) model is the use of cost-of-goods sold[2] (COGS) in calculating value-add. Thus, value-added labor productivity for firm $i$ is:

$$L(VA)_i = \frac{(Sales_i - COGS_i)}{LaborCost_i} \tag{3}$$

and for capital (K):

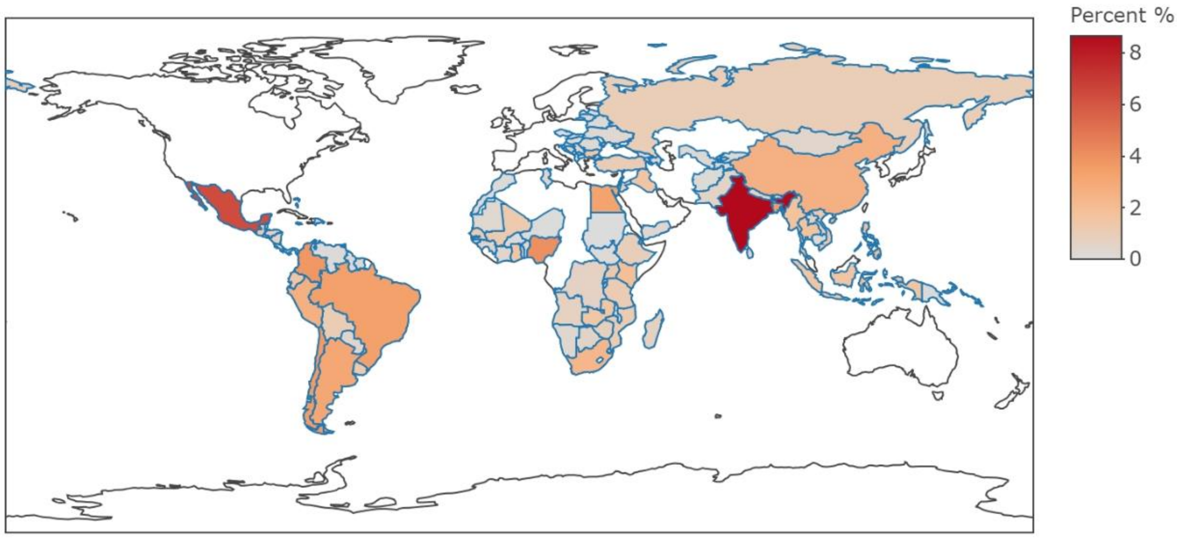
$$K(VA)_i = \frac{(Sales_i - COGS_i)}{Capital_i} \tag{4}$$

where all values are in 2009 USD terms. As part of the seemingly unrelated regression, $L(VA)_i$, $K(VA)_i$ and TFP estimates from the VAKL model are used together when analyzing the effect of weather on value-added productivity, while $L(out)_i$, $K(out)_i$ and TFP estimates from the YKLM model are used when examining output-based productivity. During the calculation of TFP, the World Bank removes outliers three standard deviations from the mean on each key economic indicator. For consistency, I also set these observations to missing. Countries represented in the data are shown in Figure 1, with darker colors representing a greater proportion of the total dataset. What is clear is that countries generally regarded as highly developed are excluded from the survey. This includes western Europe, Scandinavia, the United States, Canada, Japan, and Australia. Thus, my analysis is particularly relevant for low and middle-income economies. Firms from India are the largest group by country and represent 8.66 percent of all firms

[2] In the World Bank survey, terminology used is the accounting cost-of-goods sold. This is synonymous with cost of inputs.

used in my analysis. Meanwhile, the largest number of firms by World Bank region is from Latin America which make up 34.2 percent of all respondents.

Figure 1 - Countries in Dataset (Proportion of Firms in Total Dataset)




Summary statistics are shown in Table 2. On average, yearly output-based capital productivity per firm was $16.12 a year (standard deviation (SD) of $56.28) per dollar of capital employed, while average value-added capital productivity was $9.46 (SD of $33.00). Average output per dollar cost of labor per year was $11.31 (SD $20.68), while the average value-added productivity per labor dollar per year was $6.37 (SD $12.18).

**Berkeley Earth Temperature Data**

Data on temperature variation is from the Berkeley Earth project's gridded daily dataset (Berkeley Earth, 2019) for years 2005 through 2017. Each data point is recorded at the 1° latitude by 1° longitude level, centered around 0.5°, and represents the daily surface air temperature anomaly from the mean monthly temperature[3] for that grid reference. Berkeley Earth uses a specific program, known as Berkeley Average, to

[3] With the mean being calculated from temperature readings over the period from January 1951 to December 1980.

calculate mean temperatures from 14 databases and 14.4 million temperature observations across over 44,000 sites (Rohde, A. et al., 2013). One benefit of using this dataset is that it provides very little error in the calculation of average temperature compared to its peers, especially during the timeframe used in this paper where the average annual error is less than 0.1°C (Rohde, 2013). To match firm location to temperature data, the central co-ordinate for each WBES city or region was selected, rounded to the nearest 0.5° on both latitude and longitude, and then matched to the Berkeley Earth dataset[4]. In total, 4,758 Berkeley Earth temperature data points were matched for each location. Finally, this data is sorted into bins as described in Data Matching Principles below.

Summary statistics for the Berkeley Earth dataset are shown in Table 3. Across the entire dataset, locations experienced 287.9 days within 2°C of the locational monthly mean on average. Europe and Central Asia had the highest level of variation, with an average of 157.6 days of normal temperatures, and Africa had the least amount of variation with 319.4 days per year lying within 2°C of the monthly mean. Across all regions, locations had 19.1 days of extreme temperature at least 4°C from normal per annum on average. South Asia was the lowest with just 5.5 days, while Europe and Central Asia were the highest with 93 days per annum.

## 4 Data Matching Principles

One important consideration with weather data is that there may be a non-linear relationship between temperature and the outcome of interest, especially when looking at extreme temperature values (Auffhammer et al., 2013; Burke et al., 2015). To control for this non-linearity and to estimate the effect of daily temperature readings on annual economic

[4] In metric terms, 0.01° longitude is about 1.1km in length at the equator and about 0.46km at 67° north and south. In this dataset, regions/cities range in distance from the equator to about 39°S and 67°N and thus the city/regional center is at most no more than 55km from the temperature reading.

statistics, I use a strategy common to this type of environmental-economic analysis where I discretize the distribution of daily data into bins representing a given temperature range over the chosen year (Deschênes & Greenstone, 2011; Zhang et al., 2018). This method captures any non-linear effects within the ranges for each bin to allow us to look at the important aggregate effect of large variations in weather on productivity. This method also captures U-shaped non-linearity between the bins as documented by Cai et al (2016). For this paper, I use five ranges: < -4°C below the city/region temperature mean, representing a much colder than normal day; -4°C to -2°, representing a mild day; -2°C to 2°C, representing an average day; 2°C to 4°C, representing a slightly warm day; and greater than 4°C to represent a hot day. To populate the bins, I take the fiscal year end for the firm's country as defined in the CIA World Factbook (2016) and count back exactly one year. One reason to use five bins is to provide a clear break (or bridge) between my key variables of interest (the > ±4°C bins) and the base category (the count of days within 2°C of the regional average). The expectation is that while very marginal changes in temperature, such as going from 1.9°C to 2.1°C or from 3.9°C to 4.1°C, are unlikely to be discernable to workers or machinery, a jump in temperature of at least 2°C is discernable. As the focus of my analysis is on the aggregate effect of highly abnormal temperatures on firm-level input productivity, I concentrate my discussion on the bins representing much warmer or colder days compared to average, rather than on the bridging bins which represent mild changes in temperature. This helps resolve many of the issues of discretizing (or categorizing) a continuous variable (Altman 2014).

Another benefit of starting with five bins is because although climate change is predicted to increase global temperatures, it is also likely to lead to more extreme events, including heat waves and winter storms (Melillo et al., 2014). To investigate this latter effect in aggregate, I include a complimentary analysis where the key independent variable combines the > 4°C and < -4°C bins to represent days with an average temperature anomaly at least 4°C from the mean, whether positive or negative, examined against the control bin of -2°C to 2°C days. This analysis is termed the Extreme Weather Model in my results section. I also investigate variations in daily maximums from their monthly means using a similar methodological approach described in the preceding paragraph. This is termed the Daily Max Model.

## 5 Conceptual Framework and Empirical Methodology

To conceptualize the role of inputs in producing firm-level output, I use a simple Cobb-Douglas production function that includes output (Y), labor (L), capital (K), and total factor productivity (TFP). This is based on work by Francis & Karalashvili (2017), Zhang et al (2018), Sorenson & Whitta-Jacobsen (2010), and Cobb & Douglas (1928). As output is a function of inputs, I have:

$$Y = TFP(L)^{\sigma_L}(K)^{\sigma_K} \tag{5}$$

Output elasticities are given for labor and capital as $\sigma_L$ and $\sigma_K$ respectively. Taking the log of both sides yields:

$$Ln(Y) = \ln(\text{TFP}) + \sigma_L Ln(L) + \sigma_K Ln(K) \tag{6}$$

Since weather conditions have the potential to affect the return to each component of output, changes in component efficiency may result in firms reallocating factor inputs in order maintain their desired level of output. The goal of the empirical analysis is to test how each log input is affected, and whether reallocation occurs as a result.

To assess the effect of environmental conditions on L, K, and TFP, I use a Seemingly Unrelated Regression (SURE) (Zellner, 1962). In choosing a SURE model, the intention is to account for any possible cross correlation in error-terms between the different types of input productivity. This maximizes the efficiency of my estimators even if OLS estimates are otherwise consistent (Martin & Smith, 2005). Note that using the SURE method only produces slightly different results compared to OLS estimators, with no difference in interpretation between OLS and SURE estimates. For this reason, only SURE estimates are presented.

The empirical aim is to estimate a system of equations, whether in OLS or SURE, of the form:

$$ln(prod^m)_{it} = \beta_0^m + \beta_1^m temp_{it} + \beta_2^m region_i + \beta_3^m lat_i + \beta_4^m (region * lat)_i + \beta_{5-n}^m firm_i + \gamma_t + \delta_j + \epsilon_{it}^m \tag{7}$$

where m represents the productivity measure of interest (L, K, TFP); $i$ represents each firm; temp is a vector of bins representing count of days in the bin for the relevant year; t represents fiscal year for firm $i$; firm is a vector of other firm specific controls; and $\epsilon_{it}^m$ represents the idiosyncratic error term for firm $i$ in year t for productivity measure m. The full empirical model includes a set of control variables, namely: a categorical variable representing whether the firm is small, medium, or large to account for differences in productivity between firms of varying size and opportunity; a dummy to represent whether a firm is in a low income country; six regional controls reconciling to the World Bank regions (*region*); the central latitude for the city/region where the firm is located (*lat*); and an interactive between region and latitude (*region*lat*). The region and latitude controls account for regional differences in productivity and environmental conditions, and follow guidance from Fisher et al. (2012) on the optimal level of geographic control for environmental/temperature controls. The authors of Fisher at al. (2012) argue that using a local fixed effects model, such as at the city/local region level, would in effect capture almost all the variation in temperature. Using a cross section of larger regions and latitudes balances the risk of over specifying the model with discerning important relationships between temperature and productivity. The model also includes both industry ($\delta_j$) and year ($\gamma_t$) fixed effects. Industry is at the two-digit ISIC level. These control for possible endogeneity bias at the industry and year levels that could affect productivity and the environmental variables of interest. In particular, the industry effect controls for the likelihood that firms across different industries will likely face different levels of productivity and environmental regulations, and that they will likely have different preferences to location. Meanwhile, the year fixed effect controls for global time trends in temperature, productivity, and pollution control. Summary statistics of the relevant variables are shown in Table 2 through Table 4.

Since many of the variables used in this analysis are categorical or dummy variables, base categories are selected for each to serve as a standard of comparison within the model. For the temperature variable, the key base category is the count of days in the previous fiscal year where the daily temperature was within 2°C of the average for that region for that month. This bin is excluded from the model with the remaining $\beta_1$ estimators interpreted in comparison to this reference group. Finally, since the World Bank uses a stratified random sample in their survey design, I cluster standard errors at the strata level per guidance in Abadie et al.(2017). The strata include firm size, geographic location, and industry. While it varies by model, typically this produces about 6,500 clusters.

## 6 Results

My empirical results include estimates for the effect of unseasonable temperature on both output-based and value-added L, K, and TFP. In the case of the output-based factors of production, the variables represent each factor’s contribution to firm sales. In comparison, the value-added factors of production represent each factor’s contribution to gross profit. As discussed previously, greater emphasis is given to results for the value-added variables. This is because the value-added measures more accurately represent the effect of localized climatic conditions on firm activity, while output based measures include climatic conditions imported from elsewhere. All productivity measures are expressed in natural logs and have been multiplied by 100 for easier interpretation.

Three competing models, each examining a different set of key independent temperature variables, are examined. Controls are consistent across all models. The first model, the Extreme Weather Model, uses as its key independent variable the count of days in a fiscal year with an average daily temperature at least 4°C above or below the long-term monthly mean. The second, the Hot and Cold Weather Model, includes all temperature bins as separate independent variables. However, my interpretation of this model focuses on the two most extreme temperature bins: the number of days with an average temperature at least 4°C above the long-term mean, and the number of days with an average temperature at least 4°C below the long-term mean. The third model, dubbed the Daily Max Model, replicates the second model, but with bins built based on daily maximum temperatures instead of daily average temperatures. In each SURE model the count of days within 2°C of the mean for that observation/year is dropped to act as the control group. As such, all results are compared to the number of days in a year where the firm experienced temperature in line with the long-term regional temperature average, but with an allowance around 2°C. Table 1 provides a summary of the key relationships between weather and labor, capital and TFP productivity for the value-added models.

Table 1 Summary of Key Results

| | Seemingly Unrelated Regression - Value Added | | |
|---|---|---|---|
| | Daily Average Temperature | | |
| | Labor | Capital | TFP |
| Extreme Weather Model | -0.105** | -0.233** | -0.126** |
| | (0.043) | (0.102) | (0.052) |
| Hot & Cold Model: > +4°C days | -0.159** | 0.09 | -0.118 |
| | (0.072) | (0.079) | (0.088) |
| Hot & Cold Model: < -4°C Days | -0.02 | -0.587*** | -0.139 |
| | (0.095) | (0.217) | (0.112) |
| | Daily Maximum Temperatures | | |
| | Labor | Capital | TFP |
| Daily Max Model | -0.129** | -0.185 | -0.178** |
| | (0.065) | (0.121) | (0.073) |
| Full Set of Controls | Yes | Yes | Yes |

### 6.1 Labor Productivity and the Environment

There is a clear negative and statistically significant association between value-added labor productivity and all three measures of extreme heat and unstable weather. In the value-added Hot & Cold Model, each additional day with a temperature at least 4°C above the long-term monthly average is predicted to reduce labor productivity by 0.159 percent ($p<0.05$) (Table 6, column 4). As the average level of value-add per dollar spent on labor across all regions and years is $6.37, this represents a marginal reduction of about 1.01 cents of value-added labor per dollar spent. Similarly, in the value-added Daily Max Model (Table 8, column 4), a negative and statistically significant relationship is also present between labor productivity and each day of abnormally high daily maximum temperatures. This model suggests that each additional day with a high at least 4°C above the average long-term monthly maximum reduces annual labor productivity by 0.129 percent ($p<0.05$). This represents a loss of 0.82 cents per dollar spent on labor at the mean. Finally, results from the value-added Extreme Weather Model are in Table 7, column 4. Point estimates on the extreme weather bin predict a reduction in annual value-added labor productivity of 0.105 percent ($p<0.05$) (or 0.66 cents per dollar) for each day at least 4°C away from the mean monthly temperature. Point estimates and direction of effect in all three models are robust to model specification.

Compared to the consistent and negative effect of extremely hot days on value-added labor productivity, the overall effect of temperature on output-based labor productivity is mixed. First, no statistically significant result is found in the Hot & Cold Model (Table 7, column 1). Second, smaller but statistically significant results are seen on the count of days of extreme weather and output-based labor productivity in the Extreme Weather Model (Table 6, column 1), although this result is less robust to model specification. Third, there is a statistically significant relationship (-.142 percent, $p<0.05$) between each additional day of very high daily maximum temperatures and output-based labor productivity in the Daily Max Model (Table 8, column 1). This effect has similar economic significance compared to the value-added labor estimators, with the point estimate representing a loss of 1.6 cents worth of output per dollar spent at the mean of $11.31.

The consistent negative association between extreme temperature days and value-added labor productivity suggests that labor may become less efficient in the face of higher positive variation in daily temperatures. As the estimates on output-based labor productivity are less consistent, this suggests that variation in temperature predominantly creates inefficiency in using inputs rather than creating outputs (Cai et al., 2016). This is potentially a product of value-add being a better measure of local productivity and local climatic conditions affecting productivity.

### 6.2 Capital Productivity and the Environment

Capital productivity offers an interesting contrast to labor. Beginning with value-added capital productivity, the value-added Hot & Cold

Model shows no clear relationship between warm weather and capital (Table 6, column 5). On the contrary, there is a persistent negative and statistically significant relationship between each additional day of unseasonably cold average temperatures and capital productivity across the different model specifications, including in the fully specified model shown in Table 6. Here, each additional day at least 4°C below the long-term trend is predicted to reduce value-added capital productivity by 0.587 percent ($p<0.01$). Given the average level of value-added capital per dollar invested across all regions and years is $9.46, this represents an average loss of capital efficiency of about 5.6 cents per dollar of investment for each abnormally cold day. The value-added version of the Extreme Weather Model (Table 7) follows a similar trend. Each additional day at least 4°C above or below the long-term mean is predicted to reduce value-added capital productivity by 0.233 percent ($p<0.05$). The value-added Daily Max model offers an imprecise estimate of the effect of unusually high daily maximum temperatures on capital. First, the coefficient on the bin representing warm-but-not-hot days (the number of days with max temp 2 to 4° C above the mean) is positive (0.31 percent) and statistically significant ($p<0.01$) (Table 8, column 5). Second, despite a higher level of statistical uncertainly ($p=0.128$) compared to the classical test of significance ($p<0.10$), the point estimate (-0.185 percent) on the >4°C bin suggests that there may be a negative relationship between very high daily maximum temperatures and capital productivity. This negative effect accords with the similarly negative effects high daily maximum temperatures have on both labor productivity (discussed in the section above) and TFP (discussed below). Although I am loath to draw any strong inference from the co-efficient on the bridging bins, this does provide some evidence that while slightly warmer peak temperatures may improve capital efficiency, unusually large peak daily temperatures reduce capital productivity.

With respects to my output-based models, a negative relationship between colder than normal weather and capital efficiency is also present. In the Hot & Cold Model, the point estimate for a much colder than normal average day is -0.513 percent ($p<0.01$) (Table 6, column 2). Similarly, the point estimate on the >±4°C bin in my output-based Extreme Weather Model predicts that each day at least 4°C away from long-term monthly trends reduces output-based capital productivity by -0.19 percent ($p<0.05$) (Table 7, column 2).

A key finding is that while there is a negative relationship between both value-added labor and capital and extreme temperature, labor productivity is particularly affected by unseasonable warmth, while capital productivity is affected more by unseasonable cold. One plausible explanation is that more capital is needed to achieve the same level of output during cold weather. This could potentially be due to expensive investments in insulation, heating, or new equipment that can withstand lower temperatures.

### 6.3 TFP and the Environment

No statistically significant relationship is seen between output-based TFP and temperature in any of my output-based models. For value-added TFP, there is no statistically significant association between either very warm or very cold average daily temperatures and value-added TFP in the Hot & Cold Model (Table 6, column 6). There is, however, a negative and statistically significant relationship between the joint count of both very warm and very cold days and TFP in the Extreme Weather Model(Table 7, column 6). This effect is robust to model specification. The point estimate on the model with a full set of controls suggests that each additional day of highly unseasonal average temperatures reduces annual TFP by 0.126 percent ($p<0.05$). There is also a negative association between days of unseasonably high daily maximum temperatures and value-added TFP. In the

Daily Max Model (Table 8), the point estimate implies a .178 percent ($p<0.05$) reduction in TFP each day the daily high is at least 4°C above trend.

### 6.4 Discussion of Temperature and Productivity

The analysis above depicts a complex relationship between temperature and input productivity. With respects to the effect of a day with an average temperature at least 4° warmer than normal, my Hot & Cold Model shows a clear negative effect on value-added labor productivity. This negative relationship also holds in the Daily Max Model for each day where the daily peak temperature is at least 4°C above normal. By contrast, while there is no evidence TFP is significantly affected by unseasonably high average temperatures, like labor it is negatively affected by very high daily maximums. Value-added capital productivity offers a slightly more complex outcome. Here, value-added capital productivity is less efficient on days when the average temperature is at least 4°C below trend. Capital may also be less efficient on days where the daily high is at least 4°C above trend. Although the point estimate on this latter statistic is somewhat imprecise, when taken together with TFP and labor it acts as evidence that daily highs affect all three types of input productivity. This makes intuitive sense: most manufacturers are active during the day when temperatures are likely to be at their peak, with peak temperatures likely closely connected to thermal stress (Zhang et al., 2018) and the probability of a blackout (Gaylord & Hancock, 2013). The evidence from my models suggest this negative effect is more consistent on labor productivity and TFP compared to capital.

One constant across the analysis is the strong relationship between the cumulative count of extreme temperature days and all types of value-added input productivity. This is shown by the Extreme Weather Model where the highest negative co-efficient is on value-added capital (-0.233,

$p<0.05$), followed by TFP (-0.126, $p<0.05$), and then labor (-0.105, $p<0.05$). This implies that each additional day of very warm or cold temperatures reduces the efficiency of all inputs, but capital most of all. This could be due to reduced effectiveness of machinery or the need for more machinery to compensate for weather effects on manufacturing, among other potential causes. It is also plausible that firms may be able to reduce labor costs on days affected by extreme weather. While this would result in lower employee costs on such days, the fixed nature of capital outlays gives firms fewer options to reduce their stock of property, plant, and equipment. If firms were engaged in this sort of compensatory effort, it would at least partially explain why value-add per unit cost of labor is less affected by extreme weather events than value-added capital.

Finally, one take away from my results is that compared to output-based productivity, which includes inputs affected by environmental conditions occurring elsewhere, value-add appears to be a better predictor of how environmental conditions affect firm-level productivity. I would suggest this is because value-add occurs locally and thus better captures the impact of local variation in production conditions rather than conditions imported from elsewhere. Thus, although results from the output-based model are mixed, the evidence from the value-added model that highly adverse temperatures affect firm-level input productivity is compelling.

### 6.5 Climate Change and Input Productivity

Although there is clear evidence climate change will produce days that are much warmer than long term trends (IPCC, 2007) and a less stable climate generally (Melillo et al., 2014), the exact number of days any one region will experience 4°C above or below the long-term average is not clear. As this is the key outcome of interest for my analysis, this makes it difficult to precisely calculate the effect of climate change on productivity using just my point estimates. As a compromise, I use results from my models and average trends in global temperatures to extrapolate potential changes in input productivity for the "average" firm from the countries in the data. This basic projection relies on point estimates from the value-added SURE models, linear projections of temperature[5], and serves more to place our global future in perspective rather than to predict the future for any one region. To that end, I focus on the effect of a 2°C rise in average annual global temperatures. This is done for two reasons. First, 2°C represents the upper bound for climate change from the Paris Agreement (United Nations, 2015). Second, there is evidence that a doubling of CO2 emissions translates to a 50/50 chance of a 2°C rise in average temperatures by the year 2100 (Andronova & Schlesinger, 2001). Thus, there is both a political and a scientific reason to be interested in a 2°C increase in global average temperatures. A summary of the calculations and results is shown in Table 9.

The projections proceed as follows. First, according to the Berkeley Earth dataset, global temperatures were about 0.15°C higher on average over the six years from 2012 to 2017 compared to the period 2005 to 2010[6]. This represents the first and last six years in my dataset where I have a full set of temperature anomaly values for each region. Second, for the period 2005 to 2010, the regions in my dataset averaged about 30.67 days per annum

[5] While there is some evidence of non-linear trends in my empirical models (such as where the 2°-4°C temperature buckets have a statistically significant co-efficient), I have chosen not to include them in my climate change analysis. This is done as these categories were designed to act as separation variables to split my base category from the true variables of interest (the extreme weather variables). Thus, they are likely to include daily temperature readings very close to those in the base and key independent variable categories (for example, a 2.1°C versus 1.9°C day). This may cause unexpected issues (Altman, 2014). Also, if they are included, they actually increase the estimated effect of climate change on input productivity. Thus, I stick to more conservative but more statistically sound estimates here.

[6] Author's calculation based on global average temperature anomalies available at http://berkeleyearth.lbl.gov/auto/Global/Complete_TAVG_summary.txt with the average anomaly over 2012-2017 of about 1.12°C versus 0.97°C over 2005-2010.

with average daily temperatures at least 4°C above the long-term mean[7]. For the period between 2012 and 2017 this was 34.64 days, an increase of about 3.97. Third, extrapolating these figures out to a 2°C climate change goal would result in the firms covered in the dataset experiencing an average of 66.24 days with average daily temperatures at least 4°C per annum above historical trends. Using the statistically significant point estimates from Table 6, this translates to a predicted loss of 8.43 percent of value-added labor productivity, or about 54 cents per dollar invested at the margin[8], and a 6.25 percent decline in value-added TFP.

Using this same methodology but for the Extreme Weather Model in Table 7, firms experienced an average of 47.08 days of extreme weather per year between 2005 and 2010. For the period 2012 to 2017, the same firms would have experienced 49.25 days on average, an increase of about 2.17 days per annum. With the 0.15°C increase in global temperatures for the same period, this suggests that firms in the data would experience about 36.21 extreme weather days per year if yearly average temperatures rose by 2°C, the upper bound of the UN climate change goal. 36.21 days of extreme weather per year translates into a predicted loss of 3.73 percent of value-added labor per dollar or about 23.76 cents per dollar[9], a loss of value-added capital of 7.49 percent or about 70.9 cents per dollar of capital invested at the margin[10], and a loss of value-added TFP of about 5.39 percent.

Even if there are compensatory effects to reduce the impact of climate change on productivity such that these figures overstate the true relationship, the data available shows that a 2°C increase in global

[7] Note that this number varies from the firm-level average exposure as detailed in Table 3 for two reasons. First, the number presented here represents each year from 2005-2017 regardless of whether a World Bank survey was conducted in that location for that year. And second, due to variation in the number of observations between years and region.
[8] Based at the mean value-added labor of $6.37
[9] At the value-added labor mean of $6.37
[10] At the value-added capital mean of $9.46

average temperatures will have economically significant effects on firm-level input productivity. Of course, climate change may ultimately affect global average temperatures by more or less than 2°C. To account for this, trends in how productivity is predicted to change for a change in global average temperatures between 0.5°C to 4.5°C are shown in Figure 2 and Figure 3. For Figure 2, using the statistically significant point estimates of very warm days from the value-added Hot & Cold Model, at higher levels of global warming, labor is predicted to be 17 percent less productive at 4°C. Importantly, for the average firm with a mean of $6.37 of value-added labor per dollar spent, the marginal benefit of labor is predicted to turn negative if global temperatures were to rise to about 3.8°C. Figure 3 looks at the effect of unstable weather and climate change as investigated in the value-added version of the Extreme Weather Model. Here, although labor at the margin is still productive across all global warming scenarios, the net marginal benefit for each additional unit of capital for the average firm would turn negative if global average temperatures increase by about 3.1°C. At this point unstable weather would incentivize firms to switch to more labor.

Figure 2 Climate Change and VA Productivity - Hot & Cold Model: Days >4°C

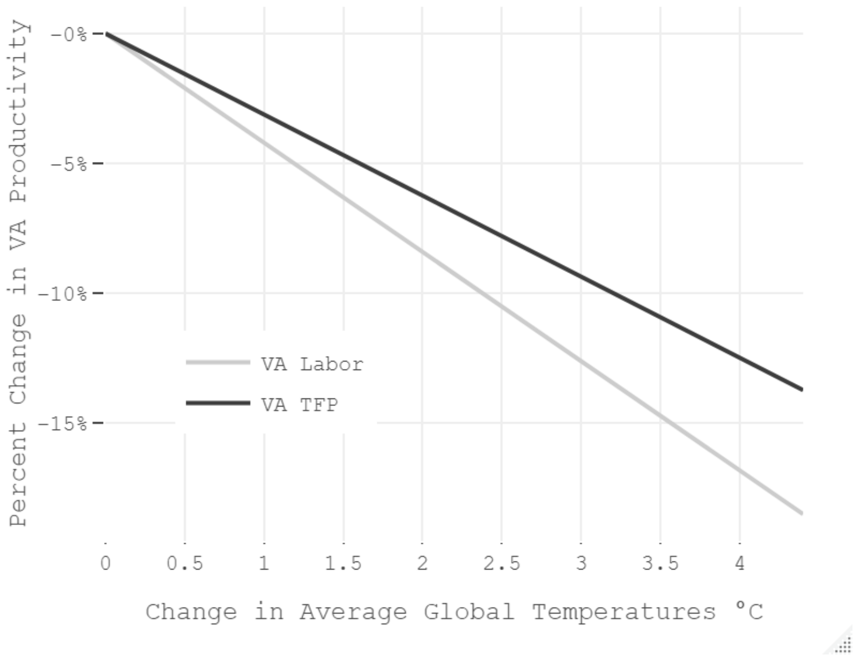
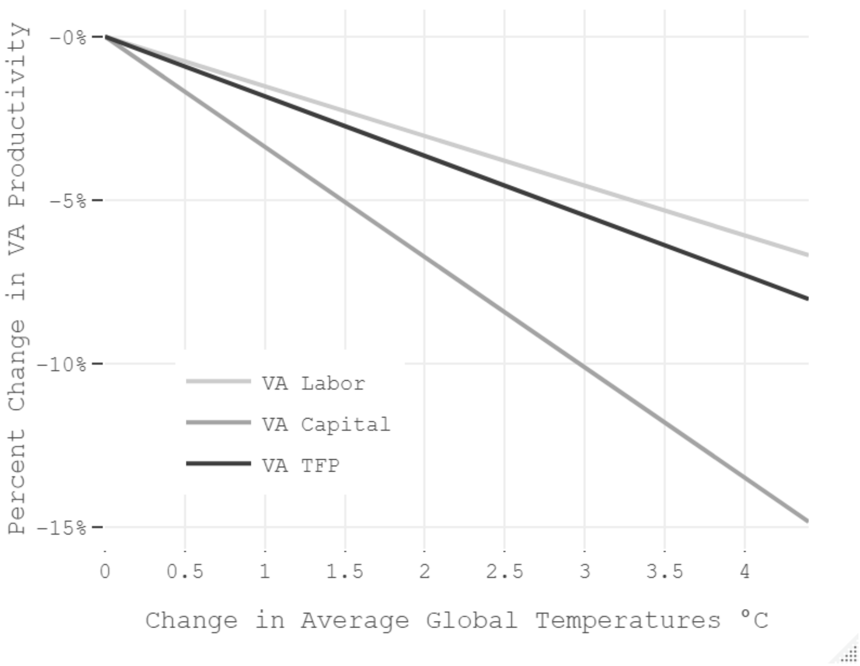



Figure 3 Climate Change and VA Productivity -Extreme Weather Model




## 7 Conclusion

In this paper I provide clear evidence of a relationship between temperature and productivity for firms in developing countries. Results indicate that manufacturing inputs are affected by temperature variation from long-term monthly averages, not just very warm days. I obtain evidence to suggest that labor and TFP are adversely affected by large increases in temperature compared to average trends, capital by large decreases, but all three by large variations in daily temperature means and maximums. This has obvious implications if climate change produces a less stable climate that leads to greater variation in daily temperatures. For example, if climate change primarily manifests as global warming proxied as higher ambient or peak temperatures throughout the day, then value-added labor will become less productive, providing incentives for firms to switch from labor to capital inputs. In this scenario, climate adaptation policy must consider risks to labor's share of production, and any likely affect climate change will have on a range of market outcomes including unemployment and returns to education. Alternatively, if climate change primarily manifests as a less stable climate, then all forms of productivity will suffer, but capital most of all. In this scenario, climate adaptation would require firms to invest in more capital for the same level of output, or switch to more labor or technical efficiency. Governments may also need to consider more investment in climate abatement strategies such as a robust and reliable electricity grid. Regardless, manufacturing efficiency will be adversely affected by climate change due to greater variation in average temperatures, resulting in lower economic growth for a given level of inputs.

Ultimately, my results present a complex relationship between weather and input productivity in the developing world, as evidenced by the different results between value-based and output-based productivity and between different models and types of input productivity. As such, more research on how climate change will affect input productivity and what climate change implies for firms and their efficient allocation of inputs is warranted.

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# 9 Tables and Figures

Table 2 World Bank Productivity Descriptive Statistics

| Productivity Measure/Region | Obs. | Mean | Std. Dev. |
|---|---|---|---|
| **Sales - Capital** | **28,861** | **16.12** | **56.28** |
| Africa | 7,104 | 15.9 | 55.9 |
| East Asia - Pacific | 3,543 | 21.2 | 61.8 |
| Europe and Central Asia | 1,852 | 12.2 | 39 |
| Latin America | 9,871 | 15.1 | 60.4 |
| Middle East and North Africa | 2,336 | 11.9 | 40.5 |
| South Asia | 4,155 | 18.8 | 55.7 |
| **Sales - Labor** | **28,861** | **11.31** | **20.68** |
| Africa | 7,104 | 10.1 | 17.4 |
| East Asia - Pacific | 3,543 | 12.2 | 24 |
| Europe and Central Asia | 1,852 | 10.7 | 22.7 |
| Latin America | 9,871 | 8.8 | 14.3 |
| Middle East and North Africa | 2,336 | 13.9 | 25.3 |
| South Asia | 4,155 | 17.3 | 28.8 |
| **Sales - ln(TFP)** | **28,861** | **2.56** | **1.39** |
| Africa | 7,104 | 2.52 | 1.09 |
| East Asia - Pacific | 3,543 | 2.75 | 1.58 |
| Europe and Central Asia | 1,852 | 2.67 | 1.74 |
| Latin America | 9,871 | 2.52 | 1.33 |
| Middle East and North Africa | 2,336 | 2.67 | 1.43 |
| South Asia | 4,155 | 2.44 | 1.56 |
| **VA - Capital** | **28,861** | **9.46** | **33** |
| Africa | 7,104 | 10 | 35 |
| East Asia - Pacific | 3,543 | 13.3 | 41.8 |
| Europe and Central Asia | 1,852 | 7 | 27.1 |
| Latin America | 9,871 | 8.8 | 30.9 |
| Middle East and North Africa | 2,336 | 7.9 | 30 |
| South Asia | 4,155 | 8.8 | 29.7 |
| **VA - Labor** | **28,861** | **6.37** | **12.18** |
| Africa | 7,104 | 6.4 | 13.3 |
| East Asia - Pacific | 3,543 | 7.1 | 14.3 |
| Europe and Central Asia | 1,852 | 5.8 | 11.5 |
| Latin America | 9,871 | 5.2 | 9.7 |
| Middle East and North Africa | 2,336 | 8.2 | 13.5 |
| South Asia | 4,155 | 7.6 | 12.7 |
| **VA - ln(TFP)** | **28,861** | **2.79** | **1.41** |
| Africa | 7,104 | 2.79 | 1.34 |
| East Asia - Pacific | 3,543 | 2.82 | 1.38 |
| Europe and Central Asia | 1,852 | 2.71 | 1.68 |
| Latin America | 9,871 | 2.77 | 1.43 |
| Middle East and North Africa | 2,336 | 2.98 | 1.45 |
| South Asia | 4,155 | 2.71 | 1.38 |

Table 3 Berkeley Earth Descriptive Statistics (Firm Level)

| **Count of days by region** | **Obs.** | **Mean** | **Std. Dev.** |
|---|---|---|---|
| **Neutral** | **28,660** | **287.9** | **71.2** |
| Africa | 6,944 | 319.4 | 43.4 |
| East Asia - Pacific | 3,543 | 258.9 | 74.3 |
| Europe and Central Asia | 1,852 | 157.6 | 25.4 |
| Latin America | 9,830 | 299.6 | 72.4 |
| Middle East and North Africa | 2,336 | 256.4 | 55.2 |
| South Asia | 4,155 | 307.9 | 38.9 |
| **Large Negative** | **28,660** | **7.29** | **12.7** |
| Africa | 6,944 | 1.7 | 3.5 |
| East Asia - Pacific | 3,543 | 9.5 | 14.3 |
| Europe and Central Asia | 1,852 | 32.3 | 12.6 |
| Latin America | 9,830 | 8.4 | 13.4 |
| Middle East and North Africa | 2,336 | 5.8 | 6.4 |
| South Asia | 4,155 | 1.9 | 5.0 |
| **2C to 4C Lower** | **28,660** | **23.94** | **30.9** |
| Africa | 6,944 | 11.6 | 15.6 |
| East Asia - Pacific | 3,543 | 56.5 | 60.8 |
| Europe and Central Asia | 1,852 | 44.2 | 9.0 |
| Latin America | 9,830 | 18.8 | 21.8 |
| Middle East and North Africa | 2,336 | 23.8 | 12.2 |
| South Asia | 4,155 | 20.0 | 19.3 |
| **2C to 4C Higher** | **28,660** | **35.1** | **28.2** |
| Africa | 6,944 | 28.8 | 24.6 |
| East Asia - Pacific | 3,543 | 31.4 | 26.6 |
| Europe and Central Asia | 1,852 | 71.1 | 11.3 |
| Latin America | 9,830 | 29.7 | 28.5 |
| Middle East and North Africa | 2,336 | 58.2 | 30.2 |
| South Asia | 4,155 | 32.5 | 18.4 |
| **Large Positive** | **28,660** | **11.8** | **20.3** |
| Africa | 6,944 | 4.4 | 7.7 |
| East Asia - Pacific | 3,543 | 9.8 | 20.2 |
| Europe and Central Asia | 1,852 | 60.8 | 24.8 |
| Latin America | 9,830 | 9.5 | 16.4 |
| Middle East and North Africa | 2,336 | 21.8 | 16.1 |
| South Asia | 4,155 | 3.6 | 5.5 |

Table 4 Other Summary Statistics

| **Firm Counts by Latitude** | **Count** | **Proportion** |
|---|---|---|
| North of 60°N Latitude | 242 | 0.01 |
| North of 40°N Latitude | 2,157 | 0.07 |
| North of 20°N Latitude | 7,239 | 0.25 |
| Within 20° Latitude of Equator | 14,828 | 0.51 |
| South of 20°S Latitude | 4,395 | 0.15 |

| **Firm Counts by Country and Firm Size** | **Count** | **Proportion** |
|---|---|---|
| Low Income Country | 17,518 | 0.61 |
| High Income Country | 11,343 | 0.39 |
| Medium Sized Firm | 10,944 | 0.38 |
| Large Sized Firm | 6,147 | 0.21 |

| **Firms by ISIC Code** | **Count** | **Proportion** |
|---|---|---|
| 15 & 16 | 6,128 | 0.21 |
| 17 | 1,953 | 0.07 |
| 18 | 3,815 | 0.13 |
| 19 | 679 | 0.02 |
| 20 | 831 | 0.03 |
| 21 | 401 | 0.01 |
| 22 | 1,030 | 0.04 |
| 23 & 24 | 2,545 | 0.09 |
| 25 | 1,699 | 0.06 |
| 26 | 1,680 | 0.06 |
| 27 | 717 | 0.02 |
| 28 | 2,536 | 0.09 |
| 29 | 1,449 | 0.05 |
| 30, 31, 32, & 33 | 994 | 0.03 |
| 34 & 35 | 551 | 0.02 |
| 36 | 1,853 | 0.06 |

Table 5 Hot & Cold Model: Temperature variation from monthly mean on Value-added Labor productivity

| | SURE 1/3 (Labor Productivity) | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Each day > 4 degrees C below than mean | -0.330*** | -0.116 | -0.121 | -0.059 | -0.02 |
| | (0.082) | (0.084) | (0.083) | (0.089) | (0.095) |
| Per day 2 to 4 degrees C below mean | 0.101*** | -0.008 | -0.012 | 0.034 | 0.091 |
| | (0.031) | (0.051) | (0.050) | (0.053) | (0.055) |
| Per day 2 to 4 degrees C above mean | 0.099** | 0.063 | 0.086** | 0.075* | -0.005 |
| | (0.042) | (0.039) | (0.038) | (0.040) | (0.043) |
| Per day > 4 degrees C above mean | -0.182*** | -0.171*** | -0.173*** | -0.171*** | -0.159** |
| | (0.053) | (0.053) | (0.052) | (0.060) | (0.072) |
| Medium Company (20-100 Employees) | | | 9.752*** | 10.360*** | 10.792*** |
| | | | (1.382) | (1.372) | (1.365) |
| Large Company (over 100 Employees) | | | 17.691*** | 18.423*** | 18.722*** |
| | | | (1.755) | (1.736) | (1.728) |
| Low Income Country | | | 4.835** | 4.193** | 1.081 |
| | | | (2.134) | (2.033) | (2.151) |
| Regional Controls | | | | Yes | Yes |
| Industry & Year FE | | Yes | Yes | Yes | Yes |
| Latitudinal Controls | | | | | Yes |
| Latitudinal by Regional Controls | | | | | Yes |
| Constant | 130.469*** | 101.655*** | 92.027*** | 97.287*** | 102.976*** |
| | (1.857) | (2.739) | (3.185) | (5.456) | (5.633) |

Table 6 Hot & Cold Models: Temperature variation from monthly means on output and value-Added L, K, and TFP productivity

| | Seemingly Unrelated Regressions | | | | | |
|---|---|---|---|---|---|---|
| | Output-Based Productivity (1) | | | Value Added Productivity (2) | | |
| | L | K | TFP | L | K | TFP |
| Each day > 4 degrees C below than mean | -0.061 | -0.513*** | -0.038 | -0.02 | -0.587*** | -0.139 |
| | (0.101) | (0.196) | (0.079) | (0.095) | (0.217) | (0.112) |
| Per day 2 to 4 degrees C below mean | 0.231*** | 0.192 | -0.037 | 0.091 | -0.014 | -0.008 |
| | (0.062) | (0.137) | (0.049) | (0.055) | (0.139) | (0.066) |
| Per day 2 to 4 degrees C above mean | -0.129*** | -0.038 | 0.067** | -0.005 | 0.066 | 0.035 |
| | (0.045) | (0.077) | (0.030) | (0.043) | (0.168) | (0.047) |
| Per day > 4 degrees C above mean | -0.105 | 0.013 | -0.058 | -0.159** | 0.09 | -0.118 |
| | (0.076) | (0.134) | (0.062) | (0.072) | (0.079) | (0.088) |
| Constant | 149.02*** | 187.80*** | 286.12*** | 102.98*** | 145.19*** | 321.18*** |
| | (5.635) | (9.418) | (3.556) | (5.633) | (10.030) | (5.277) |
| Observations | 40280 | 40280 | 40280 | 36049 | 36049 | 36049 |

Note: Standard errors are clustered by survey strata and are in parentheses * $p<0.10$; ** $p<0.05$; *** $p<0.01$. Key dependent variables represent the count of days in the previous financial year above or below the mean average temperature for that region/city for that month compared to the count of days that were within 2°C of the mean for that month. Productivity is expressed as output/sales and value-add per cost of labor, capital, and TFP respectively. Only the full empirical models are shown. Full results with controls are available in the online appendix. All values are in 2009 USD terms.

Table 7 Extreme Weather Model: Temperature variation from the monthly mean on output and value-added L, K, and TFP productivity

| | Seemingly Unrelated Regressions | | | | | |
|---|---|---|---|---|---|---|
| | Output-Based Productivity (1) | | | Value-Added Productivity (2) | | |
| | L | K | TFP | L | K | TFP |
| Each day with > 4 degrees C below and > 4 degrees C above mean | -0.087** | -0.190** | -0.05 | -0.105** | -0.233** | -0.126** |
| | (0.044) | (0.089) | (0.038) | (0.043) | (0.102) | (0.052) |
| Medium Company (20-100 Employees) | 15.688*** | 12.004*** | 8.873*** | 10.818*** | 5.391** | 16.917*** |
| | (1.399) | (2.413) | (1.031) | (1.365) | (2.470) | (1.506) |
| Large Company (over 100 Employees) | 29.027*** | 25.883*** | 11.602*** | 18.731*** | 16.082*** | 26.145*** |
| | (1.748) | (3.123) | (1.282) | (1.728) | (3.289) | (2.029) |
| Low Income Country | 4.596** | -27.037*** | -29.353*** | 0.964 | -28.660*** | -36.921*** |
| | (2.089) | (3.864) | (1.710) | (2.148) | (4.048) | (2.382) |
| Constant | 149.010*** | 187.700*** | 286.126*** | 102.978*** | 145.082*** | 321.180*** |
| | (5.626) | (9.425) | (3.556) | (5.630) | (10.033) | (5.279) |
| Observations | 40280 | 40280 | 40280 | 36049 | 36049 | 36049 |

Table 8 Daily Max. Models: Extreme daily temperatures on output and value-added L, K, and TFP Productivity

| | Seemingly Unrelated Regressions | | | | | |
|---|---|---|---|---|---|---|
| | Output-Based Productivity (1) | | | Value-Added Productivity (2) | | |
| | L | K | TFP | L | K | TFP |
| Per day of max temp > 4° C above mean | -0.142** | -0.184 | -0.054 | -0.129** | -0.185 | -0.178** |
| | -0.068 | -0.113 | -0.051 | -0.065 | -0.121 | -0.073 |
| Per day with max temp 2 to 4° C above mean | -0.118*** | 0.176*** | 0.053** | -0.001 | 0.310*** | 0.070* |
| | -0.034 | -0.067 | -0.024 | -0.033 | -0.068 | -0.037 |
| Medium Company (20-100 Employees) | 15.671*** | 12.255*** | 8.818*** | 10.751*** | 5.625** | 16.889*** |
| | -1.388 | -2.406 | -1.029 | -1.357 | -2.45 | -1.499 |
| Large Company (over 100 Employees) | 29.038*** | 26.001*** | 11.505*** | 18.665*** | 16.096*** | 26.046*** |
| | -1.744 | -3.133 | -1.28 | -1.722 | -3.282 | -2.017 |
| Constant | 150.391*** | 183.303*** | 287.446*** | 103.670*** | 139.973*** | 321.803*** |
| | -5.448 | -9.062 | -3.65 | -5.459 | -9.443 | -5.283 |
| Observations | 40280 | 40280 | 40280 | 36049 | 36049 | 35741 |

Note: Standard errors are clustered by survey strata and are in parentheses * $p<0.10$; ** $p<0.05$; *** $p<0.01$. Key dependent variables represent the count of days in the previous financial year above or below the mean daily maximum temperature for that region/city for that month compared to the count of days that were within 2° of the mean of the daily maximum for that month. Productivity is expressed as output/sales and value-add per cost of labor, capital, and TFP respectively. Only the full empirical models are shown. Base company is a small company of less than 20 employees. Regions and income levels are defined by the World Bank. Full results with controls are available in the online appendix. All values are in 2009 USD terms.

Table 9 Average Climate Effects on Productivity

| | Period 2012-2017 compared to 2005-2010 | | | Estimated Climate Effect on VA Productivity | | |
|---|---|---|---|---|---|---|
| | Avg. Increase in Temp. | Average increase in days of extreme weather | @2°C | OLS | In Percent | Per $ Invested/Spent |
| | | Model of each day averaging > 4°C above long-term monthly trends | | | | |
| | 0.15°C | 3.97 Days | 52.99 Days | | | |
| Est. Effect on Labor | | | | -.159*** | -8.43% | 54 cents |
| Est. Effect on TFP | | | | -0.118 | -6.25% | |
| | | Model of each day averaging > 4°C above or below long-term trends | | | | |
| | | 2.17 days | 28.97 Days | | | |
| Est. Effect on Labor | | | | -0.105** | -3.04% | 19 cents |
| Est. Effect on Capital | | | | -.233** | -6.75% | 63.84 cents |
| Est. Effect on TFP | | | | -0.126** | -3.65% | |

Note: Due to rounding in the table, numbers will not reconcile directly. Average increase in temperature is calculated using the mean annual global temperature anomaly for 2005-2010 of 0.966°C per year compared to 1.116°C per year in 2012-2017. All Values are in 2009 USD terms. All estimates of the effect of climate on VA productivity are done at the mean value for each measure of productivity.