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## The economic impacts of temperature on industrial productivity: Evidence from Indian manufacturing

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# **Working Paper 278**

## **The Economic Impacts of Temperature on Industrial Productivity: Evidence from Indian Manufacturing**

**Anant Sudarshan**

**Meenu Tewari**

**July 2014**



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## Abstract

We provide empirical evidence indicating that changes in surface temperatures may directly impact manufacturing output through their impact on worker productivity. We utilize a multi-year panel of manufacturing plants in India, as well as daily worker productivity measures from selected case-study units to show that (i) manufacturing output decreases at high temperatures by 1-3 percent per degree celsius; (ii) this reduction appears to be driven by declining worker productivity. Our results suggest that climate-economy models may underestimate the costs of climate change by neglecting to account for reduced worker productivity. The causal channel we identify could explain a portion of the strong negative correlation observed between temperature and GDP.

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July 1, 2014

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# 1 Introduction

Nations across the world are attempting to determine an appropriate set of policy actions to address climate change concerns. In order to do so, it is critical to understand both the costs of a climate related policy intervention and the associated benefits. For this reason, quantifying the link between environmental factors and economic performance is a central part of the research agenda within modern environmental economics. In particular, climate change policy cannot be sensibly framed at the national level without reasonable estimates of economic and human vulnerability and an understanding of the degree to which projected changes in local climate might influence the competitiveness and productivity of different sectors of the economy. Unfortunately, while the costs of taking action are immediately salient in policy debate, incomplete evidence exists on benefits because of the difficulty in fully quantifying avoided damages.

These considerations become all the more important when viewed in the light of recent evidence from empirical studies using country level panel data that have identified a negative, and plausibly causal, relationship between surface temperatures and developing country GDP (Dell et al., 2012; Hsiang, 2010). From this observation follows the question of exactly why this link exists?

For the most part, environmental economists and scientists have largely focused on two mechanisms through which even moderate climate change might affect human welfare. The first channel is through an increased potential for extreme climate events (droughts, hurricanes, heat waves) resulting in large one-time economic losses (Mendelsohn and Dinar, 1999) and as recent evidence suggests, occasionally longer lasting spillover impacts (Antilla-Hughes and Hsiang, 2013). This explanation is unlikely to explain why gradual and small temperature shocks seem to influence national output.

A second channel is through the direct effect of climate on human health (Barreca et al., 2013). The third is through the impact of climate change on agriculture (Auffhammer et al., 2006; Schlenker and Roberts, 2009). While

crop productivity is certainly influenced by temperature and rainfall variation, agricultural output alone seems insufficient to explain the observed link between temperature and GDP. This link appears to remain present both in countries with an economically unimportant agriculture sector and in output from non-agricultural sectors (Dell et al., 2012).

Other causal channels have therefore been suggested, including temperature impacts on mortality, conflict and worker productivity. For example, Hsiang (2010) examines economic output for a set of countries in the Caribbean and Central America and finds that output from the services sector decreases in high temperature years. Although it remains challenging to isolate specific mechanisms using aggregate data<sup>1</sup>, the author shows that one mechanism consistent with this observation is the direct impact of temperature on worker productivity, as predicted by physiological studies of heat stress in human beings.

In this paper we investigate this hypothesis further. In doing so, we provide a partial answer to the question of why increases in surface temperatures appear to reduce economic output in non-agricultural sectors. We provide empirical evidence that suggests that this mechanism may be an important contributor to the relationship between surface temperatures and developing country economic output. Although our evidence is far from conclusive, nevertheless it presents a starting point for thinking more seriously about this mechanism.

Specifically, we put together a multi-year, nationwide panel dataset of manufacturing plants (factories) in India and directly estimate the impacts of annual temperature shocks on annual factory output. We show that these impacts are economically significant (an output decline of about one to three percent per degree Celsius), and have a magnitude and non-linear relationship to temperature that is consistent with physiological studies of heat stress when exposed to high wet bulb globe temperatures. We also find that temperature

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<sup>1</sup>For instance, because the setting for this study is a region of the world heavily dependent on tourism, it is possible that demand shifts coincident with temperature shocks might explain the economic effects found here.

impacts on plant output seem most acute in sectors where the value added per worker is high and where electricity intensity (used as a proxy for the likelihood of climate control) is low.

We then augment this nationwide panel with independently collected, daily production data from a set of case-study manufacturing sites. This dataset allows us to directly observe high frequency, worker level performance outcomes. In these independent datasets we show that temperature shocks are similarly associated with decreased worker output, with output reductions primarily occurring when temperatures (more accurately, wet bulb globe temperatures) are high.

It is worth remarking that the Intergovernmental Panel on Climate Change, in its most recent Fourth Assessment Report (Working Group II) on Impacts, Adaptation and Vulnerability, states that “*Climate-change vulnerabilities of industry, settlement and society are mainly related to extreme weather events rather than to gradual climate change (very high confidence).*” Arguably this confidence in the relative immunity of non-agricultural sectors to gradual environmental change is too optimistic. The evidence in this paper, while leaving much room for further research, suggests that in some manufacturing settings, especially labor intensive manufacture in developing countries, gradual climate change may have direct negative impacts that are economically significant, because of the impact of temperature on labor.

The remainder of this paper is organized as follows. In Section 2 we briefly summarize the underlying evidence from heat stress studies on human productivity and provide a simple framework for thinking about how these physiological effects might impact economic output in a manufacturing plant. Next, in Section 3 we describe the sources of our data on manufacturing plant output and weather (temperature and precipitation). In Section 4 we present evidence of temperature impacts on manufacturing using national level plant output data and annual variation in temperature. In Section 5, we present evidence relating daily temperature to daily worker productivity from a set of case study sites. We also briefly discuss qualitative evidence on local adaptive strategies from one of our case study sites in Section 6. In Section 7 we utilize



predicted changes in temperature distributions for India from two different climate models to estimate the upper-bound of economic costs that might occur owing to this mechanism (absent any adaptation). These estimates cannot be treated as predictive of actual costs net of adaptation, but they help contextualize the importance of the temperature-productivity link. We conclude in Section 8.

## 2 Theory and Mechanisms

The physics of how temperature affects human beings is well known. The physical exchange of heat between the human body and surrounding air is fundamentally related to health because in order to maintain normal body temperatures, the human body must dissipate the heat it generates internally to the ambient (Parsons, 1993). When energy is expended while working, internal heat generation increases and correspondingly greater rates of heat loss become necessary. If this balance cannot be maintained for a given activity level, it becomes necessary to reduce the rate at which energy is consumed or to suffer the adverse consequences of over-heating including heat strokes (Kjellstrom et al., 2009; ISO, 1989).

The primary mechanism the body uses to dissipate heat is through the evaporation of sweat. The efficiency of such dissipation depends primarily on ambient temperatures but also on humidity and wind speed (the movement of air over the skin). At elevated temperatures or high humidity, heat stress might begin to reduce productivity. These ambient parameters can be encapsulated in various ways to form indices capturing the threat of heat stress (Parsons, 1993), and perhaps the most commonly accepted index is the Wet Bulb Globe Temperature (ISO, 1989).

Ignoring the local wind-speed (which indoors is largely determined by access to fans) the Wet Bulb Globe Temperature (WBGT) is determined largely by two ambient factors, temperature and humidity. WBGT can be approximated from temperature and relative humidity using a formula reported in Lemke and Kjellstrom (2012), who discuss and compare several ways of arriv-

WBGT (°C)	<26	26	27	28	29	30	31	32	33	34	35	36	37	38
300W, % loss	0	0	0	3	9	17	25	35	45	55	64	74	81	85
400W, % loss	0	0	9	17	25	35	45	55	64	74	81	85	88	90

Table 1: Human productivity loss at high temperature. Source: Kjellstrom et al. (2013)

ing at this measure using different types of meteorological data. This equation serves well as an estimate of WBGT indoors (outdoor levels may be different on accounting for solar radiation).

$$WBGT_{id} = 0.567T_a + 0.216\rho + 3.38 \quad (1)$$

where  $WBGT_{id}$  is measured in °C,  $T_a$  is the air temperature and  $\rho$  is the water vapour pressure and can be calculated from the relative humidity using the physical relationship below.

$$\rho = (RH/100) \times 6.105 \exp\left(\frac{17.27T_a}{237.7 + T_a}\right) \quad (2)$$

The literature on heat stress also suggests that the response of human beings to temperature (or more precisely, WBGT) is not uniformly linear. Intuitively we might expect that at very cold temperatures, productivity (or at least comfort) might increase in temperature and at moderate levels, temperature variations might have no impact. At higher levels however, heat stress should become progressively more severe. While the precise shape of the dose response relationship is not well known or even necessarily deterministic, empirical evidence (as well as theory) is consistent with this pattern. Figure 1 reproduces a graph from Hsiang (2010) based on a meta-analysis of over 150 ergonomic studies. Table 1 provides results at higher temperatures from Kjellstrom et al. (2013). Temperature effects on human performance have also been reported in commercial office settings (Tanabe et al., 2007).

One final point relates to the time-scales at which temperature may affect human beings. Unlike other environmental stressors (such as certain air

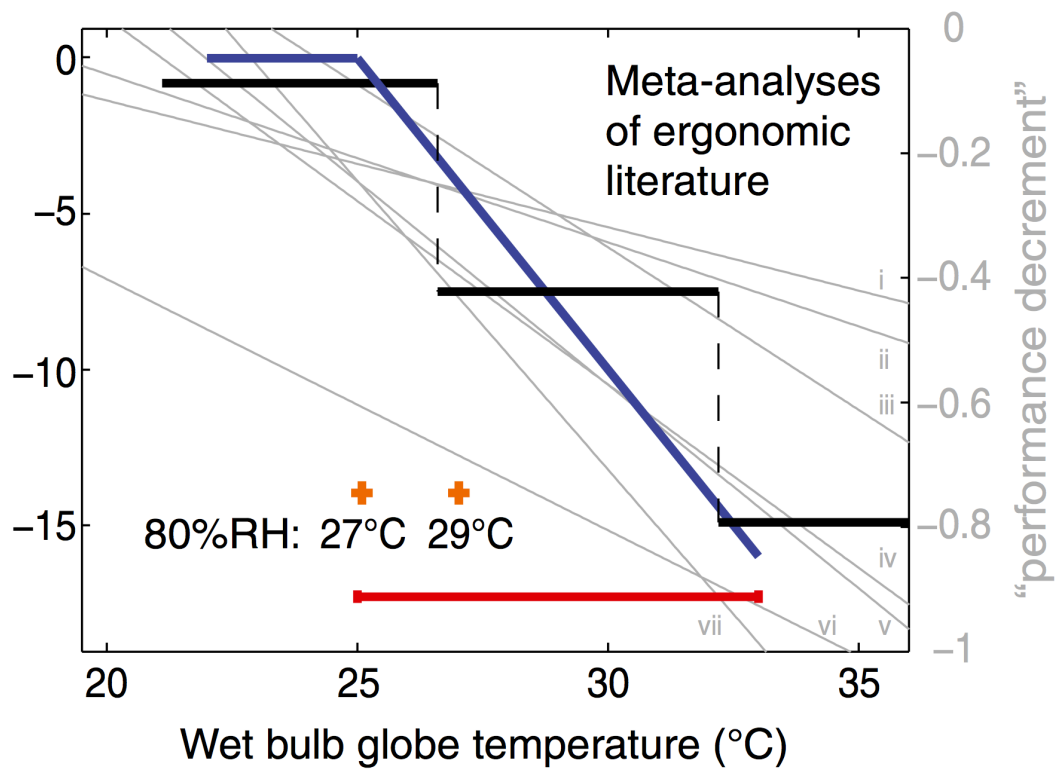


Figure 1: Reduction in productivity measured in ergonomic studies with increasing wet bulb globe temperature. Productivity declines are marked after 25 degrees Celsius. Figure reproduced from Hsiang (2010)

pollutants for example), the effects of exposures to high temperatures can be expected to be visible on short time scales. At the same time these impacts are unlikely to disappear when temperature changes are sustained (absent adaptive actions taken to reduce exposures). Thus it is plausible that sustained temperature differences between populations might lead to sustained differences in the productivity of labor and also that these differences should be detectable using both short run and more sustained temperature shocks.

## 2.1 Worker Performance and Economic Output

The physiology of how which temperature and humidity affects human beings is well known but it is not obvious how significant this might be as a factor influencing productive economic output.

There are several reasons for this. First, daily workplace activity does not normally require exertion nearing physical limits. This is particularly so in formal, skilled work in the manufacturing and service sectors, as distinct from purely manual and unskilled labour that might play a significant part in the construction or mining sectors.<sup>2</sup> Secondly, most labour in manufacturing (or services) can be expected to take place indoors or in shielded conditions. These work conditions provide some protection from ambient temperatures even absent air conditioning. Lastly, the *economic* impact of reductions in worker productivity may be very different from the physiological impact. The marginal costs of a reduction in the physical or cognitive effectiveness of workers engaged in high value added activities may be very high. Conversely the marginal cost of decreased effectiveness may be minimal or zero in the case of low value added tasks.

As an example, manufacturing units in the diamond sector typically employ some workers to undertake a sorting activity which involves separating raw mined stones into quality grades. Even a small reduction in the ability of workers to carry out this sorting process without errors may result in extremely

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<sup>2</sup>The mining sector, where temperature and humidity exposures can be high enough to create occupational health hazards, has long been an important setting for research on heat stress (Wyndham, 1969)

large economic losses to the firm, since errors will increase the fraction of high quality stones that are discarded. On the other hand, for a worker involved in a low value added activity (such as loading coal into a boiler or overseeing non-critical processes), slightly reduced performance in high temperature conditions need not translate to significant economic costs.

These distinctions can be easily understood in the context of a simple production function model. Consider a plant with output following a simple Cobb-Douglas production equation as below, where  $Y$  is total output,  $L, E, K$  represent labour, energy and capital inputs and  $A$  is the total factor productivity.  $L$  in turn is written as a function of input labour  $L_o$  and  $T_i$ , the indoor or workplace temperature (or wet bulb globe temperature). Further let  $T_i = \mathbf{a} + \mathbf{b}T_a$  denote the dependence of workplace temperature on the ambient  $T_a$ . Adaptive technologies such as air conditioning for instance, might drive  $\mathbf{b}$  towards zero, breaking the link between  $T_i$  and  $T_a$ . Then,

$$Y = AL(T, L_o)^\alpha E^\beta K^\gamma \quad (3)$$

Let

$$L(T, L_o) = \begin{cases} L_o & \text{if } T_i \text{ is less than } T_c \\ L_o e^{-\theta T_i} & \text{if } T_i \text{ is greater than } T_c \end{cases}$$

Differentiating  $Z = \log(Y)$  with respect to  $T_a$  then leaves us with

$$\frac{dZ}{dT_a} = \begin{cases} 0 & \text{if } \mathbf{a} + \mathbf{b}T_a \text{ is less than } T_c \\ -\alpha\theta\mathbf{b} & \text{if } \mathbf{a} + \mathbf{b}T_a \text{ is greater than } T_c \end{cases}$$

In other words, temperature shocks may not affect productivity when temperatures are moderate. At higher temperatures ( $T_a > (T_c - a)/b$ ),  $Z$  declines with temperature. This decline is higher when  $\alpha$  is large, which might represent a firm where the value added by labour is high. It is also larger when  $\mathbf{b}$  is large, i.e when the relationship between the ambient temperature  $T_a$  and workplace temperature  $T_i$  is strong.

Taken together this suggests three features we might expect to see in the

response of manufacturing plant output to temperature.

**Test 1** If manufacturing output responds negatively to temperature due to its effects on worker productivity then this response should occur primarily at higher temperatures (above approximately  $25^{\circ}C$ ).

**Test 2** Temperature impacts should be greatest in sectors where value added by labour is high.

**Test 3** Temperature impacts should be greatest in sectors where air conditioning is likely to be limited.

These tests also help distinguish between different mechanisms through which temperature might influence manufacturing output. For instance, one might hypothesize that temperature could be correlated with industrial output due to some form of spillover from shocks to the agricultural sector.<sup>3</sup> However spillovers from agriculture might suggest temperature response patterns that would not necessarily match those described in Tests 1-3. Agricultural growing seasons in India take place during a time of the year where temperatures are relatively moderate and one of the two primary growing seasons is in the winter. Thus if non-agricultural sectors respond to temperature shocks primarily through agriculture related economic spillovers then these impacts should be highest when temperature shocks occur at the cooler temperatures found in the growing season. Similarly worker environment in the plant would not necessarily influence output shocks if such spillovers were at work.

With this background, we follow a two part empirical strategy to determine whether temperature matters for manufacturing productivity. First we examine aggregate data at the annual level from a nationwide survey of manufacturing plants in India. Next we dig down to examine worker level output directly, collecting detailed micro-data from a set of case study sites located in different regions of India and in different industrial sectors. Our objective will be to verify whether the predictions of the simple model we have outlined in this section are indeed reflected in these different and independent datasets.

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<sup>3</sup>Burgess et al. (2011) suggest that some of the observed health impacts of temperature may partially owe to agricultural productivity shocks

## 3 Data Sources

We use three primary sources of data for our empirical work. The first is a nationally representative, annual panel data set of individual manufacturing plants in India. The second is a dataset of daily worker output collected from a set of weaving units in Surat. The third is meteorological data, including surface temperature and rainfall. In what follows, we describe these in a little more detail.

### 3.1 Annual Manufacturing Plant Survey Data

Our data on plant level output comes from India's Annual Survey of Industry. The ASI is a detailed survey of individual manufacturing plants carried out on an annual basis in every state within India. The survey is carried out every year by the Ministry of Statistics and Program Implementation (MoSPI), Government of India through its network of Zonal/ Regional/ Sub- Regional offices. The population eligible to be surveyed consists of all industrial plants registered under India's Factories Act. Registration normally implies that a plant has at least 10 employees in total (although this is not the only condition). Each annual cross-section includes every unit from the population of registered firms who employ over 100 workers (not including short term contract labour) as well as a random sub-sample covering 18 percent of units smaller than this cut-off.

The survey is intended to capture critical variables relating to factory level production inputs and outputs (in both physical and monetary units and including energy inputs), annual income and expenditures under various heads, labour utilization, wages and annual man-days worked. Of primary importance to us is that the survey provides a measure of the total value of output produced at the end of the financial year for every plant. This is calculated by multiplying the market price of all products manufactured with the production quantity and is a quantity reported on financial returns as well. It is this quantity that we use as our primary measure of economic output.

We focus on survey years between 1998-99 and 2008-09. Between these

years, survey micro-data may be purchased with a panel identifier so that it is possible to identify repeated observations on plants across years. The panel dataset as made available by MoSPI does not provide the geographical location of a factory. However an alternative version of the same data is made available with the district in which a plant is located, but without a panel identifier for each plant. We match observations across both data views to generate our final dataset which contains both a plant identifier and a district identifier for each observation. The panel is unbalanced since only large firms with over 100 employees are surveyed every year, with smaller firms appearing in multiple years only if they are surveyed. Entry and exit further reduce the number of observations per unit. We restrict attention only to plants in the manufacturing sector (the ASI has a small number of survey observations from mining, hospitality and utility sector units).

Before we use the panel thus obtained, we also carry out a few data-cleaning operations. We trim the top 2.5 percent and bottom 2.5 percent of the distribution of observations by output value and workforce size. This is done to transparently eliminate outliers (units with implausibly large output values or zero and negative output) that may be associated with data entry errors, missing values or otherwise represent special cases. We also remove a small number of manufacturing units who report having less than 10 workers employed because this represents a discrepancy between the criterion used to select the survey sample and reported data. Such discrepancies may be associated with false reporting since firms with less than 10 workers are subject to very different labor laws and taxation regimes under Indian law. Finally we drop units that appear only twice or less in our panel.

All remaining observations form part of our dataset. Overall we are left with about 22,000 manufacturing units that are observed at least three times over the nine years of our panel. We redefine the panel identifier from the ASI to restrict attention only to those units whose top level sector of operation (2 digit NIC code, e.g ‘textiles’) does not change over the panel duration. In cases where manufacturing units switch sectors at the 2 digit NIC level we define a new panel identifier (in effect estimating a new set of fixed effects for



the unit before and after the change in sector). This is done to ensure that year to year output comparisons are carried out only for factories that have not significantly changed manufacturing activities.<sup>4</sup>

The ASI does have some drawbacks that limit the inferences we are able to draw from it. First, a time series measure of individual firm output is available only over a limited period of time (1998-2008). Because our estimation strategy relies only on within firm variation in output coincident with variation in temperatures across years, a short time series limits the temperature variation that is empirically observed and therefore reduces our ability to identify impacts as precisely as a longer panel dataset might enable.

Secondly, the survey is not a good representation of small manufacturing units in India. Many firms that are not registered under the Factories Act because full time, contractual employees fall below the registration cut-off, are excluded from the survey. This informal and small scale manufacturing sector nonetheless plays an important role in Indian manufacturing and with limited means to adapt is plausibly more vulnerable to climate shocks of all kinds. To the extent that we cannot observe this population our results may under-estimate the vulnerability of the manufacturing sector in India to temperature. At the same time, focusing on registered firms may provide results that are more generalizable and represent climate sensitivity for firms that have a certain minimal size and capital investment and therefore presumably, a certain minimal level of adaptive capacity. While developing countries tend to have a large informal and small scale manufacturing sector, there are important economic and technological advantages to operating at a larger scale and therefore over time one might expect manufacturing to agglomerate and the left tail of small units to shrink. For instance, there is evidence that this process has been occurring in China (Liu and Li, 2012; Wen, 2004).

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<sup>4</sup>This is only a crude correction since a plant may change product mix while retaining the same 2-digit NIC classification.

## 3.2 Worker Daily Output Data

The national level panel described in the previous section provides a wide breadth of sector and regional coverage of units. A disadvantage though is that all measures of economic output are observed only annually and for the manufacturing unit as a whole. As a consequence it is impossible to directly observe worker level output, fundamentally the quantity that we are interested in.

We therefore complement the ASI by collecting daily worker level output data from a set of three weaving units in Surat. Our data spans one financial year (2012-2013) and tracks about 151 workers.

Our choice of the textile sector (more precisely, weaving) is motivated by a number of factors that make it well suited for our purposes. First, the textile sector as a whole (NIC code 1713) and the weaving sector in particular are economically important in India. The textile sector is estimated to make up about 14 percent of India's total industrial production (and about 3 percent of GDP) and to contribute to about 27 percent of foreign exchange from exports.

Secondly the sector is highly labour intensive. The textile sector accounts for about 21 percent of total industry employment in India of which a significant share can be attributed to weaving units. The 2011 Ministry of Textiles Annual Report estimates that the power-loom sector employs 5.7 million people. The workforce in mechanized weaving units is largely engaged in semi-skilled or skilled but relatively low value added activity.<sup>5</sup>

Thirdly workers in small weaving units are largely temporary and paid on a piece rate basis linked directly to their output. This makes it possible to collect high frequency output measures at the worker level which are often not available in settings where fixed monthly or longer term payments and contracts are used. In the weaving units of Surat, employment is not contracted on a monthly basis. Instead workers are paid for the days when they show up to work. Payments are made on the basis of a simple measure of worker level physical output, namely metres of cloth produced, multiplied by a per

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<sup>5</sup>Weaving units precede both dyeing and printing firms, and apparel manufacture shops (including embroidery) in the textile industry supply chain

meter payment (about INR 2.00 per metre in Surat)<sup>6</sup>. In the firms we study, this output is also essentially the final output for the plant and is then sold in the wholesale markets or to dying and printing firms. Thus the worker output directly corresponds to plant revenue.

Fourth, the work involved is not physically strenuous. A weaving worker is primarily responsible for operating mechanized looms (each loom can be regarded as a work station). A worker must walk up and down between work stations<sup>7</sup>, occasionally adjusting alignment, restarting feeds when interrupted and making occasional corrections as needed. The fact that this work is physically low intensity is important because this is very different from settings where heat stress is known to be a significant health (as opposed to productivity) concern (mining for instance, see Wyndham (1969)). Finding temperature impacts on worker output in this setting is therefore more likely to imply that this may be an important mechanism affecting productivity across a range of industries.

Lastly, because weaving workers are mobile and can choose whether to show up to work on any given day we can examine the impacts of temperature shocks on attendance as distinct from productivity on the job (both of which may affect final output). There exists some limited evidence on this second channel from the United States, based on empirical work using the American Time Use Surveys (Zivin and Neidell, 2010).

### 3.2.1 Meteorological Data

Meteorological data used in this paper comes from two sources. Our first objective is to match plant output from the Annual Survey of Industries to local temperature (or wet bulb globe temperature). The Annual Survey of Industries enables us to locate every surveyed unit down to the level of a district in the country. Districts in India are an administrative subdivision of a state and

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<sup>6</sup>Indian minimum wage laws are both low and not legally binding on small firms. We can therefore ignore complications introduced by payment non-linearities at a minimum wage lower bound as in Zivin and Neidell (2012).

<sup>7</sup>A single worker typically works on about 6-12 looms

for most purposes are the most granular unit at which administrative and economic data is reported. There are 609 districts in the country, with an average size of the order of 4000 square kilometers. We therefore match observations in the ASI data with temperature and precipitation observations aggregated to the district level. To do this we use a 1.0 degree gridded data product released by the Indian Meteorological Department (IMD) which provides daily temperature and rainfall measures interpolated from the IMD’s monitoring stations across the country. This dataset represents the highest quality temperature record we are aware of for India.

A key strength of this dataset is that it is based on data from quality controlled ground level monitors and not sub-sampled measures from regional climate models or reanalysis data (see Auffhammer et al. (2013) for a discussion of some of the concerns that arise when using temporal variation generated from climate models). This gridded temperature and rainfall data is then mapped to a district measure by locating the district centroid and then assigning to each district the weighted average of temperature and rainfall measures from all grid points within a 200km radius of the centroid. Weights are taken inversely proportional to the square of the (great-circle) distance between grid points and the district centroid. Our original temperature and precipitation records are reported daily over the entire nine year period of interest, but we aggregate these up to annual measures as needed (since factory output is reported annually). The availability of daily data is critical however in order to accurately generate degree day measures for each year and each district (we discuss this in more detail in Section 4).

One last point is worth noting. As discussed in Section 2, the environmental quantity of most direct relevance to heat stress on workers is not simply temperature but rather the wet bulb globe temperature, an index that also accounts for ambient humidity. Unfortunately creating a nationwide WBGT measure using Equation 1 is difficult because reliable time series data on relative humidity across India is not easily available. To be specific, although water vapour pressure or humidity measures are available as part of reanalysis datasets, these models were not necessarily designed to provide reasonable

estimates of temporal variation in humidity and related parameters.<sup>8</sup> In addition little is known about how relative humidity might change over time due to the effects of climate change.

For this reason in Section 4 we use dynamic variation in temperature to estimate the effect of heat on industrial output in our nationwide analysis. However, as a robustness check we also repeat our analysis using a wet bulb globe measure obtained by combining temperature with *long run average* measures of daily relative humidity between 1981-2010 from the NCEP/ NCAR reanalysis datasets<sup>9</sup>. Dynamic variation in this index is therefore still driven only by variation in temperatures over grid points in our dataset.

The second data source for local temperature comes from weather station readings. We use this data to construct ambient temperature, relative humidity and rainfall measures for our various case study sites, each of which is matched to a quality controlled weather station located in the same city<sup>10</sup>.

## 4 Temperature and Manufacturing Output

We begin by investigating whether the apparently causal relationship between temperature and national GDP (or sectoral output) observed in previous work (Dell et al., 2012) can be identified when studying the output of individual manufacturing plants. By focusing on micro-data from manufacturing plants (rather than aggregate national accounts), we are able to more directly investigate whether worker productivity is indeed the channel causing some of these temperature associations observed in national output data.

To identify the impact of temperature on manufacturing plant output we exploit presumably quasi-random variation in year to year district average

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<sup>8</sup>Auffhammer et al. (2013) discuss some of the considerations involved in using intra-annual temperature variation from reanalysis data. Because relative humidity is not a primary parameter against which these models are calibrated, these concerns are likely to be significantly more serious when using humidity output from climate models

<sup>9</sup>The NCEP/NCAR outputs are unfortunately available only over a relatively coarse 2.5 by 2.5 degree grid which we interpolate using a procedure similar to that followed for temperature

<sup>10</sup>We use weather station CWOP ID: 42840 for the Surat weaving units

temperatures and estimate the response of the industrial units to this variation, relative to their own average production level and controlling for capital inputs available at the start of the financial year. In doing so we identify the impacts of temperature on output through a comparison of year to year variation in a single plant’s output with year to year variation in temperature. This ensures that we can isolate the effect of temperature, independent of other variables that might be associated with cross-sectional temperature differences between units but might independently affect output (such as altitude for example). We are also able to control for price shocks or other macro-economic variables that might influence the sector as a whole through the use of time fixed effects.

Formally we estimate the following regression equation,

$$V_{i,t} = \alpha_i + \gamma_t + \omega K_{i,t} + \phi W_{i,t} + \beta T_{i,t} + R_{i,t} + \epsilon_{i,t} \quad (4)$$

where  $V_{i,t}$  is the recorded value of output produced by a specific industrial unit  $i$  during financial year  $t$ . This quantity is essentially the product of physical output with average prices per unit product produced (aggregated over all outputs).  $\alpha_i$  is a fixed effect representing average level of output for each manufacturing unit.  $\gamma_t$  are time fixed effects capturing national changes in manufacturing output year to year.  $T_{i,t}$  is our primary variable of interest, namely the average temperature during the financial year  $t$  (so that a year is calculated from April 1 through March 31).  $R_{i,t}$  is a control for rainfall.

$K_{i,t}$  is a control variable that measures the total working capital available to the plant at the start of the financial year (a measure that includes cash generated from the previous years output less expenditures). Capital on hand at the start of the financial year is converted by the plant into labour wages, raw material purchases or energy inputs and these in turn are transformed via the factory production function into outputs. Thus being able to explicitly control for capital stocks at the start of the year enables us to cleanly identify the impact of temperature realizations during the year on output produced in the year, controlling for a fundamental measure of inputs available at the start of the year. Working capital at the start of the financial year is also plau-

sibly exogenous to temperatures experienced during the year and to realized labor productivity. This would not be true of labor, energy or raw material expenditures actually realized during the year. For instance, in our case study of weaving workers in Surat we note that workers appear to produce smaller amounts of woven cloth on high temperature days. These productivity declines can be expected to translate to lower labor expenditures (since wages are linked to output) and to lower raw material use (since finished cloth is mechanically correlated with raw cloth inputs).

Equation 4 is estimated and the results reported in Table 2 column 2. Other specifications are presented as a robustness check. We estimate models with and without controls for capital at the start of the year as well. We also include the total number of workers  $W_{it}$  on the right hand side to check that our results are not driven by a fall in labor employed. We regress both the absolute output as well as logged output (significantly less affected by outliers). We also estimate a model using the log of output per worker as a dependent variable (one disadvantage of this is that the ASI data is quite noisy since employment numbers are often incorrectly reported by industry and do not include contract labour).

Across all models the coefficient on temperature remains negative and significant. In the most conservative specification, with logged output and both capital and worker controls we obtain a point estimate suggesting a 2.8 percent decrease in output for a one degree change in average annual temperature (aggregated over all days in the year). It is interesting to note that this estimate is close to the reported percent change in economy wide output for a one degree change in temperature in Hsiang (2010) (2.4 percent) as well as the percentage decline in labour supply reported by Zivin and Neidell (2010) (1.8 percent).

## 4.1 Non-linearities in Temperature Response

The results in Table 2 suggest that temperature might matter for manufacturing productivity. However if the effect being identified here involves the

Table 2: Effect of Temperature on Manufacturing Industry Output

	<i>Dependent variable:</i>					
	Plant Output Value	Log Plant Output Value	Log (Output/Worker)	Plant Output Value	Log Plant Output Value	Log (Output/Worker)
	(1)	(2)	(3)	(4)	(5)	(6)
mean temp	-.043*** (0.013)	-0.042*** (0.012)	-0.036*** (0.012)	-0.032*** (0.010)	-0.028*** (0.010)	-0.022*** (0.012)
rainfall	0.013*** (0.003)	0.009*** (0.003)	0.006*** (0.003)	0.003 (0.002)	0.001 (0.002)	0.00 (0.002)
capital		0.386*** (0.010)	0.346*** (0.009)	0.384*** (0.003)	0.339*** (0.006)	0.197*** (0.006)
Plant FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Capital Controls	N	Y	Y	Y	Y	Y
Worker Controls	N	N	Y	N	Y	N
Units	22,149	22,149	22,149	22,149	22,149	22,149
R <sup>2</sup>	0.0076	0.4615	0.4876	0.6705	0.6595	0.2930

*Note:*

1. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

2. Cluster robust standard errors (Arellano-Bond) correcting for serial correlation and heteroskedasticity

3. Maximum temperature is on average 6°C above the mean temperature

4. Coefficients for models 1-3 are expressed as percentages of average output level.



response of workers to heat, then we should expect to see a non-linear response of output to temperature (see Figure 1 and 1 both of which suggest that temperature effects might become most important above 25 degrees Celsius).

To see whether this seems to be the case in our data (Test 1 in Section 2.1 we let  $V(T_d)$  represent the daily output of a manufacturing unit as a function of the daily temperature,  $T_d$ . In general  $V(T_d)$  may be represented as follows

$$V(T_d) = V(T_o) + \int_{T_o}^{T_d} \frac{\partial V}{\partial T} dT \quad (5)$$

We may approximate the general non-linear response to temperature by specifying a stepwise linear function of production in temperature following the procedure in Hsiang (2010) and Burgess et al. (2011)). Thus we obtain,

$$\bar{V}(T_d) = \bar{V}(T_0) + \sum_{k=1}^N \beta_k D_k(T_d) \quad (6)$$

Here

$$D_k(T_d) = \int_{xl_k}^{xu_k} \mathbf{1}[\mathbf{T}_d \leq \mathbf{x}] dx \quad (7)$$

where  $\mathbf{1}[\dots]$  represents an indicator function which is 1 when the statement in brackets is true and 0 otherwise. In other words  $D_k(T_d)$  measures the degree days within the year within a given temperature interval. Provided we assume that  $V(T_d)$  does not vary with the time of year, the formulation above is equivalent to estimating annual production as a piecewise linear function of degree days in different temperature bins where the coefficient associated with each degree day bin represents the change in production caused by an increase of one degree-day within that bin. In other words we can write annual output  $V_t$  as a function of degree days  $D_k$  as follows

$$V_t = V_0 + \sum_{k=1}^N \beta_k D_k \quad (8)$$

Because we observe district temperatures at a daily level throughout the years of our study it is possible to calculate a degree day measure associated with each year. We may then estimate a regression of the form

$$V_{i,t} = \alpha_i + \gamma_{s,t} + K_{i,t} + \sum_{k=1}^N \beta_k D_k + f(R_{i,t}) + \epsilon_{i,t} \quad (9)$$

and observe whether  $\beta_k$  values associated with fluctuations in degree days vary in the way the heat stress literature suggests. In other words, if temperature impacts industrial productivity because of its impact on workers, we should expect to find the hypothesis  $\beta_k = 0$  true for low temperatures and to see negative values of  $\beta_k$  for higher degree day bins.

This response function also suggests that it is the degree day model of Equation 9 that should be of primary interest to us since the estimated impact of temperature on productivity from Equation 4 is simply an average value over degree day changes actually observed in the literature. Historic variations in temperature however do not necessarily correspond to the predictions of climate models. For India, these models predict a significant increase in the number of extreme temperature days and not a secular increase in temperatures over the year. In other words, the predicted impacts of climate change are to increase the number of degree days in higher temperature buckets, while reducing those in lower temperature bins (see Section 7 for more details).

Table 3 presents results for the same specifications as Table 2 but using degree day bins instead of mean temperature on the right hand side (as in Equation 9). We find evidence that the mean temperature estimates in Table 3 are driven largely by changes in the highest temperature degree day bin.

## 4.2 Heterogeneity in Impact: Labour Value Added

In Section 2.1 we argued that if temperature shocks result in reduced worker productivity we should expect that this effect should result in percentage declines in production that are highest in manufacturing sectors with a high value added per worker. Conversely, in sectors where the value added per worker

Table 3: Non-Linear Effect of Temperature on Manufacturing Industry Output

	<i>Dependent variable:</i>				
	Plant Output Value (1)	(2)	Log Plant Output Value (3)	Log (Output/Worker) (4)	(5)
Below 20°C	0.010 (0.025)	0.005 (0.025)	0.003 (0.024)	-0.004 (0.023)	-0.005 (0.024)
20°C to 25°C	-0.032 (0.026)	-0.029 (0.026)	-0.045*** (0.022)	-0.038* (0.021)	-0.031 (0.023)
Above 25°C	-0.062*** (0.016)	-0.053*** (0.015)	-0.038*** (0.014)	-0.030** (0.013)	-0.022 (0.012)
rainfall	0.009*** (0.003)	0.007** (0.002)	0.003 (0.002)	0.001 (0.002)	0.00 (0.002)
capital	0.386*** (0.010)	0.346*** (0.009)	0.390*** (0.006)	0.339*** (0.006)	0.197*** (0.006)
Plant FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Capital Controls	Y	Y	Y	Y	Y
Worker Controls	N	Y	N	Y	N
Units	22,149	22,149	22,149	22,149	22,149
R <sup>2</sup>	0.4615	0.4876	0.6705	0.6595	0.2930

*Note:*

1. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

2. Cluster robust standard errors (Arellano-Bond) correcting for serial correlation and heteroskedasticity

3. Maximum temperature is on average 6°C above the mean temperature

4. Coefficients for models 1-3 are expressed as percentages of average output level.

is low, one might expect that plant output may be less affected by climate shocks.

In order to test this hypothesis we require a measure of the value added by labour within a particular sector. The approach we use is to calculate for each plant in our dataset the ratio of wages paid over every year to output in that year. This quantity is not the same as the marginal value of an additional unit of labour but we use this to proxy for firms where labour costs capture a significant share of output value and presumably therefore, labour adds a significant amount of value. We discretize this variable creating a dummy variable for every quartile of the distribution.

Next we regress the log of factory output on temperature on mean temperature interacted with the wage share dummies as in Equation 10. This allows us to flexibly examine whether there exists a relationship between temperature effects on output and the importance of labour, in particular whether plants in the highest quartile of labor wage shares show greater output changes during high temperature years.

$$\log(V_{i,t}) = \alpha_i + \gamma_t + \beta T_{i,t} \times VA_i + f(R_{i,t}) + \epsilon_{i,t} \quad (10)$$

Here  $VA_i$  is the constructed dummy variable. We are interested in the coefficients of the interaction between temperature  $T_{i,t}$  and  $VA_i$ . Table 4 summarizes our estimates. We find that plants with a higher wage share of output are indeed significantly more negatively impacted by temperature shocks. While not a perfect implementation of Test 2 in Section 2.1, this provides suggestive evidence suggesting temperature might matter in this context because of its impact on workers.

### 4.3 Heterogeneity in Impact: Electricity Inputs

In Sections 4.1 and 4.3 we implemented the Test 1 and Test 2 as outlined in Section 2.1. A third test of the mechanism outlined in this paper involves trying to find evidence relating climate control to temperature sensitivity. Air cooling is one obvious adaptive measure that a manufacturing plant could use

Table 4: Impact of temperature on plant output: Wage share of output

	<i>Dependent variable:</i>	
	plant output	log(plant output)
	(1)	(2)
meant	-0.0356*** (0.013)	-0.038 (0.010)
wage share dummy		
<b>Q2</b>	-0.1875 (0.163)	-0.384*** (0.104)
<b>Q3</b>	-0.072 (0.197)	-0.628*** (0.149)
<b>Q4</b>	-0.088 (0.213)	-0.831*** (0.229)
wage share dummy X meant		
<b>Q2</b>	-0.0073 (0.006)	0.002 (0.004)
<b>Q3</b>	-0.021*** (0.007)	-0.002 (0.005)
<b>Q4</b>	-0.029*** (0.008)	-0.018** (0.008)
Plant FE	Y	Y
Year FE	Y	Y
Capital Controls	Y	Y
Number of Units	22150	22150
Mean Obs. per Unit	4.8	4.8
R <sup>2</sup>	0.521	0.709

*Note:*

1. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01
2. Cluster robust standard errors (Arellano-Bond)

to mitigate against any climate effects on workers.

We do not directly observe in the ASI surveys whether or not a plant uses air cooling but we do observe the reported expenditures of electricity. We create a new variable for each plant defined as the ratio of electricity expenditures to total cash on hand at the start of the year (capital). This quantity is a useful proxy for the importance of electricity expenditures. Also because air cooling is an extremely electricity intensive technology, plants with high spending on electricity during the year (as a fraction of cash on hand at the start of the year) are arguably more likely to be using climate control.

We therefore carry out a similar test as reported in Table 4 except that we look for differences in temperature sensitivity interacted with dummy variables for each quartile of electricity intensity. Assuming this quantity is correlated with the use of air cooling, we might expect to see temperature sensitivity *decrease* for plants with higher electricity expenditures. Indeed we do see this pattern in the data, albeit somewhat imprecisely estimated for the model using log of plant output as the dependent variable.

#### **4.4 Testing Price Shocks to Inputs**

Equation 3 provides a simple way to think about how temperature might influence output through its impact on factor inputs of production. We have argued thus far that a plausible mechanism involves temperature impacts on labor. However it is also possible that temperature shocks might change the price of other inputs - especially inputs linked to agricultural output - and that the production shocks we see might therefore reflect input price changes rather than the effectiveness of labor.

One argument against this alternative explanation is the observation that non-linearities in output response to temperature are difficult to explain within the context of agricultural production shocks alone because agricultural growing seasons do not coincide with the hottest months of the year. It is also not clear why the impact of input price shocks should vary with electricity consumption or labour wage-share. In the sections that follow we also directly

Table 5: Impact of temperature on plant output: Electricity inputs

	<i>Dependent variable:</i>	
	plant output	log(plant output)
	(1)	(2)
meant	-0.061*** (0.013)	-0.039*** (0.012)
electricity intensity dummy		
Q2	-0.258 (0.137)	0.009 (0.131)
Q3	-0.482 (0.188)	0.173 (0.177)
Q4	-0.461 (0.221)	0.565 (0.202)
wage share dummy X meant		
<b>Q2</b>	0.016*** (0.005)	0.010** (0.005)
<b>Q3</b>	0.030*** (0.007)	0.012* (0.006)
<b>Q4</b>	0.031*** (0.008)	0.006 (0.007)
Plant FE	Y	Y
Year FE	Y	Y
Capital Controls	Y	Y
Number of Units	22150	22150
Mean Obs. per Unit	4.8	4.8
R <sup>2</sup>	0.480	0.685

*Note:*

1. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01
2. Cluster robust standard errors (Arellano-Bond)

test for the presence of a temperature effect on labour by examining worker productivity data.

Nevertheless, the ASI surveys allow us to more directly test this proposition because plants are asked to report their most common input materials and the per unit price for these inputs each year. We create a price index defined as the log of the mean reported per unit price for the three most common inputs used by a plant. We then use fixed effect regressions similar to Equation 4 to test whether the price index for a given plant changes in years when local temperatures rise. Note that any price shocks that affect the broader population of manufacturing plants are captured by time fixed effects. These fixed effects may not capture input price shocks that vary with local average temperatures.

We report our results in Table 6 where we find no evidence that the price index we estimate changes (increases) in high temperature years or an increase in high temperature days within the year. Although we are limited by the relatively poor data quality of price reports by plants (28 percent of survey observations have no price or expenditure reports for even a single input variable), these results do suggest that input price shocks may not be an important explanatory factor in this setting.

## 4.5 Estimates using Wet Bulb Globe Temperature

As we described in Section 5 the environmental quantity of most direct relevance to heat stress on workers is not simply temperature but rather the wet bulb globe temperature, an index that also accounts for ambient humidity. Unfortunately creating a nationwide WBGT measure using Equation 1 is difficult because reliable time series data on relative humidity across India is not easily available. Although water vapour pressure or humidity measures are available as part of reanalysis datasets, these models were not necessarily designed to provide reasonable estimates of temporal variation in humidity and related parameters. In addition significantly less is known about how relative humidity might change over time due to climate change effects.



Table 6: Impact of temperature on input price index

	<i>Dependent variable: Input Price Index</i>	
	(1)	(2)
meant	0.063 (0.040)	
DD1		0.023 (0.087)
DD2		0.121 (0.081)
DD3		0.050 (0.051)
rainfall	0.002 (0.007)	0.002 (0.007)
Plant FE	Y	Y
Year FE	Y	Y
Capital Controls	Y	Y
Number of Units	22150	22150
Mean Obs. per Unit	4.8	4.8
R <sup>2</sup>	0.480	0.685

*Note:* 1. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

For this reason we have used dynamic variation in temperature alone to estimate the effect of heat on industrial output in our analysis thus far. This ensures that our results are driven only by variation in temperature and not potentially spurious variations in humidity measures from reanalysis data. However as a robustness check we also repeat our estimation of Equation 4 using an approximate wet bulb globe measure. This is obtained by combining temperature with *long run average* measures of daily relative humidity between 1981-2010 from the NCEP/ NCAR reanalysis datasets. Dynamic variation in this index is therefore still only driven by variation in temperatures over grid points in our dataset although the introduction of humidity likely increases noise in the climate variable to some degree.

Table 7 summarizes our results which look very similar to those in Table 2.

## 5 Temperature and Daily Worker Output

In Section 4 we provided evidence suggesting that output from individual manufacturing plants appears to decrease with an increase in average temperatures, and the number of high temperature days in the year. We also find that output associations with temperature are reduced in plants which use greater electricity (a proxy for the use of climate control) and in plants where an indicator for worker value addition is low. These patterns are consistent with a causal mechanism that involves the impact of temperature on worker productivity, through the physiological mechanism of heat stress.

One concern however, is that manufacturing plants may also show reductions in output due to changes in the factor prices of agriculture linked inputs rather than temperature. Since we do not observe relative prices of factor inputs we cannot directly test whether this occurs. One suggestive piece of evidence that this mechanism is unlikely to be the explanation lies in the pattern of temperature response - if input shocks provide the explanation for our results, we might expect that they would be largest at the relatively lower temperatures prevalent during the agricultural season than during high tem-

Table 7: Effect of Wet Bulb Globe Temperature on Manufacturing Industry Output

	<i>Dependent variable:</i>					
	Plant Output Value (1)	(2)	(3)	Log Plant Output Value (4)	(5)	Log (Output/Worker) (6)
wbgt	-.042*** (0.015)	-0.044*** (0.014)	-0.036** (0.014)	-0.036*** (0.013)	-0.030** (0.012)	-0.022* (0.013)
rainfall	0.013*** (0.003)	0.009*** (0.003)	0.007*** (0.003)	0.003 (0.002)	0.001 (0.002)	0.00 (0.002)
capital		0.386*** (0.010)	0.346*** (0.009)	0.390*** (0.006)	0.339*** (0.006)	0.197*** (0.006)
Plant FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Capital Controls	N	Y	Y	Y	Y	Y
Worker Controls	N	N	Y	N	Y	N
Units	22,149	22,149	22,149	22,149	22,149	22,149
R <sup>2</sup>	0.0076	0.4615	0.4876	0.6705	0.6595	0.2930

*Note:*

1. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

2. Cluster robust standard errors (Arellano-Bond) correcting for serial correlation and heteroskedasticity

3. Maximum temperature is on average 6°C above the mean temperature

4. Coefficients for models 1-3 are expressed as percentages of average output level.

peratures. In addition, it is not clear why such a mechanism would vary with worker value addition or electricity use.

Nevertheless, it is worthwhile to examine, in a specific case study plant whether the mechanism we propose can be detected when directly observing worker productivity, rather than plant output. In this section therefore we examine how daily worker level output, measured directly, changes with daily temperature shocks. We also examine settings where climate control is known to be in use and directly compare the sensitivity of worker output to temperature in these settings, with productivity response in settings without climate control.

The use of daily output measures also serves a secondary purpose. The mechanism of heat stress that we have hypothesized has a clear physiological basis which would predict that heat stress should become visible over fairly short periods of exposure. This characteristic may be somewhat unique to this mechanism, since other proposed explanations for the impact of temperature on non-agricultural sectors (conflict, economic spillovers, demand shocks) are unlikely to be detectable at very short time scales. Thus by examining whether temperature responses can be detected in daily worker output, we are able to conduct an important check of consistency with the proposed mechanism.

In order to estimate the impact of temperature on productivity, we begin by linking daily worker level output data from weaving firms in Surat, with a measure of local ambient wet bulb globe temperature (WBGT) from a local climate station. We utilize quasi-random day to day variation in WBGT to estimate the impact of changing temperature on worker output. By using high frequency output data we are also able to control for individual fixed effects at the level of the worker.

More precisely, we estimate coefficients of the linear model below through ordinary least squares.

$$\log(Y_{i,d}) = \alpha_i + \gamma_M + \omega_W + \beta_k WBGT_d \times D_k \times IsAC + \theta R_{i,d} + \epsilon_{i,d} \quad (11)$$

Here  $Y_{i,d}$  is worker output, measured in meters of cloth, for worker  $i$  on day  $d$ .

We use both output and log output as the independent variable (the latter being less sensitive to outliers).  $\alpha_i$  is a worker specific fixed effect allowing an idiosyncratic daily output level for each worker.  $\gamma_M$  is a month fixed effect allowing for general shocks to daily productivity affecting all workers each month ( $M$ ). This captures seasonalities and market effects of all kinds that might influence output during the year.  $\omega_W$  is a *day of week* fixed effect that captures unobserved shifts in production associated with specific days of the week (for example there may be lower production on weekends).  $R_{i,d}$  is a control for rainfall.  $WBGT_d$  represents the average daily wet bulb temperature on day  $d$ . We interact the effect of daily wet bulb temperature,  $WBGT_d$  with a dummy variable  $D_k$  for different bins of the temperature distribution. This allows us to separately estimate the marginal effect on output of a change in temperature within different regions of the distribution.

Table 8 summarizes our results (omitting all fixed effects for clarity). We report coefficients associated with a one degree change in wet bulb globe temperature on the output variable (or log output variable), conditional on the value of wet bulb globe temperature. We split the response curve into four wet bulb globe temperature bins<sup>11</sup>:  $< 21^\circ C$ ,  $< 21^\circ C - 25^\circ C$ ,  $< 25^\circ C - 27^\circ C$  and  $\geq 27^\circ C$ . Alternatively, one could create WBGT bins corresponding to quantiles of the observed distribution - this results in different bin sizes and locations for each site but ensures an equal amount of data in each bin. Table 9 is similar to Table 8 but uses breakpoints corresponding to local WBGT quantiles. Row 3 provides the baseline effect associated with an increase in WBGT, and Rows 4-6 provide the incremental change for fluctuations in wet bulb globe temperature at higher WBGT bins. Across all models, identification comes from correlations between dynamic variation within a units output (worker or line) with dynamic variation in temperature, controlling for rainfall, time invariant averages and a monthly time fixed effects.

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<sup>11</sup>Break points of 25 and 27 degrees allow a comparison to the breakpoints used in Hsiang (2010)

The overall pattern of temperature response seems very similar to that observed with the annual ASI data. In the coldest quartile, a one degree increase in wet bulb globe temperature appears to be associated with a small increase in output. At higher temperatures the incremental effect of a one degree change in temperature is negative.

Table 8: Effect of Wet Bulb Globe Temperature on Worker Output

	<i>Dependent variable:</i>	
	log(meters)	meters
	(1)	(2)
(1) rainfall	0.006 (0.008)	1.512 (0.958)
(3) WBGT:[<21]	0.017** (0.007)	1.290 (0.821)
(4) WBGT:[21-25]	-0.020* (0.012)	-2.446 (1.542)
(5) WBGT:[25-27]	-0.026* (0.015)	0.222 (1.845)
(6) WBGT:[≥27]	-0.083** (0.037)	-5.765* (2.961)
Worker FE	Y	Y
Month FE	Y	Y
Weekday FE	Y	Y

*Note:* 1. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01  
2. Cluster robust standard errors

## 5.1 Worker Absenteeism

In Section 5 we investigated the relationship between temperature shocks and the output produced by workers (or groups of workers). Previous research has suggested (Zivin and Neidell, 2010) that high temperature days might also reduce worker attendance and that therefore productivity might be influenced by absenteeism.

For weaving workers in Surat, we are able to observe whether or not a worker is present for work at the establishment he normally works for and can

Table 9: Effect of Wet Bulb Globe Temperature Quantiles on Worker Output

<i>Dependent variable:</i>		
	log(meters)	meters
	(1)	(2)
(1) rainfall	0.008 (0.008)	1.590* (0.964)
(3) WBGT	0.018*** (0.006)	1.762** (0.826)
(4) WBGT:Q2	-0.012 (0.013)	-1.876 (1.447)
(5) WBGT:Q3	-0.053** (0.021)	-1.575 (2.073)
(6) WBGT:Q4	-0.066** (0.034)	-5.278* (2.773)
Worker FE	Y	Y
Month FE	Y	Y
Weekday FE	Y	Y

*Note:* 1. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01  
2. Cluster robust standard errors  
3. WBGT quantiles for Surat: [0,21.4], (21.4,25.4], (25.4,26.9], (26.9,28.5]

therefore test to see if absences are associated with high temperature days. We therefore estimate a simple linear probability model as follows

$$IsPresent = \alpha_i + \gamma_M + \omega_W + \beta_k WBGT_d \times D_k + \theta R_{i,d} + \epsilon_{i,d} \quad (12)$$

where *IsPresent* is a binary variable that takes the value 0 when the worker does not report for work and 1 otherwise<sup>12</sup>. The covariates on the right have the same definitions as in Equation 11.

We report our results in Table 10. We find no evidence that temperature shocks on a given day increase worker absenteeism. This may not be surprising for the case of weaving units since these workers are paid only when they arrive at work and therefore face a clear cost of not working on any given day. Since incomes are low, the relative income effect of absenteeism is therefore substantial. Absenteeism may also hurt workers if regularly absent workers can be quickly and easily replaced (as seems plausible in this context, where labour is substitutable and there are no long term contracts).

We also examined the relationship between worker absenteeism and the average wet bulb globe temperature over the preceding seven days. We again find no significant effect. Overall, the evidence suggests that worker absenteeism may not be a major consideration. In developing countries, for much of the workforce, the opportunity costs of absenteeism may be fairly high and protection from heat through staying at home relatively low. This differs from developed country settings (such as the US workforce population analyzed by Zivin and Neidell (2010)).

## 6 Qualitative Evidence and Adaptation

This paper has focused thus far on examining worker and plant productivity data and quantifying how changes in these outcomes occur with temperature shocks. In this section we summarize some qualitative evidence on adaptation

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<sup>12</sup>Of course a worker who does not report for work at the firms we observe may work elsewhere so a measure of absence is not quite the same as observing a day off. Nevertheless the two are likely strongly correlated.



Table 10: Effect of Temperature on Worker Absenteeism

	<i>Dependent variable:</i>			
	Worker Absence			
	(3)	(4)		
WBGT:[<21]	0.001 (0.002)			
WBGT:[21-25)	-0.027 (0.031)		0.003 (0.005)	
WBGT:[25-27)	-0.041 (0.066)		-0.004 (0.005)	
WBGT:[≥27]	-0.056 (0.112)		-0.011 (0.010)	
rainfall	-0.002 (0.003)	-0.003 (0.003)		
Mean Week WBGT		0.003 (0.014)		(0.003)
Mean Week Rain		0.006 (0.005)		0.006 (0.009)
Worker FE	<i>N</i>	<i>N</i>	<i>Y</i>	<i>Y</i>
Month-Year FE	<i>Y</i>	<i>Y</i>	<i>Y</i>	<i>Y</i>
Weekday FE	<i>Y</i>	<i>Y</i>	<i>Y</i>	<i>Y</i>

*Note:*

1. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01
2. Cluster robust standard errors (Arellano-Bond)
3. extraleave is a count of total unplanned absences per day)
4. Absent is a binary variable with value 1 when worker is absent

to temperature that emerged from interviews with both weaving and diamond firms in Surat. These interviews also provide some evidence suggesting that temperature is in fact seen as a determinant of productivity by small firms and that some firms do report taking adaptive actions. A formal survey on these questions is also planned but not part of the discussion in this section.

We conducted a set of interviews with owners of textile and diamond units during field work in Surat to learn whether firms viewed temperature as a factor influencing worker performance and whether and how adaptation options were being adopted.

Plant owners in both the diamond and textile sectors were aware of how temperature may influence worker performance. Mechanisms they cited included temperatures impact on workers physical ability to carry out their work, their mental attention to the job, the speed at which they work, the number of breaks required and faults made especially during peak summer periods and on the hottest days. While temperature was not the first order factor reported by firms as influencing worker output, anecdotal evidence suggested that rising summer temperatures had become enough of an issue in the last few years for many firms to begin to adopt a measures to mitigate temperature impacts.

Weaving plants in our case studies for example were already taking a number of low cost actions to mitigate the impact of ambient temperatures on workers. First, breaks were built into the work day and increased in hotter weather. In some cases staggered work-shifts were used. Second, weaving units would attempt to locate worker intensive machinery in basements or lower floor of buildings where temperatures are lower and constructed large windows to enable better air circulation on upper floors. In one instance, the owner of a small weaving firm reported having made inquiries for a lower cost air cooling systems and had placed an order with a Chinese firm to purchase such a system.<sup>13</sup> In another weaving plant, owners reported plans to put in place a

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<sup>13</sup>This planned capital investment would make this firm something of an outlier amongst similar weaving units. A key factor determining the use of air cooling technologies is the cost of electricity to operate these. In highly competitive, small scale industry with low profit margins, these costs may not be economically sensible, even if cooler working temperatures

wage bonus in the summer months to encourage both attendance and output. Efforts such as these represent an example of the type of adaptive strategy (and expense) that may grow more common if temperatures rise (through climate change or urban heat island effects) or if competition for labour increases during the hottest months.

The diamond sector in Surat, where we also conducted interviews, is interesting as a counterpoint to the weaving industry. Although both are highly labor intensive, the value added by diamond workers is significantly higher and workers in this sector are often highly skilled.

We were unable to collect worker level output data from these plants but found that air-conditioning investments seemed significantly more common in diamond firms, even where the unit size is small and the number of workers employed was low (of the order of 10-20 workers).

In larger diamond units nearly all production steps were found to take place under climate controlled conditions. In the smallest firms this was not necessarily the case, but steps in the production chain involving tasks with very high value addition tended to be air conditioned, even when the rest of the unit was not. For example the first production task in most Surat diamond cutting units is a sorting activity where rough cut mined stones are brought in, assessed for quality, and sorted into different bins. Low value stones may be sold to other polishing units while the higher value stones are retained for polishing and cutting. An associated step is assessing the cutting strategy for the retained stones to extract the highest value.

Sorting is done by skilled workers and is work that requires very little physical effort but a significant degree of concentration and skill. Mistakes made during sorting have the potential to be very costly for the firm since they may result in mis-classifying high value stones as low value stones or vice versa and miscalculating extraction and cutting strategies. We found that even the smallest units tended to use air-conditioning at the sorting step of their production process.

These examples and anecdotes signal that at least in one city, where temperatures were to result in slightly increased output.

peratures have been rising with the formation of local heat islands, firm owners believe that temperature has an impact on worker performance and through that mechanism on output and profitability.

## 7 Climate Model Projections

Climate change projections suggest that India is likely to see significant shifts in annual high temperature degree days and a corresponding reduction in cooler days, for a net increase in annual average temperatures. While there are various projections available, each with some modeling uncertainty, two that are commonly cited are the (i) the A1F1 "business-as-usual" scenario of the Hadley Centre Global Environmental Model, version 1 (HadGEM1) from the British Atmospheric Data Centre and (ii) the A2 scenario of the Community Climate System Model (CCSM) 3, from the National Center for Atmospheric Research (NCAR 2007).

Figure 2 provides a projection of changes in the annual distribution of days across temperature bins for India as documented in Burgess et al. (2011). These estimates are based on these model projections of future temperature distributions and historical climate data from the Reanalysis 1 project of the Climactic Research Unit of the National Center for Environmental Prediction / National Center for Atmospheric Research (NCEP). Perhaps the most striking feature of these projections is the skewed nature of projected climate change impacts that suggest a significant increase in annual degree day bins at temperatures above 25 degrees celsius (77 degrees Fahrenheit).

We overlay on these projections our estimate of the non-linear effects of temperature on manufacturing output from Table 3 (column 3). The figure suggests that if high temperatures do indeed matter for manufacturing output, then adaptive measures may be necessary to mitigate impacts that would otherwise be high. These adaptive measures include air conditioning or air cooling investments but could also take the form of reallocation of manufacturing to cooler regions or greater emphasis on urban planning measures (green cover, water bodies) that are designed to lower local temperatures.

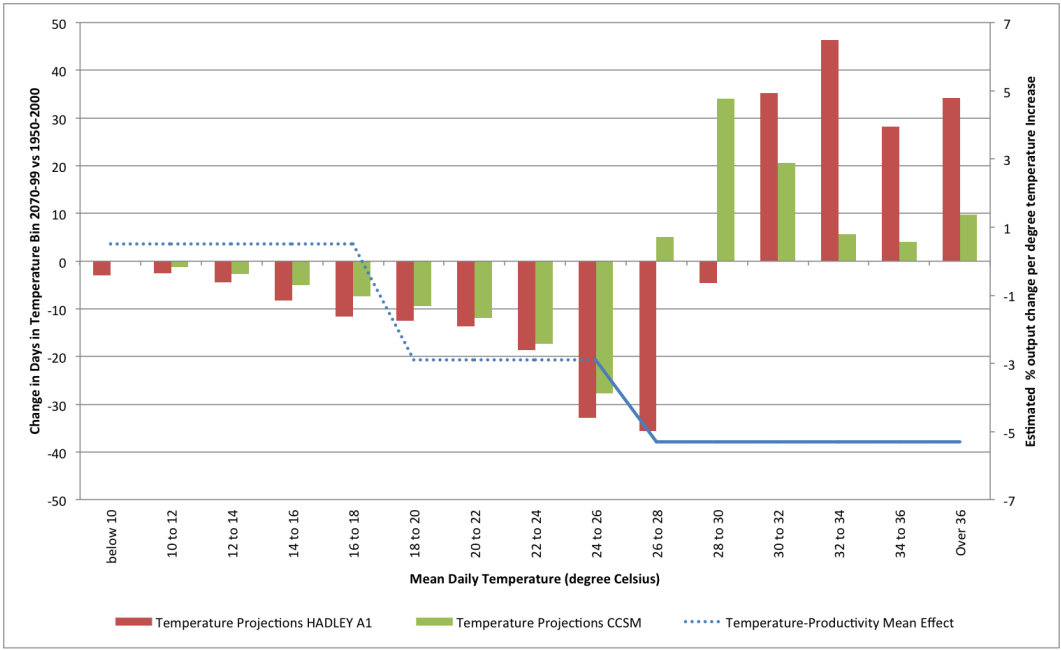


Figure 2: Historical and projected temperatures under a business as usual climate change scenario for India. See Burgess et al. (2011) for climate change projections. Lines denote estimated productivity effects of temperature with solid lines representing statistically significant effects

Ignoring adaptation, the projected changes in degree days in Figure 2 combined with our mean estimates of the impact of temperature on productivity from column 2 of Table 3 allows us to compute a back of the envelope estimate of the impact of projected climate change on manufacturing output in India. Although this exercise cannot be interpreted as a prediction of long run impacts, it does place the potential importance of this mechanism into context.

We collapse projected and historical temperature distributions into the coarser temperature bins (Under 20, 20-25 and 25+ degrees celsius) over which we estimate productivity effects of temperature. Temperature appears to have insignificant effects in the first two bins but has strong negative impacts in the third bin. The predicted changes in daily average degrees in the three bins are (-1.79, -0.64, 3.34) for ( $\leq 20^{\circ}C$ ,  $20^{\circ}C - 25^{\circ}C$ ,  $> 25^{\circ}C$ ) respectively in the

Hadley model projections. The change in the daily average degrees above  $25^{\circ}C$  in this projection is extremely high and a consequence of the large number of extreme temperature days the population weighted model outputs predict for India (see Figure 2) as well as the fact that both populations and industrial activity are concentrated in relatively warmer parts of the country. For the CCSM model predicted changes in the highest degree day bin are lower but still significant (-1.17, -0.55, 1.32). Assuming the lower projection is the more reasonable estimate, our empirical estimates suggest that absent adaptation, the estimated impact on manufacturing would be -6.99% (95% CI = [-2.77%, -10.69 %]).

Because this number is large, it appears that adaptation investments would be adopted. Adaptive measures such as air-cooling are technologically feasible but certainly not costless. For this reason, policy or technology measures reducing the cost of adaptation may have significant benefits. Other plant level responses could include greater mechanization, shifting of manufacturing to cooler areas and increasing the number of workers while reducing hours worked. Public policy responses to reduce local temperatures could include urban planning and investments in urban green cover and waterbodies.

Lastly we should note that although projections of future temperatures have significant uncertainty, climate factors are not the only channel through which urban temperatures can rise. Heat island effects in urban areas (where most industrial plants are located) can easily lead to temperature hotspots that are a few degrees warmer than surrounding rural areas. These local factors could be mitigated by urban planning and land use change. Our analysis suggests that enhancing worker productivity may be one clear benefit of taking such action.

## 8 Conclusions

This paper presents empirical evidence from the manufacturing sector in India suggesting that manufacturing output may decrease as temperatures increase. While results are indicative and only a starting point to further research we

present some evidence that temperature may influence output because of its impact on labor.

We refer to the literature on heat stress and the impact of temperature on human performance indices to argue that this physiological mechanism may result in labor that is less productive as ambient temperatures rise and this reduction in labor productivity may in turn impact industrial output. We suggest that this mechanism may partially explain the link between temperature shocks and developing country economic output, documented in previous studies (Dell et al., 2012).

By examining multiple datasets recording both plant output and worker productivity, we are able to better isolate a specific mechanism. By using micro-data at the level of individual plants we are able to more precisely control for unobservables that might otherwise affect studies using more aggregate data. We rely on time-series variation in plant or worker output to identify parameters and in doing so we avoid drawing conclusions that may be biased by plant characteristics that might covary with local temperature. Finally, we also examine data from plants with climate control to document that air cooling cuts off the link we observe between temperatures and output. This both tests the proposed mechanism and also identifies the usefulness of air-cooling as an adaptive technique.

Absent adaptation, we show that the economic impacts of climate change via the channel of reduced worker productivity may be significant - an average of 2.8 percent of manufacturing output reduction per degree change in temperature, with variations depending on adaptive investments, labor value addition and the degree of mechanization. Because these impacts are significant, adaptation should be expected if temperatures increase (either due to climate change or urban heat island effects). Such adaptation is by no means costless and therefore policy efforts to reduce these costs (encouraging lower cost cooling systems, investing in better urban design etc.), may have significant benefits.

Much of the research on the economic effects of temperature has focused on the agricultural sector. As a complement to that research it might be fruitful

to better understand the mechanisms through which temperature impacts industrial productivity. This paper suggests that worker productivity may be an important channel through which temperature increases may impact industrial output. Further research using data from other countries as well as undertaking experimental work in industrial settings would prove extremely useful in helping us understand both how temperature changes in the future may impact growth, the extent of costs incurred and the degree to which affordable adaptation can occur. It would also shed some light on how historic temperature differences across different parts of the world may have contributed to existing differences in economic output between nations.

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