ISSN No. 2454 – 1427

CDE
June 2015

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Working Paper No. 244

http://www.cdedse.org/working-paper-frameset.htm

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The Impact of Temperature on Productivity and Labor Supply: Evidence from Indian Manufacturing*

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Cross-country studies have found that hotter years are associated with lower output in poor countries. Using high-frequency micro-data from manufacturing firms in India, we show that worker heat stress can substantially explain this correlation. Ambient temperatures have non-linear effects on worker productivity, with declines on hot days of 4 to 9 percent per degree rise in temperature. Sustained heat also increases absenteeism. Similar temperature induced productivity declines are replicated in annual plant output from a national panel. Our estimates imply that warming between 1971 and 2009 may have decreased manufacturing output in India by at least 3 percent relative to a no-warming counterfactual.

Keywords: temperature, heat stress, worker productivity, climate change.

JEL: Q54, Q56, J22, J24

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1 Introduction

Recent studies have uncovered a systematic negative correlation between high temperatures and aggregate output, especially in developing countries. Dell, Jones, and Olken (2012) use a global country panel and find reductions in both agricultural and non-agricultural output for poor countries in years with higher than average temperatures. Similarly, Hsiang (2010) finds that temperature is correlated with lower output in the services sector in Central America and the Caribbean. This intriguing relationship, suggestive of a direct link between temperature and growth, may be of significant importance given new scientific evidence on rising local and global temperatures. Anthropogenic climate change has already led to a five fold increase in the probability of extreme temperature days over pre-industrial periods (Fischer and Knutti, 2015). Within countries, warming due to urban heat islands has raised city temperatures well above regional averages (Mohan et al., 2012; Zhao et al., 2014).

Isolating the specific mechanisms underlying these correlations has remained a challenge. The impact of temperature change has been most extensively studied in the agricultural sector where high temperatures are associated with lower yields of specific crops (Lobell, Schlenker, and Costa-Roberts, 2011; Schlenker and Roberts, 2009; Mendelsohn and Dinar, 1999; Auffhammer, Ramanathan, and Vincent, 2006). Yet agriculture alone cannot account for observed output declines, which are apparent in countries with both large and small agricultural sectors. Heat effects on mortality, political conflict and thermal stress on workers have been proposed as alternative explanations, but isolating any of these channels with national output data is difficult.[1]

We present new evidence that heat stress on workers is an important mechanism through which temperatures influence economic output. For this we collect primary data on daily worker productivity and attendance from selected Indian firms in the cloth weaving, gar-

[1] Dell, Jones, and Olken (2014) review this literature.

ment manufacture, steel rolling and diamond cutting industries. We find that high ambient temperatures reduce the productivity and attendance of workers. We estimate output declines of between 4 and 9 percent per degree on days when wet bulb globe temperatures are above 27 degrees Celsius. The largest effects are seen for manual processes in the hottest parts of the country. Sustained high temperatures also lower attendance. An additional day of elevated temperatures is associated with a 1 to 2 percent increase in absenteeism of contracted workers. This estimate turns out to be quantitatively similar to changes in time allocation induced by warmer temperatures in the United States (Zivin and Neidell, 2014). Interestingly, for daily wage workers, for whom the cost of occasional absences is high, we find little correlation between temperature and absenteeism.

We augment our worker-level analysis using a nationally representative panel of manufacturing plants in India over the years 1998-2008. We find a non-linear relationship between temperature and annual plant output, similar to that observed for daily worker productivity, for this much longer time period. The value of annual factory output declines during years with a greater number of high temperature days at a little over 3 percent per degree-day.

The size of these temperature impacts suggests potential benefits from investing in adaptation. We exploit the phased rollout of climate control within the garment firm we study and find that workplace cooling effectively breaks the link between high ambient temperatures and worker output, but does not eliminate temperature effects on absenteeism.[2] These benefits notwithstanding, the costs of these technologies often limit their deployment. We conduct a survey of 150 diamond cutting and polishing firms to study investments in air-conditioning and find that it is selectively used for labor intensive processes and those with high value addition. These deployment patterns are consistent with the selective deployment of costly climate control to mitigate temperature effects on worker productivity.

[2]These benefits may also accrue from technologies that indirectly influence temperatures. For example, Adhvaryu, Kala, and Nyshadham (2014) suggest that there may be productivity gains from low heat lighting options such as LEDs.

Our empirical estimates are consistent with physiological studies of heat stress in the laboratory and with country panel studies. Our estimates suggest that the impact of temperature on human beings may explain a significant portion of the observed relationship between temperature and output in poor countries with limited climate control. Moreover, since our data come from settings that do not involve heavy physical labor or outdoor exposure, the productivity impacts we identify may be quite pervasive. Temperatures over the Indian sub-continent have recorded an average warming of about 0.91 degrees between 1971-75 and 2005-2009. Based on our estimates, this warming may have reduced manufacturing output in 2009 by 3 percent relative to a no-warming counterfactual, an annual economic loss of over 8 billion USD (Section 5). These estimates are conservative because they do not account for the costs of incurred adaptation or capture the impacts of local urban heat islands.

The remainder of this paper is organized as follows. Section 2 summarizes the physiological evidence on heat stress. Section 3 describes the compilation of our various data sources and their matching with weather data. Section 4 presents results, first from firm-level micro data and then from a national panel of manufacturing plants. Section 5 quantifies the importance of estimated temperature effects in the context of climate model predictions for India. Section 6 concludes.

2 Mechanisms

The physics of how temperature affects human beings is straightforward. Heat generated while working must be dissipated to maintain body temperatures and avoid heat stress. The efficiency of such dissipation depends primarily on ambient temperature but also on humidity and wind speed. If body temperatures cannot be maintained at a given activity level, it may be necessary to reduce the intensity of work (Kjellstrom, Holmer, and Lemke, 2009; ISO, 1989).

Several indices of ambient weather parameters have been used to measure the risk of heat stress. Most widely accepted is the Wet Bulb Globe Temperature (Parsons, 1993; ISO, 1989). Directly measuring WBGT requires specialized instruments and we use the following approximation, whenever data on humidity is available:

$$
\begin{aligned}
&WBGT = 0.567 T_A + 0.216\rho + 3.38, \\
&\rho = (RH/100) \times 6.105 \exp\left(\frac{17.27 T_A}{237.7 + T_A}\right).
\end{aligned}
\tag{1}
$$

Here T_A represents air temperature in degrees Celsius and ρ the water vapour pressure calculated from relative humidity, RH.[3]

Laboratory studies have documented a non-linear relationship between temperature and human efficiency in performing ergonomic and cognitive tasks. At very low levels, efficiency may increase with temperature, but for wet bulb globe temperatures above 25 degrees Celsius, task efficiency appears to fall by approximately 1 to 2 percent per degree.[4] These levels are not considered unsafe from the point of view of occupational safety and are commonly observed in developing countries (Figure A.4). Seppanen, Fisk, and Faulkner (2003) and Hsiang (2010) provide a meta-analysis of this evidence.[5]

While lab estimates provide a useful benchmark, they do not adequately capture manufacturing environments in which the temperature-productivity relationship can be moderated through incentives embedded in wage contracts, the varied nature of tasks performed by a given worker, and mechanization. These factors influence both physical productivity and worker absenteeism through changes in patterns of morbidity and time allocation. Moreover, the economic costs of reductions in the efficiency of physical processes depend on the

[3] Lemke and Kjellstrom (2012) compare different WBGT measures and show that this equation performs well at approximating ambient WBGT.

[4] Similar effects have also been observed in some office settings, such as call centers (Seppanen, Fisk, and Lei, 2006).

[5] In some sectors, such as mining, temperature and humidity exposures can be high enough to create serious health hazards. These settings are often used for research on heat stress and for designing occupational safety regulation (Wyndham, 1969).

value these processes add to the final product. The data we collect allow us to examine the multiple channels through which temperature effects operate in real manufacturing settings.

3 Data Sources

We use five independent datasets to investigate our heat stress hypothesis. Together, these span a range of manufacturing environments with varying degrees of mechanization, climate control, labor intensity and value addition. We cover firms with regular salaried workers as well as firms with casual workers on piece-rate contracts.

Our high-frequency data on worker output and attendance comes from selected plants in three industries: cloth weaving, garment manufacture and rail production. Cloth weaving and garment manufacture are both labor-intensive but weaving workers are paid piece rates while garment workers receive monthly salaries. Climate control is absent in the weaving units and present in some of the garment units. The rail mill we study is highly mechanized, with some climate control, and workers spend most of their time supervising and correcting automated processes.

In addition to compiling worker output data, we conducted a survey of 150 diamond cutting and polishing firms in Surat. Most of these invest in air-conditioning but only for some areas in the plant. We examine whether there is greater deployment of climate control in tasks that are relatively labor intensive or those that involve significant value addition. Such a pattern could reflect their concerns with worker heat stress.

Each of our micro-data sites represents an important manufacturing sector in the Indian and global economy. Textiles and Garments employ 12 percent and 7 percent of factory workers in India, 90 percent of world diamond output passes through the town of Surat where we conducted our survey, and the Bhilai rail mill is the largest producer of rails in the world.[6]

Our last data set is a nationally representative panel of manufacturing plants across India. The data comes from the Annual Survey of Industry (ASI), a government database covering all large factories and a sample of small ones. We use multiple rounds of the ASI data to construct a panel of manufacturing plants with district identifiers and combine annual plant data over the period 1998-2008 with temperatures for the district in which the plant is located. This allows us to estimate temperature effects over multiple regions and sectors and over a longer time period than possible with our other data sets. Figure A.1 shows the geographic distribution of ASI plants and locations of the micro-data sites.

Our data and variable construction is described below with technical details in the Appendix. Table 1 provides a quick overview of the datasets we use.

3.1 Production and Attendance Data

Weaving Units: We use daily output and attendance for workers in three cloth weaving units located in the city of Surat in the state of Gujarat in western India. Each worker operates between 6 to 12 mechanized looms producing woven cloth. Workers walk up and down between looms, occasionally adjusting alignment, restarting feeds when interrupted and making other necessary corrections. The cloth produced is sold in wholesale markets or to dying and printing firms. Panel C in Figure A.2 is a photograph of the production floor in one of these units.

Protection from heat is limited to the use of windows and some fans. All workers are paid based on the meters of cloth woven and no payments are made for days absent. For most types of cloth, workers were paid 2 rupees per meter and the median daily production per

[6]For employment shares, see Annual Survey of Industries, 2009-10, Volume 1. Figures for the Surat diamond industry are taken from (Adiga, 2004) and those for the rail mill are from http://www.sail.co.in/bhilai-steel-plant/facilities.

worker was 125 meters.[7] We obtained payment slips for each day worked during the financial year April 2012-March 2013 and digitized these to generate a worker level dataset of daily output and attendance covering 147 workers who worked at any point during the year.

Garment Manufacturing: These data come from eight factories owned by a single firm producing garments, largely for export. Six of the factories are in the National Capital Region of Delhi (NCR) in North India, the other two are in Hyderabad and Chhindwara in South and Central India respectively. Many different types and styles of garments are produced in each factory, mostly for foreign apparel brands. Production is organized in sewing lines of 10-20 workers and each line creates part or all of a clothing item. The lines are usually stable in their composition of workers, although the garment manufactured by a given line changes based on production orders. Panel B in Figure A.2 shows a typical sewing line.

Measuring productivity is less straightforward than for weaving units because garment output depends on the complexity of operations involved. However, the garment export sector is highly competitive and firms track worker output in sophisticated ways. We rely on two variables used by the firm's management for this purpose: *Budgeted Efficiency* and *Actual Efficiency*. The first of these is an hourly production target based on the time taken to complete the desired operations by a special line of 'master craftsmen'. The second is the actual hourly output. We use Actual Efficiency, averaged over each day, as a measure of the combined productivity of each line of workers, and use Budgeted Efficiency as a control in our regression models.

There are a total of 103 sewing lines in the eight plants and our data cover working days over two calendar years, 2012 and 2013. The median days worked by a line is 354 and we have a total of 30,521 line-days in our data set. In addition to line output, the management

[7]Since payments are made strictly based on production, incentive effects on output arising from non-linearities caused by minimum wages can be ignored (Zivin and Neidell, 2012).

provided us with attendance records for all sewing workers. To restrict attention to regular, full-time employees, we study absenteeism within a stable cohort of 2700 workers present for at least 600 days over the two-year period. Unlike the weaving workers in Surat, these workers were paid paid monthly wages which do not directly penalize workers for small variations in productivity or occasional absenteeism.

During the period we consider, the firm was in the process of installing centralized climate control in its plants. Production floors in five manufacturing units in the NCR were already equipped with air washers that control both temperature and humidity to reduce wet bulb globe temperatures. The sixth unit in the NCR did not have air-washers installed until 2014. Workers at this site had access only to fans or evaporative coolers which are not effective dehumidifiers. The two plants in Hyderabad and Chhindwara were also without air-washers but average temperatures in these areas are lower than in the NCR.

The gradual roll out of air washers in the NCR allows us to compare temperature effects between units with and without climate control. Although this variation is not experimentally induced, the different estimates are indicative of the ability of firms to mitigate temperature impacts with workplace cooling. Even with climate control, workers continue to be exposed to uncomfortable temperatures outside. This could influence their health and productivity at work, as well as their attendance. With both attendance and output data, we are able to separately examine the effects of climate control on these two dimensions.

Rail Production: The rail mill at Bhilai has been the primary supplier of rails for the Indian Railways since its inception in the 1950s. It is located within one of India's largest integrated steel plants in the town of Bhilai in Central India. Rectangular blocks of steel called *blooms* are made within the plant and form the basic input. They enter a furnace and are then shaped into rails that meet required specifications. When a bloom is successfully shaped into a rail, it is said to have been *rolled*. When faults occur, the bloom is referred to as *cobbled* and is discarded. Apart from rails, the mill produces a range of miscellaneous products, collectively termed *structurals* that are used in large building projects. Panel A in Figure A.2 shows part of the production line.

There are three eight-hour shifts on most days, starting at 6 a.m.[8] Workers are assigned to one of three teams which rotate across these shifts. For example, a team working the morning shift one week, will move to the afternoon the next week and the night shift the following week. The median number of workers on the factory floor from each team is 66. Our production data records the team and the number of blooms rolled for each working shift during the period 1999-2008. We have a total of 9172 shifts over 3339 working days. We also have personnel records that allow us to relate temperatures to plant level absenteeism. These cover 857 working days in the period February 2000-March 2003.[9]

The production of rails is highly mechanized and the mill runs continuously with breaks only when machinery needs repair, maintenance, or adjustment for different products. Workers who manipulate the machinery used to shape rails sit in air-conditioned cabins. Others perform operations on the factory floor. This is the most capital intensive of our four data sites and the combination of automation and climate control could limit the effects of outside temperatures on output.

Diamond Polishing: In August 2014, we surveyed a random sample of 150 firms in the city of Surat, the same location as our weaving units. The sample was selected from over 500 manufacturing units formally registered with the Surat Diamond Association. Diamond polishing is an interesting contrast to weaving. Like weaving, diamond units are small and labor-intensive, but the value of output is much higher. Perhaps for this reason, diamond firms in Surat invest substantially in air-conditioning.

Diamond polishing can be broadly classified into five distinct operations: (i) sorting and

[8]Some days have fewer shifts because of inadequate production orders or plant maintenance.

[9]These data were first used in Das et al. (2013), which also contains a detailed account of the production process in the mill.

grading, (ii) planning and marking, (iii) bruting, (iv) cutting, (v) polishing. Most firms perform all five operations, but to varying degrees. Smaller firms, for example, do more sorting and cutting and transfer the stones to larger firms for final polishing. Labor intensity also varies by unit and process. We asked each firm about their use of air-conditioning in each of the five operations listed above and the number of workers and machines used in each operation. They were also asked to rate, on a scale of 1-5, the importance of each of these processes to the quality of final output. We use these responses to estimate the probability of climate control investments as a function of the characteristics of different manufacturing processes.

Panel of Manufacturing Plants: The Annual Survey of Industry (ASI) is compiled by the Government of India. It is a census of large plants and a random sample of about one-fifth of the smaller plants registered under the Indian Factories Act. Large plants are defined as those employing over 100 workers.[10] The ASI provides annual data on output, working capital, input expenditures, and the numbers of skilled and unskilled workers employed. The format is similar to census data on manufacturing in many other countries.[11]

A drawback of the ASI from our perspective is that it excludes small manufacturing enterprises not registered under the Factories Act. These units contribute about 5% to Indian net domestic product and may have more limited means to adapt to temperature change.[12] The weaving units we study are an example. Plants surveyed in the ASI thus primarily inform us about temperature sensitivity within larger firms in the formal sector.

We create a panel of all manufacturing plants that appeared in the ASI data during the period

[10]For some areas of the country with very little manufacturing, the ASI covers all plants, irrespective of their size.

[11]See Berman, Somanathan, and Tan (2005) for a discussion on the measurement of variables in the ASI and its comparability with manufacturing data in other countries.

[12]This figure has been computed using data from the Central Statistical Organisation cited in Sharma and Chitkara (2006). The informal sector contributes 56.7% to net domestic product and about 9% of the sector's output comes from manufacturing enterprises.

1998-2008, with each plant matched to a district in India.[13] Details on panel construction and preliminary data-cleaning operations are described in the Appendix. Our final panel is unbalanced, with 39,763 plants in all of which 21,525 appear more than twice.

3.2 Meteorological Data

We match our daily micro-data from weaving, diamond and garment firms to climate data from public weather stations in the same city. We use temperature and humidity measures to compute daily WBGT. Rainfall (in mm) is available for most regions and is used as a control in our models. For NCR weather stations our rainfall measure is the fraction of hours reporting precipitation.

For the steel plant at Bhilai, public weather station data was unavailable for the period for which we have production data. For this plant, and for all those in the ASI panel, we rely on a $1° \times 1°$ gridded data product of the Indian Meteorological Department (IMD) which provides daily temperature and rainfall measurements based on the IMD's network of monitoring stations across the country. For Bhilai, we use the weighted average of grid points within 50 km of the plant, with weights inversely proportional to distance from the plant. For the ASI plants, we do not have exact plant co-ordinates and therefore estimate district average daily temperature and rainfall by averaging over grid points within the geographical boundaries of the district in which the plant is located.

A strength of these data is that they are from quality controlled ground-level monitors and not simulated from reanalysis models.[14] A limitation is that the IMD dataset does not contain measures of relative humidity and cannot be used to compute WGBT. In examining

[13]Districts are the primary administrative sub-division of Indian states. There were 593 districts in India at the time of the 2001 Census and plants are matched to a district following the 2001 census definition.

[14]See Auffhammer et al. (2013) for a discussion of some of the concerns that arise when using temporal variation in climate parameters generated from reanalysis data.

heat effects on output for the rail mill and for plants in the ASI panel, we therefore use only the dynamic variation in temperature and rainfall.[15]

4 Results

4.1 Worker Productivity

Given the physiological basis of heat stress, temperature effects on productivity should become apparent over fairly short periods of exposure. This makes daily data especially valuable in isolating heat stress from other climate factors, such as agricultural spillovers or demand shocks, that operate over longer time scales.

For weaving and garment units, we use the daily output measures described in Section 3 to estimate

$$log(Y_{id}) = \alpha_i + \gamma_M + \gamma_Y + \omega_W + \beta_k WBGT_{id} \times \mathrm{D_k} + \theta R_{id} + \epsilon_{id}. \tag{2}$$

Y_{id} denotes output produced by worker or sewing line i on day d. Fixed-effects for the i^{th} unit are α_i and $\gamma_M, \gamma_Y, \omega_W$ are fixed-effects for month, year and day of the week respectively. R_{id} is rainfall. Together, these control for idiosyncratic worker productivity levels and temporal and seasonal shocks. To capture non-linearities in the effects of heat-stress, we interact the daily wet bulb temperature, $WBGT_{id}$, with a dummy variable D_k for different temperature ranges. This allows us to separately estimate the marginal effect on output for a degree change in temperature within different temperature bins. We split the response curve into

[15]Table A.2 in the Appendix provides results from an alternative approach where we use humidity values from climate models and combine these with the IMD gridded temperatures to approximate WBGT for all districts.

four wet bulb globe temperature bins: $< 20°C$, $< 20°C - 25°C$, $< 25°C - 27°C$ and $\geq 27°C$. These breakpoints facilitate a comparison of our estimates with those in Hsiang (2010).

For the Bhilai rail mill we have three output measures per day corresponding to different shifts across which three worker teams are rotated. Since productivity varies across night and day shifts, we use a shift-day as our unit of observation and allow for nine team-shift fixed effects, α_{ts}. We do not observe hourly temperatures so all shifts in a particular day are assigned the average daily temperature.

Table 2 presents our estimates for temperature effects on worker output. Column 1 is for the rail mill, columns 2-4 for garment manufacturing lines and columns 5-6 for cloth output from weaving units. Estimates from climate-controlled plants are shaded. Columns 2 and 3 offer a within-firm comparison of units in the NCR with different levels of climate control. Column 4 presents data from garment plants located in the milder climate of Hyderabad in South India and Chhindwara in Central India. The most systematic declines in productivity are observed for the highest temperature bin. Above 27 degrees, a one degree change in WBGT is associated with productivity declines ranging from 3.7 percent for garment lines in the milder climate of South and Central India, to about 8 percent for garment lines and weaving units without climate control.

We also estimate the output-temperature relationship more flexibly using cubic splines with four knots positioned at the 20th, 40th, 60th and 80th quantiles of the temperature distribution at each location. Figure 1 shows the predicted impact of temperature on output using these spline fits. Output at 25 degrees is normalized to 100%. The pattern of these results is very similar to those in Table 2, although estimates are less precise.

The clearest evidence in support of the heat-stress hypothesis comes from a within-firm comparison of garment manufacturing units with different workplace temperatures. Production lines on floors without access to air-washers in the NCR show a sharp drop in output with

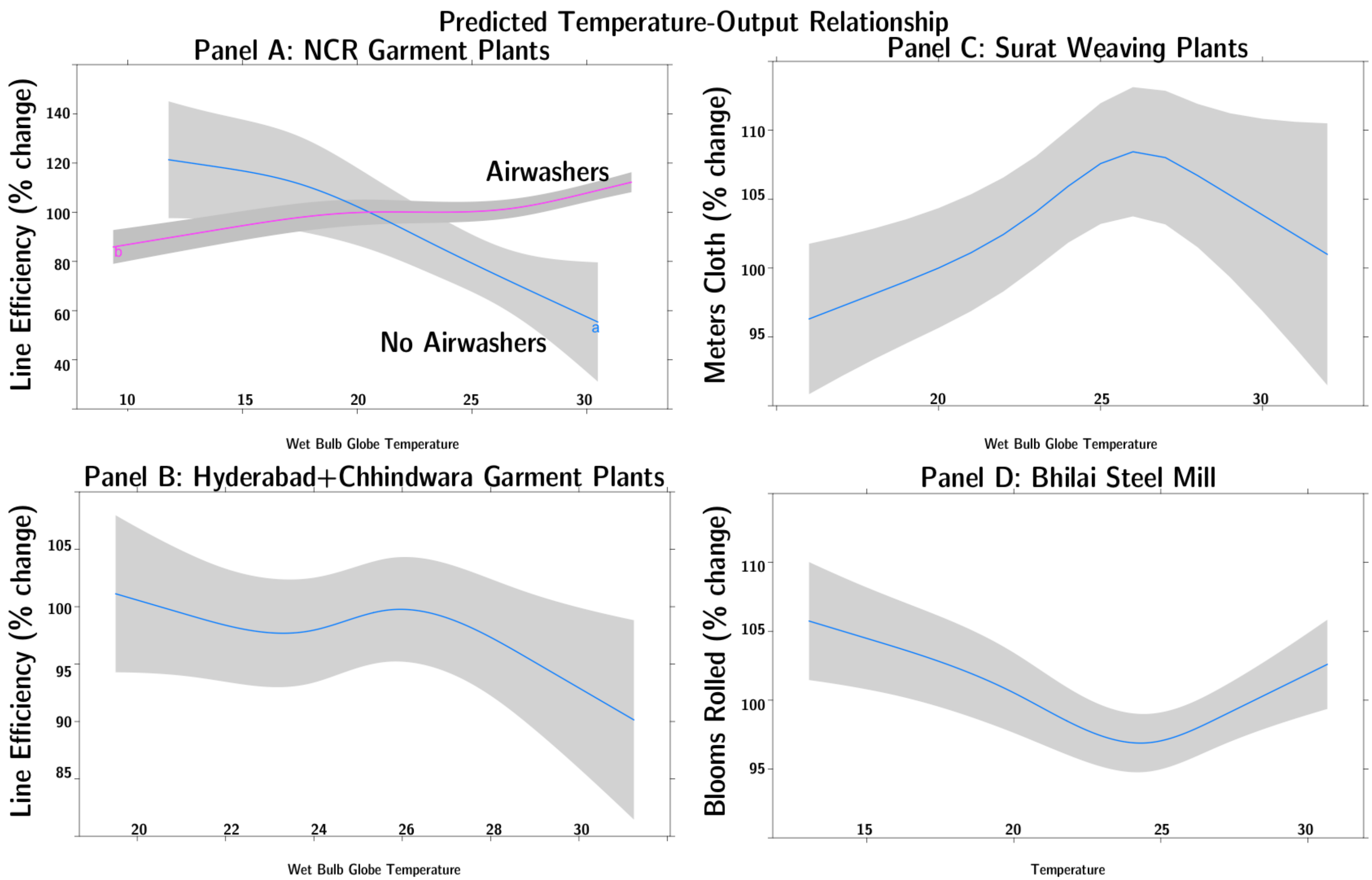

Figure 1: Restricted cubic spline models of the impact of temperature on output measures. Panel A: Logged efficiency in garment plants in NCR with airwashers (5 plants) and without airwashers (1 plant). Panel B: Logged efficiency for garment plant in Hyderabad and Chhindwara without air-washers. Panel C: Logged meters of cloth produced by weaving workers in Surat. Panel D: Rolled blooms against temperature (Bhilai Rail Mill). Note: 90 percent confidence intervals, output at 25 degrees normalized to 100 percent. Fits are linear at the tails.

increasing wet bulb globe temperatures in the highest temperature bin. Garment lines located in Hyderabad and Chhindwara - where air-washers were not installed - also show a drop in efficiency but the estimated response is smaller, most likely due to the moderate ambient temperatures in these areas relative to Delhi. The temperature effect disappears for units in the NCR with climate control.

In small weaving units of Surat, we find non-linear temperature effects similar to garment manufacturing in the NCR, except that higher temperatures influence garment output for a much wider temperature range than for weaving units, where heat effects are discernible only in the highest WBGT bin. Although these two work environments differ on many dimensions, part of the explanation may lie in the piece-rate contracts which push weaving workers to maintain output levels. In contrast we see no significant impact of high temperatures on output in the highly mechanized rail mill. The production of rails involves the heating and casting of steel which may be directly influenced by ambient temperatures even if there is no effect on workers. This may be one reason for the more complicated response function for the rail mill (Figure 1).

Note that the estimated effects of temperature on output cannot be explained by more frequent power outages on hot days. The data in all panels of Figure 1 comes from manufacturing settings with power backups. Additionally, for garment manufacturing in the NCR, we compare co-located plants for whom the incidence of power outages should be similar. Weaving plants reported that the electricity utility in Surat occasionally scheduled pre-announced weekly power holidays on Mondays. Any effect of such power outages, notwithstanding the availability of back-up power, is controlled for by the inclusion of fixed-effects for each day of the week.

4.2 Absenteeism

Research based on data from the United States has found that temperature influences labor-leisure tradeoffs and the allocation of time across indoor and outdoor activities (Zivin and Neidell, 2014). In the tropical, low-income environments we study, temperatures could influence hours worked and absenteeism both through voluntary time-allocation decisions and because sustained heat induces fatigue and changes the disease environment.

We were able to obtain detailed histories of worker attendance for all our micro-data sites other than the two garment plants in Hyderabad and Chhindwara. Using these absence records (described in Section 3), we construct a time series of total absences per day and use an exposure-response framework to model the relationship between attendance and temperature. We estimate:

$$log(A_{t_0}) = \alpha + \beta E_{t_0} + \gamma X_{t_0} + \epsilon_{t_0}. \tag{3}$$

A_{t_0} is the number of absences on day t_0, E_{t_0} is the accumulated heat exposure at time t_0 and X_{t_0} includes rainfall as well as month and day of week effects.

We use three different measures of exposure. Our simplest formulation uses only contemporaneous temperatures as a measure of exposure. Next, we set exposure equal to the mean of wet bulb globe temperatures experienced over the previous $k = 7$ days, thereby allowing lagged temperature histories to have cumulative effects on absenteeism. We estimate separate coefficients for different quartiles of weekly exposure measured in this way to allow for non-linearities in the exposure-response function. Our estimates of Equation 3 using these two measures are in Table 3.

We find heat exposure increases absenteeism for garment and rail mill workers. For the highest exposure quartile, a $1°C$ increase in the average weekly WBGT results in a 6 percentage point increase in absences for garment workers and a 10 percentage point increase for rail mill workers. In contrast, we see no absenteeism effects for weaving workers, perhaps because they earn no wages for days absent.

In our third and most flexible specification of exposure, the entire K-day history of temperature levels and the length of a hot spell together determine exposure levels. We estimate a non-linear distributed lag model, $E_{t_0} = \sum_0^K \tau_{wk} w_{t_0-k}$, where τ_{wk} is the weight attached to lag period k at the temperature level w.[16] Gasparrini (2013) describes how this class of models can be estimated with least squares using a composition of two functions f and g to transform a vector of observed temperature histories into exposure levels, $E_{t_0} = \sum_0^K f \cdot g(w_{t_0-k})$. Here g transforms temperatures based on their lag k and f maps the resulting output to derive total exposure. We use two independent third order polynomials to represent f and g, yielding a flexible non-linear model, and estimate parameters τ_{wk}.[17] The fitted model is then used to predict changes in absenteeism under different WBGT trajectories.

Figure 2 illustrates two scenarios for each of the three production processes we consider. The left column shows the predicted change in the logarithm of daily absences for a $1°C$ increase in WBGT, over a $25°C$ reference, sustained for k days, with k ranging from 1 to 10. In the right column, we plot predicted absenteeism for different temperature levels sustained over a ten day period. We find that longer hot spells increase absenteeism for both rail and garment workers (panels A and B). Absences increase at the rate of approximately 1 to 2 percent with every additional day of elevated temperatures. As with the simpler linear models of Table 3, absenteeism effects on daily wage weaving workers (Panel C) are not statistically different from zero. Interestingly, increased worker absenteeism is visible even where the work-place itself uses climate control. These investments therefore appear to allow only partial adaptation to the impact of temperature on labor. They mitigate productivity

[16] These models are an extension of distributed lag models which represent E_{t_0} as a weighted sum of temperatures so that $E_{t_0} = \tau_0 w_{t_0} + \tau_1 w_{t_0-1} + ... + \tau_K w_{t_0-K}$ with weights τ provided by some function of the lag period whose parameters can be estimated from the data. The non-linear DLM allows total exposure to be influenced by temperature levels w in addition to lag durations.

[17] Details on this procedure are found in Gasparrini (2013). We use the authors' code provided in the R package *dlnm* for estimation.

losses while at work but do not prevent temperature-related changes in attendance.

We include month fixed-effects in all our empirical models and our estimates therefore represent short-run temperature impacts. We do this to isolate the role of heat stress from other mechanisms and also because the result of long-run increases in temperature cannot be identified separately from other seasonal factors with the type of data sets we use. In the Appendix (Figure A.3), we show that there are seasonal changes in the availability of casual workers during high temperature months.

4.3 Investments in Climate Control

Concerns about heat effects on workers may be reflected in the pattern of investments in climate control technologies. We survey diamond polishing units and find both frequent use of air-conditioning and also substantial variation in its availability across different production areas within the same plant. We use data from 750 processes in our 150 firms to estimate the probability of using air-conditioning for a process as a function of its (i) the labor-intensity (ii) mechanization and (iii) importance in determining stone quality. The first of these variables is measured by the share of the firm's workers engaged in the process, the second by the share of the plant's machines used, and the third is a purely self-reported assessment by management. As controls, we use the total number of workers to proxy for firm size, and the years since the first air-conditioning investment.

Figure 3 summarizes our results. We find that diamond polishing units in Surat choose to preferentially cool high value and labor-intensive processes. Our results are similar when we include firm fixed- effects and thereby identify investment decisions by relying only on the variation across process areas within plants. It is possible that investing in air-conditioning reflects a form of compensation to attract higher quality workers rather than an effort to offset negative temperature impacts. This explanation seems unlikely in this setting because wages

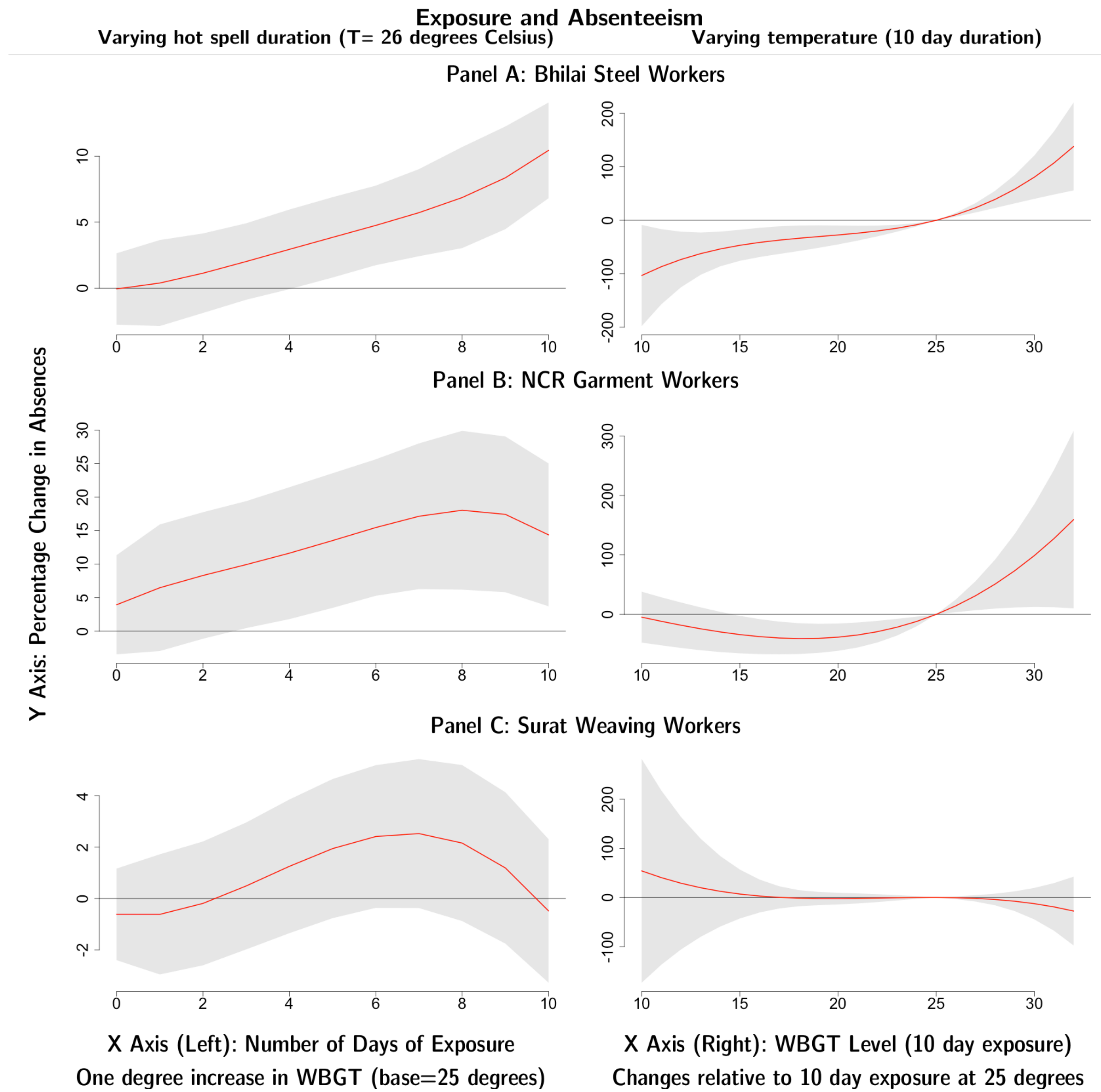

Figure 2: Predicted impact of wet bulb globe temperature on attendance measures for rail mill workers (Panel A), garment workers (Panel B) and workers in weaving firms (Panel C). Left column plots predicted percentage change in absenteeism under a one degree temperature increase sustained for varying periods of time. Right column plots predicted percentage change in absenteeism for different temperature levels sustained for 10 days (relative to levels corresponding to 25 degrees WBGT experienced for 10 days). 90 percent confidence intervals estimated assuming normal residuals.

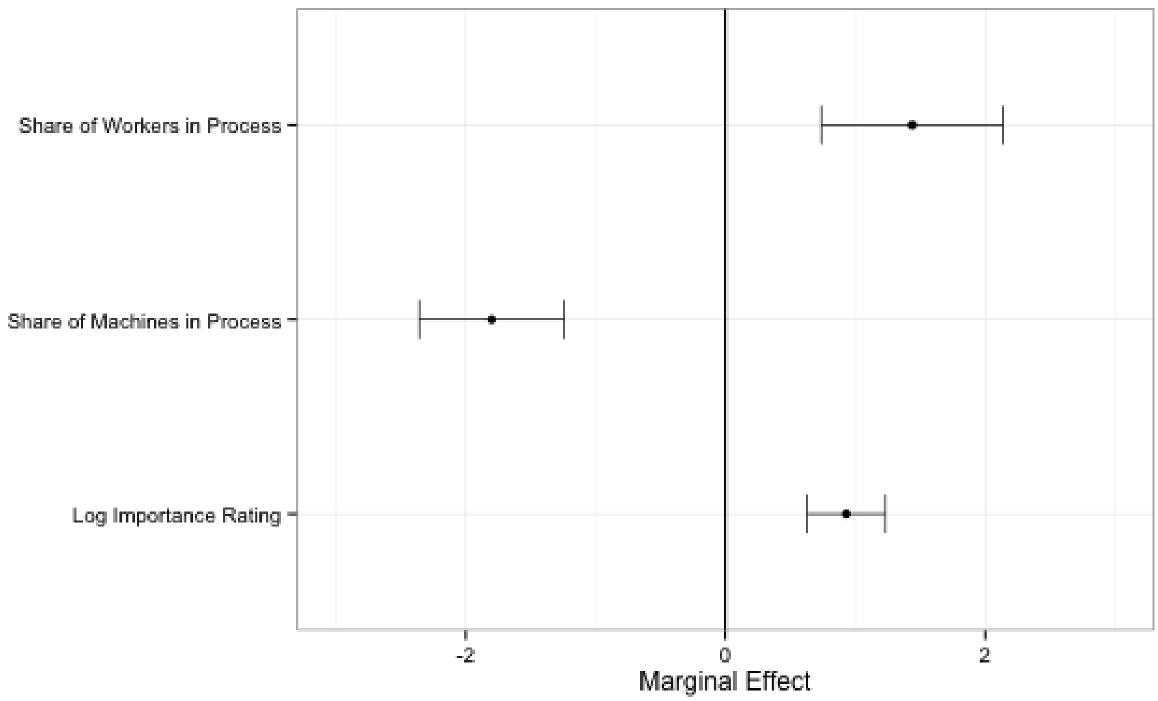

Figure 3: Marginal effect of covariates on probability of seeing climate control for a single process within the diamond production line. Bootstrapped robust standard errors. Estimated using data on 750 processes across 150 firms.

are low, workplace activities are not physically taxing and workers move between different production areas. Wage increases would probably be preferred to equivalent expenditures on air-conditioning.

4.4 Annual Manufacturing Output

We use our panel of manufacturing plants from the Annual Survey of Industry (ASI) to examine whether the temperature effects estimated from micro-data persist in the long run and whether they characterize the manufacturing sector as a whole rather than just the industries for which we were able to obtain worker data.

With the national panel our output measure is the value of annual - as opposed to daily - plant output (Section 3). However we do observe temperatures for every day within the year and can use these to generate a version of Equation 2 based on aggregated data. Denote by $V(T_d)$, the monetary value of plant output as a function of daily temperature, T_d, and assume that the non-linear response of output to temperature can be approximated by the following continuous piecewise linear function:

$$\bar{V}(T_d) = \bar{V} + \theta X + \sum_{k=1}^{N} \beta_k D_k(T_d). \tag{4}$$

$\bar{V}$ is a plant intercept term and θX includes covariates other than temperature that influence output. $D_k(T_d)$ is the number of degree days within temperature bin k for day d and are often used to summarize temperature distributions (Jones and Olken, 2010). Their construction is best explained with the following example. If we have three temperature bins, $T \leq 20°C$, $T \in [20°25°)$, $T \geq 25°C$, then a day with a mean temperature of 23 degrees contributes 20 degrees to the first bin, 3 degrees to the second bin and 0 degrees to the third bin. Using this definition of D_k, the coefficient β_k measures the linear effect (slope) of a one degree change in temperature on output, within the kth temperature bin.

Equation 5 is an aggregated version of this daily relationship, which can be taken to the data:

$$V_{it} = \alpha_i + \gamma_t + \omega K_{it} + \sum_{k=1}^{N} \beta_k D_{itk} + \phi W_{it} + \theta R_{it} + \epsilon_{it}, \tag{5}$$

Here V_{it} is the value of output produced by plant i during financial year t, α_i is a plant fixed effect, γ_t are time fixed effects capturing aggregate influences on manufacturing in year t, K_{it} is total working capital at the start of year t, W_{it} is the number of workers and R_{it} is rainfall in millimeters. We use working capital available to the plant at the start of the financial year as a control rather than actual input expenditures because the latter may respond to temperatures experienced during the year and to realized labor productivity. For example, lower labor productivity is likely to be accompanied by lower raw material use. D_{itk} is the number of degree days in year t that lie in temperature bin k, calculated for the district in which plant i is located. We use degree days within the three temperature bins given in the above example to summarize the annual temperature distribution. [18] If heat stress causes output declines, we would expect β_k to be close to zero for moderate temperatures (or even positive for low temperatures) while for higher degree-day bins we should see negative coefficients.

We estimate Equation (5) using both the level of output as well as log output as outcome variables. Results are in Table 4. For output levels, coefficients are expressed as proportions of the average output level. Columns (1) and (3) contain estimates from our base specification. Columns (2) and (4) include the total number of workers, W_{it}, as an additional control. These are not our preferred estimates because employment data is both less complete and may contain measurement errors.[19]

The results provide clear evidence of non-linear temperature effects. Output declined by between 3 and 6 per cent per degree above 25°C, depending on the specification used. For comparison with the literature, we also estimate a linear model and report results in the Appendix in Table A.1. For the most conservative specification, with both capital and worker controls, we estimate a 3.1 percent decrease in output for a one degree change in average annual temperature. Dell, Jones, and Olken (2012) find a 1.3% decrease in GDP per degree change in annual temperature in countries that were below the global median GDP in 1960, while Hsiang (2010) finds the corresponding number to be 2.4% in the Caribbean and Central America.

Based on our results from micro-data, we expect heterogeneous impacts of high temperatures,

[18] Maximum temperatures are on average 6 °C higher than mean temperatures so a day with a mean temperature of 25 °C can imply a substantial portion of time with ambient temperatures above 30 °C.

[19] Employment numbers are frequently missing in the ASI data. Plants may also under-report labor to avoid the legal and tax implications associated with hiring workers.

with the biggest production declines in manufacturing plants with high labor shares and limited climate control. To investigate these relationships in our panel, we calculate for each plant in our dataset, the output share of wages for each year and also the ratio of electricity expenditures to total cash on hand at the start of the year. We use electricity consumption as an imperfect proxy for climate control, which is typically quite electricity intensive, since we do not observe such investments directly as we did for our four industry case studies. We then classify our plants by the quartile to which they belong on each of these measures, interact these quartile dummies (Q_i) with mean temperature and estimate Equation (6) to examine whether temperature effects are heterogeneous in the manner we expect. We estimate the following model separately for labor shares and electricity quartiles:

$$V_{it} = \alpha_i + \gamma_t + \omega K_{it} + \beta T_{it} \times Q_i + \theta R_{it} + \epsilon_{it} \tag{6}$$

Results are in Table 5. Consistent with our previous results, we find that output from plants with higher labor shares is more strongly affected by temperature and that those with greater electricity consumption appear less vulnerable.

In using annual plant output data, we might be concerned about other pathways by which temperature may affect output. For example, temperature shocks might change the prices of plant inputs, especially those coming from agriculture. It may also be that temperatures lead to power outages which lower output. We perform the two following exercises to eliminate these explanations as primary drivers of the temperature effects we observe.

Although most price shocks should be captured by year fixed-effects, there may be local price changes that vary with local temperatures and affect only local inputs. The ASI surveys allow us to investigate this to a limited degree. 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 average price across the three most common inputs used by each plant. We use this index as the dependent variable in a fixed-effects model similar to Equation (5). We find no evidence that input prices change in high temperature years after controlling for year fixed effects. These results are in Appendix Table A.3.

For power supply, we control for the probability of outages using a measure of state-year outage probabilities for India constructed in Allcott, Collard-Wexler, and O'Connell (2014). We find our point estimates across temperature bins remain very similar (Appendix Table A.3).

5 The Economic Costs of Gradual Warming

The Indian Meteorological Department has documented a gradual warming trend across most parts of the country (IMD, 2015). We calculate mean annual temperatures for a five year baseline period between 1971-1975 and for a five year period from 2005-2009. Over this time average temperatures have risen by 0.91 degrees across India. Combining this with the estimated mean effect of temperature on output from the nation-wide ASI panel (3.4 percent reduction per degree from Column 4 of Table A.1), we estimate that observed warming in the last three decades may have reduced manufacturing output by about 3 percent. The manufacturing sector contributed about 15 percent of India's GDP in 2012 (about 270 billion USD), so a 3 percent decline in output implies an economic loss of over 8 billion USD annually relative to a no-warming counter-factual.

This may be an underestimate of the full costs imposed by temperature changes in recent years because it ignores the adaptive actions undertaken over this period. These would include air conditioning, shifting manufacturing to cooler regions, urban planning measures designed to lower local temperatures (green cover, water bodies), building design modifications (cool roofs) and so on. Adaptation could also include techniques to reduce the intensity of work, or the use of economic incentives to encourage worker effort. Recent work also suggests adaptive possibilities from the use of LED lighting (Adhvaryu, Kala, and Nyshadham, 2014). These measures are typically neither easy nor costless.

Measures of warming also do not sufficiently account for the presence of urban heat islands. Heat island effects in urban areas have already led to local temperatures more than five degrees warmer than surrounding areas (Mohan et al., 2012; Zhao et al., 2014). Since many manufacturing units are located in these urban hotspots, this type of surface warming is likely to significantly influence realized productivity.

Historical temperature changes aside, the economic impact of warming due to climate change is likely to be greatest in regions of the world that also have relatively high humidity. Panel A of Appendix Figure A.4 reproduces a map of annual wet bulb temperature maximums from (Sherwood and Huber, 2010). Indian summers are among the hottest on the planet, along with those in the tropical belt and the eastern United States. The areas in red in Figure A.4 all experience maximum wet bulb temperatures that are above $25°C$. This suggests that - absent adaptation - an increase in the frequency or severity of high WBGT days might rapidly impose large productivity costs in these regions. Recent temperature projections for India, under business-as-usual scenarios (specifically, the IPCC Representative Concentration Pathway scenarios, RCP 6.0 and RCP 8.5), suggest that mean warming in India is likely to be in the range of $3.4°C$ to $4.8°C$ by 2080 (Chaturvedi et al., 2012).

6 Conclusions

Extreme events excepted, the economic impact of global warming has been documented mostly through its effect on agricultural output, where high temperatures are associated with low crop yields. The Fifth Assessment Report of the Intergovernmental Panel on

Climate Change (Field et al., 2014) acknowledges that 'Few studies have evaluated the possible impacts of climate change on mining, manufacturing or services (apart from health, insurance, or tourism)'. Our main objectives in this paper were to investigate the importance of temperature on workplace productivity in manufacturing tasks which do not typically involve heavy physical labor or outdoor exposure, and to examine the mechanisms by which temperature effects occur.

We have used primary micro-data collected from a variety of work environments in India to show that elevated wet bulb globe temperatures can have economically significant effects on worker productivity and labor supply. Our use of daily data for identification rules out all mechanisms other than those that operate over a short time span. By examining plants with back-up power supply, we also eliminate power outages as a plausible alternative to heat stress.

The net economic costs due to heat stress will depend on how much adaptation takes place and at what cost. We have shown that climate control appears effective in breaking the relationship between ambient temperatures and workplace productivity but not necessarily between temperature and absenteeism. Since adaptation can be costly, we should expect selective adoption. We have documented variable adoption of climate control across sectors, firms and even within firms.

Greater exposure to high temperatures in the workplace and outside it seem inevitable, especially, though not exclusively, in the emerging countries of the tropical world, both through climate change and heat islands caused by rapid urbanization. Climate change projections for India, under business-as-usual scenarios, predict warming in the range of $3.4°C$ to $4.8°C$ by 2080 (Chaturvedi et al., 2012) and satellite images of Indian metropolitan areas show the presence of urban hotspots with temperature elevations of greater than five degrees celsius (Mohan et al., 2012).

The potential ramifications of our findings are large. While our study examines only the manufacturing sector in India, the conclusion that a physiological mechanism is at work implies that effects may be seen wherever human labor is important in the production process, the ambient temperature is high, and climate control is expensive or infeasible. Temperature impacts on worker productivity may be even more pronounced and widespread in sectors such as agriculture and construction across the world, because exposure may be higher and adaptation possibilities more limited. Observed productivity losses in agriculture that have been attributed by default to plant growth responses to high temperatures may in fact be partly driven by lower labor productivity. These possibilities are yet to be researched.

Table 1: Summary of data sources used

Data Source	Location	Type	Unit (# of obs)	Main Dependent Variable	Time Period	Climate Control
Weaving Plants	Surat	Panel	Worker (147)	Cloth Woven (Meters), Attendance	365 days	No
Garment Manufacture	NCR, Hyderabad, Chhindwara	Panel	Sewing Line (103)	Operations Completed (Efficiency), Attendance	730 days	Partial (74 lines)
Steel Rail Mill	Bhilai	Panel	Shift-Team (9)	Blooms Rolled, Attendance	3339 days (Production), 857 days (Attendance)	Yes
Diamond Cutting	Surat	Cross-Section	Process-Plant (750)	Process Characteristics (Labor, Machines, AC)		Partial
Annual Survey of Industry	National	Panel	Plant (39,763)	Plant Output	11 years	
Weather Stations	Surat, Delhi, Hyderabad, Nagpur	Match daily temperature and precipitation data for all except ASI plants and Bhilai				
IMD Gridded Data	National	Match ASI plants and Bhilai to daily temperature and precipitation measures				

Table 2: Effect of Wet Bulb Globe Temperature on Daily Output

	Dependent variable:					
	Rail Mill	Garment Manufacture Plants			Weaving Plants	
	log(blooms)	log(efficiency)	log(efficiency)	log(efficiency)	log(meters)	meters
	(1)	(2)	(3)	(4)	(5)	(6)
(1) rainfall	0.001^{***}	0.083^{**}	0.044	−0.067	0.006	1.512
	(0.0002)	(0.030)	(0.192)	(0.035)	(0.008)	(0.958)
(2) log(budgeted efficiency)		0.796^{***}	0.421^{***}	0.525^{***}		
		(0.034)	(0.126)	(0.044)		
(3) WBGT:[<20]	-0.008^{*}	0.014^{***}	-0.026^{***}	−0.15	0.001	0.530
	(0.003)	(0.004)	(0.007)	(0.097)	(0.008)	(0.596)
(4) WBGT:[20-25)	−0.0002	-0.014^{**}	-0.064^{***}	−0.004	0.008	1.700^{**}
	(0.005)	(0.007)	(0.020)	(0.009)	(0.008)	(0.813)
(5) WBGT:[25-27)	0.011^{*}	0.029^{**}	-0.149^{***}	0.004	−0.012	−0.417
	(0.006)	(0.014)	(0.026)	(0.020)	(0.013)	(1.091)
(6) WBGT:[≥27]	0.016	0.001	-0.087^{***}	-0.037^{**}	-0.077^{**}	-6.722^{**}
	(0.011)	(0.007)	(0.024)	(0.016)	(0.033)	(2.803)
Number of Plants	1	5	1	2	3	3
Number of Observations	9,172	23,827	621	6,073	53,655	53,655
Climate Control	Y	Y	N	N	N	N
Location	Bhilai	NCR	NCR	Hyderabad	Surat	Surat

Notes: 1. Shaded columns represent sites with climate control; 2. Observations refers to the total number of worker-days (weaving), line-days (garments) or shift-days (steel); 3. Arellano-Bond cluster robust errors (Arellano, 1987); 4. All models include fixed effects for workers (weaving) or lines (garments) or shift-teams (steel) and month, year and day-of-week fixed effects; 5. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 3: Effect of Temperature on Absenteeism

	Dependent variable: log(Absences)					
	Rail Mill		Garment Manufacture		Weaving	
	(1)	(2)	(3)	(4)	(5)	(6)
WBGT	0.032***		0.014*		0.012	
	(0.010)		(0.008)		(0.012)	
Weekly WBGT						
x Q1		0.051*		0.025		0.014**
		(0.030)		(0.018)		(0.006)
x Q2		0.042		−0.044*		−0.009
		(0.037)		(0.024)		(0.013)
x Q3		0.073		0.006		0.017
		(0.048)		(0.026)		(0.025)
x Q4		0.097***		0.059***		0.015
		(0.034)		(0.009)		(0.035)
rainfall	0.002	0.001	0.45***	0.51***	0.027	−0.001
	(0.002)	(0.002)	(0.17)	(0.17)	(0.029)	(0.007)
Days	857	857	662	662	365	365
Workers	198	198	2700	2700	147	147

Notes: 1. All models include month, year and day-of-week fixed effects; 2. Arellano-Bond cluster robust errors (Arellano, 1987); 3. Q1-Q4 refer to quartiles of weekly WBGT; 4. Rainfall control for NCR workers is the fraction of hours with recorded precipitation and for other models is measured in mm of rain; 5. *p<0.1; **p<0.05; ***p<0.01

Table 4: Non-Linear Effect of Temperature on Manufacturing Industry Output

	Dependent variable:			
	Plant Output Value		Log Plant Output	
	(1)	(2)	(3)	(4)
Below 20°C	0.022	0.029	−0.024	−0.026
	(0.025)	(0.024)	(0.021)	(0.020)
20°C to 25°C	−0.057**	−0.054**	−0.032	−0.027
	(0.025)	(0.024)	(0.020)	(0.019)
Above 25°C	−0.061***	−0.052***	−0.039***	−0.033***
	(0.015)	(0.014)	(0.012)	(0.011)
rainfall	0.005**	0.003	0.001	0.002
	(0.002)	(0.002)	(0.002)	(0.001)
capital	0.380***	0.341***		
	(0.009)	(0.009)		
log(capital)			0.373***	0.299***
			(0.006)	(0.005)
workers		0.002***		
		(0.0001)		
log(workers)				0.409***
				(0.007)
Worker Controls	N	Y	N	Y
Units	39,763	39,763	39,763	39,763
R^2	0.245	0.287	0.198	0.272

Notes: 1. All models include plant, year fixed effects, capital controls; 2. Arellano-Bond cluster robust errors (Arellano, 1987); 3. *p<0.1; **p<0.05; ***p<0.01

Table 5: Heterogeneity in the association of output with temperature (by wage share and electricity intensity)

	A: Wage Share Quartiles	*B: Electricity Expenditure Quartiles*
	plant output	plant output
	(1)	(2)
Mean Temperature	−0.041***	−0.065***
	(0.012)	(0.013)
Mean Temperature X		
Quartile 2	−0.006	0.019***
	(0.006)	(0.005)
Quartile 3	−0.017***	0.033***
	(0.007)	(0.007)
Quartile 4	−0.026***	0.036***
	(0.008)	(0.008)
Number of Units	39,763	39,763
R^2	0.293	0.254

Notes: 1. All models include plant and year fixed effects, rainfall and capital controls; 2. Arellano-Bond cluster robust errors (Arellano, 1987); 3. *p<0.1; **p<0.05; ***p<0.01

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Appendix: For Online Publication

A.1 Annual Survey of Industry Data Cleaning

For years between 1998-99 to 2007-08, two versions of the ASI survey data were made available by India's Ministry of Statistics and Programme Implementation. The first is a panel dataset containing plant identifiers without district identifiers. The second is a repeated cross-section containing district codes without plant identifiers. We purchased both versions and matched observations to generate a panel with district locations for each plant. This allows us to match each plant to weather data that is available at the level of a district. Our final sample has 39,763 manufacturing units distributed all over India (21,525 of which are observed in at least 3 years) and spanning all major manufacturing sectors (Figure A.1).

The following data-cleaning operations are performed on the merged ASI data to arrive at the panel dataset used in our analysis:

1. We restrict the sample to surveyed units that report NIC codes belonging to the manufacturing sector.

2. We set to missing the top 2.5 percent and bottom 2.5 percent of the distribution output value, total workers, price index, cash on hand at the opening of the year and electricity expenditures. This is done to transparently eliminate outliers since the ASI dataset contains some firms with implausibly high reported values of these variables and also many plants with near zero reported output.

3. We remove a small number of manufacturing units that report having less than 10 workers employed. 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.

4. We mark as missing all observations with zero or negative values of output, capital, workers or raw materials used and remove duplicated year-firm ID pairs.

5. We drop plants where district locations change over the panel duration and drop observations not in the manufacturing sector.

A.2 Weaving Workers Data Cleaning

Output data for weaving workers was obtained by digitizing payment slips for three firms. We found some instances of payment slips reporting very low or zero cloth woven in the day or of implausibly high levels of output. We therefore trim the bottom and top 2.5 percent of daily output measures (corresponding in the data to 3 meters of cloth as a lower bound and 346 meters of cloth as an upper bound).

A.3 Additional Results

Annual Average Temperature and Manufacturing Output

The model in Equation 5 allows for a non-linear (or piece-wise linear) output response to temperature using four temperature bins. Here we present results from the simpler linear specification. Much of the country-level literature estimates a linear model because degree days cannot be computed for all countries. The estimates in this section facilitate a comparison of our findings with other studies. We estimate the following model:

$$V_{it} = \alpha_i + \gamma_t + \omega K_{it} + \phi W_{it} + \beta T_{it} + \theta R_{it} + \epsilon_{it} \tag{7}$$

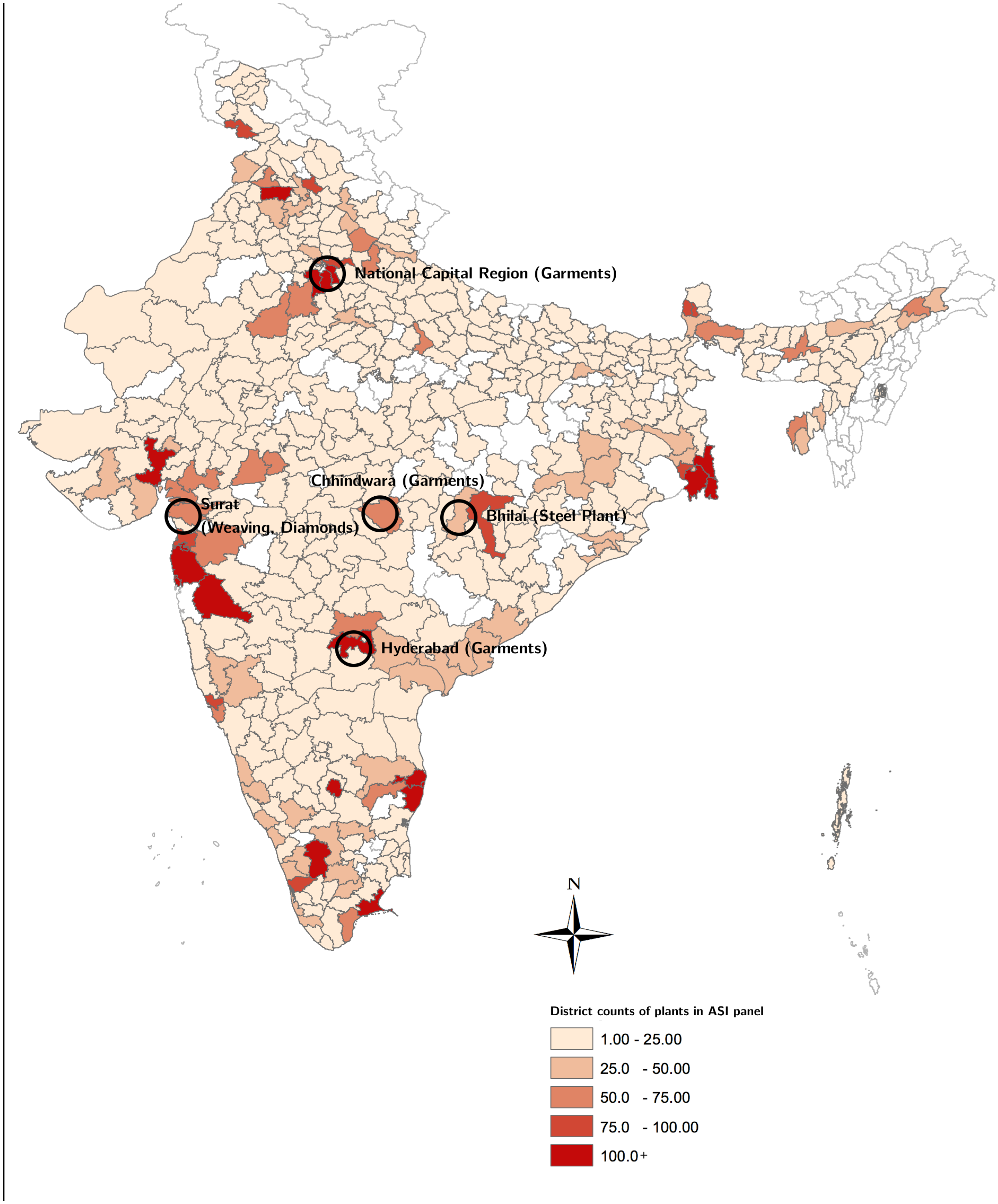

Figure A.1: Distribution of ASI plants over Indian districts and location of micro-data sites

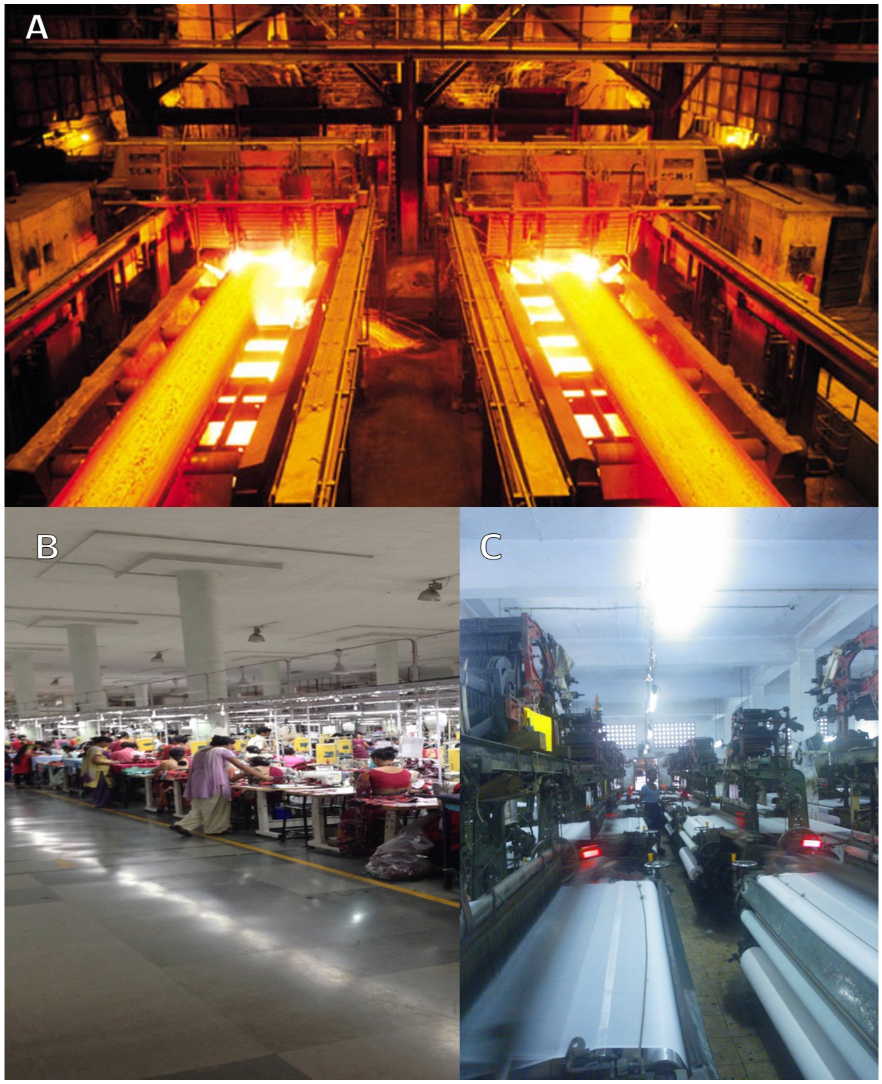

Figure A.2: Production floor images from A: Rail mill, B: Garment manufacture plants, C: Weaving units

where T_{it} is the average temperature during the financial year t (April 1 through March 31) and the other variables are as in (5). Estimates are in Table A.1.

Using estimated WBGT with the ASI panel

The impact of temperature degree days on output in Table 4 used temperature data rather than WBGT because measures of relative humidity are not available for all districts over the ten year period covered by our manufacturing plant panel. An alternative is to approximate

Table A.1: Effect of Temperature on Manufacturing Industry Output

	Dependent variable:				
	Plant Output Value			Log Plant Output Value	
	(1)	(2)	(3)	(4)	(5)
Annual Average Temperature	$-.046^{***}$	-0.045^{***}	-0.040^{***}	-0.034^{***}	-0.031^{***}
	(0.012)	(0.011)	(0.011)	(0.009)	(0.009)
rainfall	0.007^{**}	0.004^{*}	0.003	0.002	0.002
	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)
capital		0.380^{***}	0.342^{***}		
		(0.009)	(0.010)		
log(capital)				0.373^{***}	0.299^{***}
				(0.006)	(0.005)
workers			0.002^{***}		
			(0.0008)		
log(workers)					0.409^{***}
					(0.007)
Capital Controls	N	Y	Y	Y	Y
Worker Controls	N	N	Y	N	Y
Units	39,763	39,763	39,763	39,763	39,763
R^2	0.0076	0.4615	0.4876	0.6705	0.6595

Notes: 1. All models include plant and year fixed effects; 2. Arellano-Bond cluster robust errors (Arellano, 1987); 3. Coefficients for models 1-3 are expressed as percentages of average output level; 4. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

WBGT using estimates of average daily relative humidity from reanalysis models. This is not our preferred approach since reanalysis datasets are not normally calibrated to accurately estimate relative humidity - certainly not on a daily basis - and therefore this approach may increase rather than decrease measurement error, particularly since our estimation relies on temporal variation rather than cross-sectional comparisons.

Nevertheless these results make for a useful robustness check. Table A.2 presents results from models similar to those in Table A.1 using estimated WBGT measures calculated using Equation 1 and using daily long run average measures of relative humidity from the NCEP/ NCAR reanalysis datasets. Note that this output provides an average measure for each day but not temporal variation from year to year. This may be preferable in our context since this means temporal variation is still driven by the better measured temperature parameters. At the same time absolute temperatures are re-weighted across days of the year and across spatial locations to account for varying relative humidity levels.

Price Shocks and Power Outages

In this section we examine two mechanisms other than heat stress that might potentially account for the temperature-output link in the ASI data (reported in Table 4). We check robustness of the temperature effect to the inclusion of a control for power outage and examine whether local input prices respond to local temperature shocks. Table A.3 reports both results.

Column 1 provides results for a regression of a price index computed for each plant on temperature (controlling for plant fixed effects). Formally we estimate the model below where $P_{i,t}$ is the log of the plant input price index and other variables are the same as in Equation 7.

Table A.2: Effect of Wet Bulb Globe Temperature on Manufacturing Industry Output

	Dependent variable:				
	Plant Output Value			Log Plant Output Value	
	(1)	(2)	(3)	(4)	(5)
Annual Wet Bulb Globe Temperature	$-.050^{***}$	-0.051^{***}	-0.043^{***}	-0.038^{***}	-0.032^{***}
	(0.015)	(0.014)	(0.014)	(0.012)	(0.011)
rainfall	0.008^{**}	0.004^{*}	0.003	0.003^{*}	0.002
	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)
capital		0.380^{***}	0.341^{***}		
		(0.009)	(0.009)		
log(capital)				0.373^{***}	0.299^{***}
				(0.006)	(0.005)
workers			0.002^{***}		
			(0.0001)		
log(workers)					0.409^{***}
					(0.007)
Capital Controls	N	Y	Y	Y	Y
Worker Controls	N	N	Y	N	Y
Units	39,763	39,763	39,763	39,763	39,763
R^2	0.0076	0.4615	0.4876	0.6705	0.6595

Notes: 1. All models include plant and year fixed effects; 2. Arellano-Bond cluster robust errors (Arellano, 1987); 3. Coefficients for models 1-3 are expressed as percentages of average output level; 4. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

$$P_{it} = \alpha_i + \gamma_t + \omega K_{it} + \sum_{k=1}^{N} \beta_k D_k + \phi W_{it} + R_{it} + \epsilon_{it} \tag{8}$$

Note that the price index P_{it} is created only for ASI plants where input price data was reported. The price index is computed by averaging reported prices for the three most important reported inputs for each plant in each year and taking the log of the resulting price. Input price information is missing in about 28 percent of survey responses. In addition we also drop the top 2.5 percent and bottom 2.5 percent of plants within the computed input price distribution to remove outliers with very low or high reported input prices.

To control for power outages we download data made publicly available by (Allcott, Collard-Wexler, and O'Connell, 2014) and reproduce their proxy measure of state-year power outages that they construct from panel data on state-wise assessed demand and actual generation reported. We use this as a control for the intensity of power outages that might be experienced by all plants in a state and introduce this as an additional control in a specification similar to Equation 5. As Table A.3, Column 2 makes clear, our temperature response estimates seem robust to the addition of the outages control.

Seasonal Patterns in Absenteeism

Interviews with weaving firm managers in Surat revealed that hiring daily wage workers for industrial work during the summer months was difficult. Managers claimed that during the hottest months, daily wage workers preferred to go home to their villages and rely on income from the National Rural Employment Guarantee Scheme rather than work under the much more strenuous conditions at the factory. Some owners said they were actively considering the possibility of combating this preference for less taxing work by temporarily raising wages through a summer attendance bonus.

Table A.3: Testing for price shocks and robustness to power outages

	Dependent variable	
	Input Price Index	*Log Plant Output*
	(1)	(2)
Below 20°C	0.044	−0.018
	(0.085)	(0.024)
20°C to 25°C	0.125	−0.028
	(0.078)	(0.023)
Above 25°C	0.066	-0.035^{**}
	(0.048)	(0.015)
rainfall	0.004	0.003^{*}
	(0.006)	(0.002)
power outages		−0.044
		(0.079)
Number of Units	39,763	39,763
R^2	0.685	0.202

Notes: 1. All models include plant and year fixed effects and capital controls; 2. Arellano-Bond cluster robust errors (Arellano, 1987); 3. Outages measure is a state level proxy as estimated in Allcott, Collard-Wexler, and O'Connell (2014); 4. *p<0.1; **p<0.05; ***p<0.01

Figure A.3 in the Appendix suggests there may be some truth to this narrative. We see seasonal reductions in the attendance of daily wage weaving workers (Panel A), concentrated in high temperature months. These seasonal patterns are absent for the garment workers who have long term employment contracts (Panel B). It is possible that formal employment contracts - while reducing the costs to taking an occasional day of leave - significantly increase the opportunity cost of switching occupations for extended periods of time. Thus, when accounting for possible longer term responses to temperature, formal employment contracts might do better at retaining labour than daily wage arrangements. This is an area that would benefit from further research.

Climate Model Forecasts for India

Panel A of Appendix Figure A.4 reproduces a map of annual wet bulb temperature maximums from (Sherwood and Huber, 2010). It is seen that Indian summers are among the hottest on the planet, along with those in the tropical belt and the eastern United States.

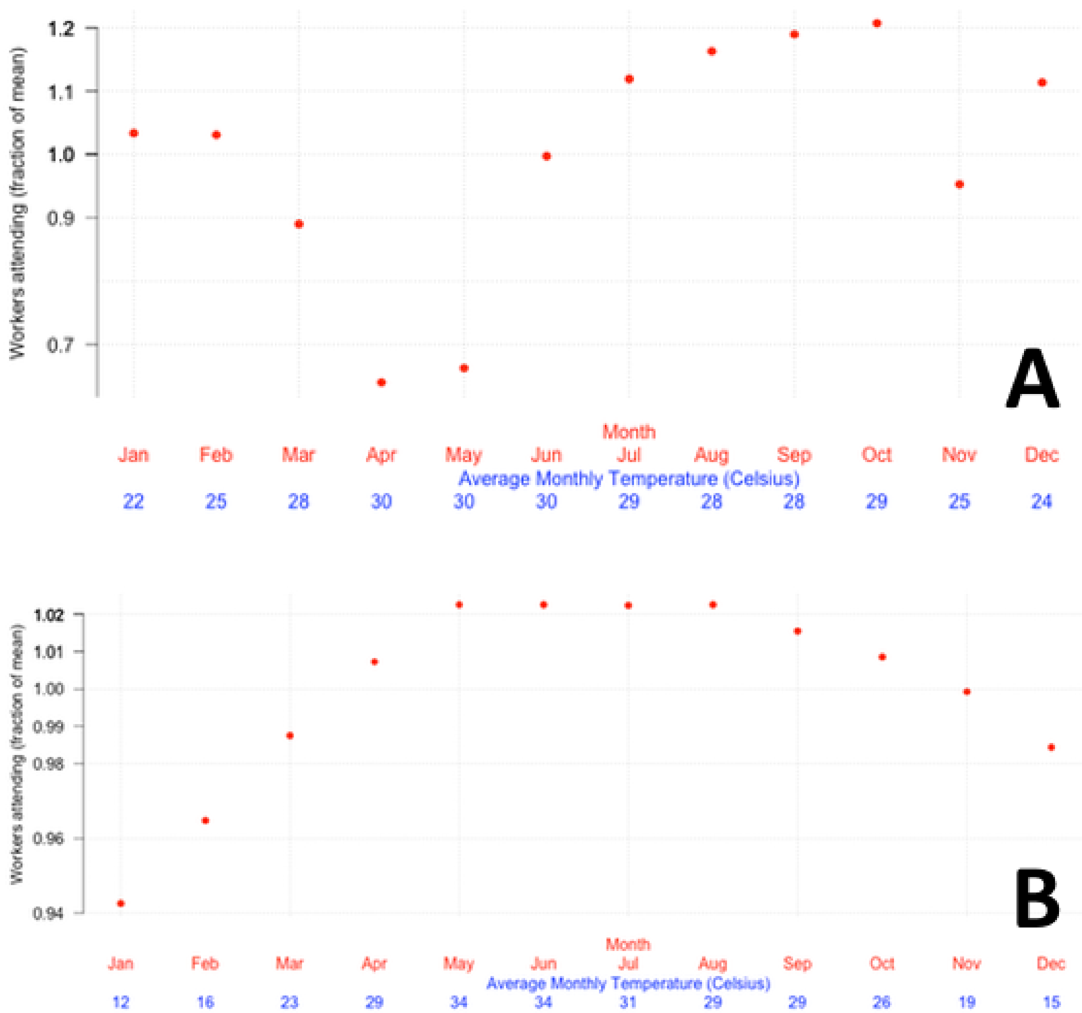

Figure A.3: Worker attendance by month for daily wage workers in weaving units (Panel A) and regular workers in garment manufacture units (Panel B)

The areas in red in Figure A.4 all experience maximum wet bulb temperatures that are above $25°C$. This suggests that - absent adaptation - an increase in the frequency or severity of high WBGT days might rapidly impose large productivity costs in these regions. Recent temperature projections for India, under business-as-usual (between RCP 6.0 and RCP 8.5) scenarios, suggest that mean warming in India is likely to be in the range of $3.4°C$ to $4.8°C$ by 2080.

Panel B of Figure A.4, (left axis), plots projections of the long run change in the annual temperature distribution for India from two climate models: (i) the A1F1 ”business-as-usual” scenario of the Hadley Centre Global Environmental Model (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. As is evident, the predicted increase in degree days is concentrated in the highest temperature bins. We overlay (right axis of Panel B of Figure A.4) our estimated marginal effects of temperature on manufacturing output using the ASI data from Table 4 (column 1). The temperature range where we estimate significant negative productivity impacts from an additional degree day is precisely the range where the largest increases in degree days are predicted by climate models.

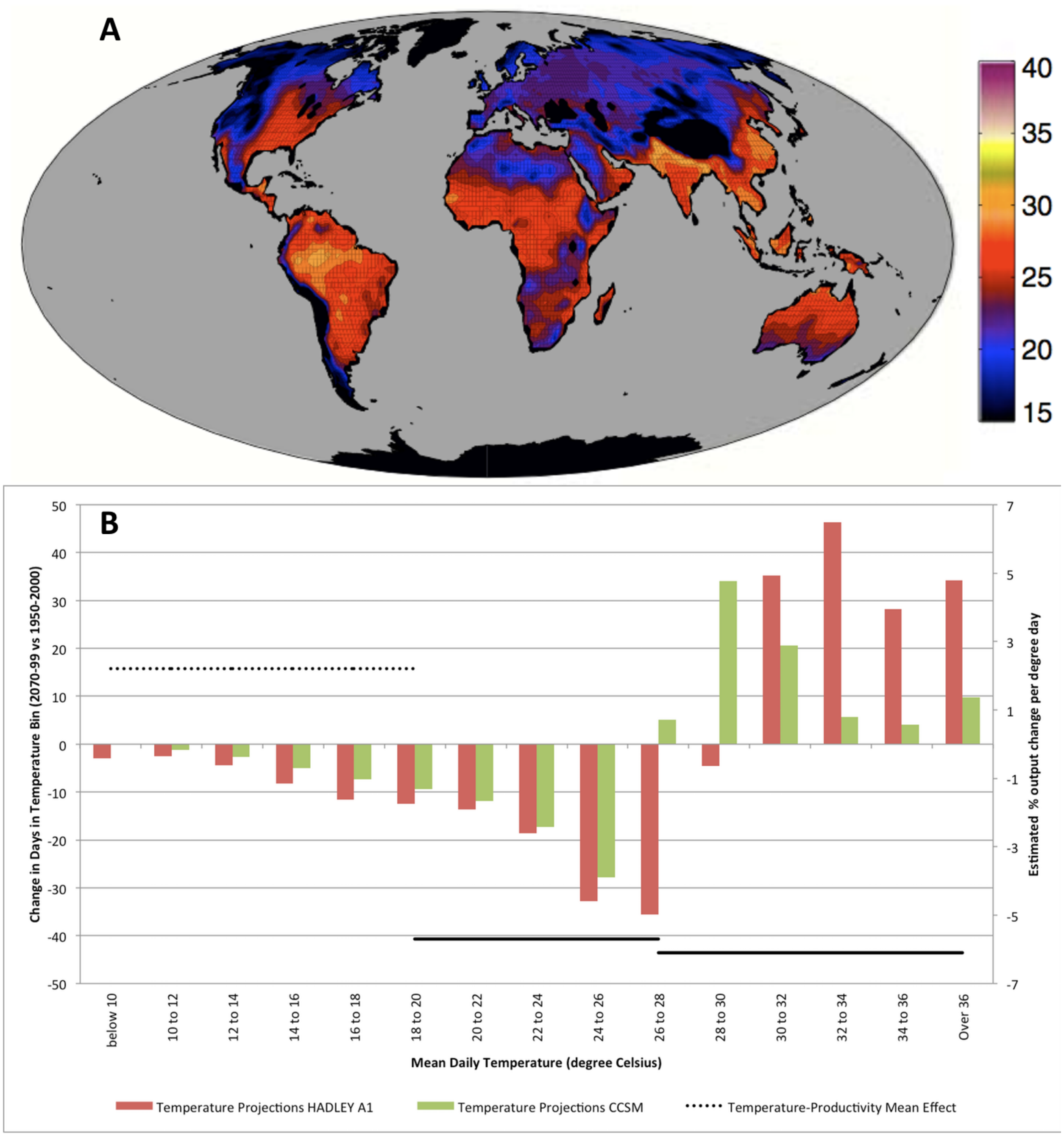

Figure A.4: Panel A: Estimated annual wet bulb globe temperature maxima, 1999-2008. Source: Sherwood and Huber (2010). Panel B: Projected temperatures under a business as usual climate change scenario for India. Source: Burgess et al. (2011). Overplotted lines denote estimated productivity impacts of temperature from Table 4, Column 1. Solid segments imply statistically significant effects