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

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Studies using aggregate economic data from different countries have found that high temperature years are systematically associated with lower output in developing nations. Heat-stress on labor has been suggested as a possible explanatory mechanism. This paper provides evidence confirming this hypothesis using high frequency data on worker output from firms in several industries as well as the annual value of output from a nationally representative panel of manufacturing plants in India. We find ambient temperature changes have non-linear effects on worker productivity, with declines as large as 9 percent per degree rise in wet bulb globe temperatures on hot days. Sustained heat also reduces attendance in firms where absenteeism is not severely penalized by the wage-contract. A within-firm comparison of plants with and without climate control suggests that these technologies can provide effective adaptation. Our estimates imply that observed warming between 1971 and 2009 in India accounts for a 3 percent decrease in manufacturing output 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 national economic 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. 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. New scientific evidence shows that 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). Furthermore, warming due to urban heat islands has significantly enhanced contemporary temperatures in cities well above regional averages (Mohan et al., 2012; Zhao et al., 2014).

Isolating the specific mechanisms that underlie these correlations remains 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 these output declines, which are observed in countries with both large and small agricultural sectors. Other mechanisms that have been proposed include heat effects on mortality, political conflict and thermal stress on workers (Dell, Jones, and Olken, 2014).

We collect primary data on daily worker productivity and attendance from manufacturing plants in several locations in India to investigate whether high ambient temperatures reduce the quality of labor via heat stress and hence reduce economic output. We put together evidence from plants in cloth weaving, garment manufacture, steel rolling and diamond cutting industries. These together reflect wide variation in automation, climate control and labor intensity. We also compare similar plants with and without climate control by exploiting the gradual rollout of this technology in one of the firms in our sample.

We identify two channels through which temperature affects labor. First, worker productivity declines on hot days. Second, sustained high temperatures are associated with increased absenteeism. We estimate output reductions of between 4 and 9 percent per degree on days when wet bulb globe temperatures are above 27 degrees Celsius. The largest estimates come from manual processes in the hottest parts of the country. For absenteeism, we find that an additional day of elevated temperatures is associated with a 1 to 2 percent increase in absenteeism in jobs where occasional absences are not penalized by the wage contract. Interestingly, this estimate is similar to changes in time allocation observed on hot days in the United States (Zivin and Neidell, 2014). In contrast, for daily wage workers, where the cost of every absence is high, we find little correlation between temperature and absenteeism.

We augment this evidence from high-frequency worker output with independent estimates based on a nationally representative panel of manufacturing plants in India over the years 1998-2008. A non-linear temperature-output relationship, similar to that observed for daily worker productivity, can also be detected over longer term annual economic output from individual manufacturing plants. We find that the value of annual factory output declines during years with a greater number of high temperature days at the rate of about three percent per degree day.

We also show that the link between high ambient temperatures and worker output (but not worker attendance) is broken in workplaces with climate control. These 'no-effect' cases are consistent with our hypothesized mechanism of heat stress and suggest that climate control technologies can provide some adaptation in the workplace. Of course such adaptation is costly and therefore only selectively adopted. Through a survey of 150 diamond cutting and polishing firms, we study investments in air-conditioning and find that climate control is adopted most frequently for labor intensive processes with high value addition. This opens up an interesting set of questions relating to the costs of adaptation and the distributional effects of temperature changes on the labor force. [1]

Our empirical estimates are consistent with effect sizes observed in both laboratory evidence and country panel studies (Dell, Jones, and Olken, 2014). This suggests that the physiological impact of temperature on human beings may explain a significant portion of the observed relationship between temperature and the economic output of poor countries, where climate control is less common. Because 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 empirical 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 our data sources and Section 4 presents results from firm level data and the national panel of manufacturing plants. Section 5 quantifies the importance of these effects in the context of climate model predictions for India and 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

[1] Also related is the question of how technology choice influences workplace temperatures. For example, Adhvaryu, Kala, and Nyshadham (2014) argue that there may be productivity gains from low heat lighting options such as LEDs.

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. We therefore use the following approximation in our analysis, whenever data on humidity is available.

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

Here T_A represents air temperature in degrees Celsius and ρ the water vapour pressure calculated from relative humidity, RH.[2]

Laboratory studies show a non-linear relationship between temperature and the efficiency of 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 (Dell, Jones, and Olken, 2014). These levels are not considered unsafe from the point of view of occupational safety and are commonly observed, especially in developing countries (Figure A.4).[3] Seppanen, Fisk, and Faulkner (2003); Hsiang (2010) provide a meta-analysis of this evidence. Similar effects have also been observed in some office settings, such as call centers (Seppanen, Fisk, and Lei, 2006).

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

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

While lab estimates provide a useful benchmark, they cannot directly inform us about the effect of temperature in real world manufacturing environments where monetary incentives embedded in wage contracts, the varied nature of tasks performed by a given worker, and differing degrees of mechanization all mediate worker productivity. Activity on the factory floor also rarely requires exertion nearing physical limits and takes place indoors or in shielded conditions. Moreover, the economic costs of reductions in the efficiency of physical processes depends on the value they add to the final product. Productivity is also not the only channel through which the quality of labor may change. Heat stress may also influence absenteeism due to greater morbidity or time allocation choices (Dell, Jones, and Olken, 2014). The data we collect - described next - allow us to separately examine these multiple channels in varying work environments and over different timeframes.

3 Data Sources

We use five independent datasets to investigate our heat stress hypothesis. These together span several manufacturing processes, varying in their degree of mechanization, climate control, labor intensity and value addition.

We compile high frequency daily data on worker output and attendance from plants in three industries: cloth weaving, garment manufacture and rail production. We exploit differences in technologies and wage contracts across these plants to estimate the impact of heat stress in the workplace. 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 is highly mechanized with some climate control, and a large fraction of worker-time is spent supervising and correcting automated processes.

In addition to collecting worker output data, we conducted a survey in 150 diamond cutting and polishing plants in Surat. These units invest substantially in air-conditioning but do so selectively for some parts of the factory. We examine whether there is greater deployment of climate control in tasks which are relatively labor intensive or those that involve significant value addition. Such a pattern would be consistent with the hypothesis that these investments represent costly adaptation against worker heat stress.

Each of our micro-data sites represents an important manufacturing sector in the Indian and global economies. 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.[4]

Our last data set is a nationally representative panel of manufacturing plants across India. The data comes from the Annual Survey of Industry, a government database covering all large factories and a sample of small ones. We use the ASI data to construct a panel of manufacturing plants with district identifiers and match annual data on the value of plant output, assets and inputs over the period 1998-2008 with average annual 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.

Additional details on data construction and definitions of our key variables are given below.

3.1 Production and Attendance Data

Weaving Units: We use daily output and attendance for workers in three cloth weaving

[4]For employment shares, see Annual Survey of Industries, 2009-10, Volume 1. Figures for the Surat diamond industry are taken from (Adiga, 2015) and those for the rail mill are from http://www.sail.co.in/bhilai-steel-plant/facilities.

units located in the city of Surat in the state of Gujarat in western India. Each worker is responsible for operating 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. Workers in all units are paid based on the meters of cloth woven and no payments are made for days absent. Payment slips are created for each day worked and we assemble our data set by digitizing these slips for the financial year April 2012-March 2013. Our data include all 147 workers who worked at any point during this year. For most types of cloth, the per-meter payment was about 2 rupees during this period and the median amount woven per worker was 125 meters of cloth per day.[5]

Garment Manufacturing: These data come from eight factories owned by a single firm producing garments, largely for export. Six of the factories we study 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. In each of the factories, many different garments are produced, 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 more difficult here 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

[5]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).

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 for the desired operations to be completed by a special line of 'master craftsmen'. The second is the output actually produced each hour. We use the Actual Efficiency, averaged over each day, as a measure of the combined productivity of each line of workers, and use the 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 financial years, April 2012 to March 2014. The median for 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 level output data we also collected attendance records for all sewing workers from firm management. To restrict attention to regular, full-time employees, we identify 2700 workers for whom attendance records were available for at least 600 days over the two year period of our data. These employees provide a stable cohort whose daily attendance decisions we are able to study. Unlike weaving workers, these workers were paid monthly wages and therefore not directly penalized for small variations in productivity or occasional absenteeism.

During the period we study, the firm was in the process of installing centralized climate control in plants. In five manufacturing units in the NCR, production floors had already been equipped with air washers. These devices control both temperature and humidity to reduce wet bulb globe temperatures. One manufacturing unit in the NCR did not have air-washers installed until 2014. Workers at this site only had access 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.

We use the gradual roll out of air washers within the NCR units to investigate whether workplace climate control changes the relationship between temperature and worker output. We do this by estimating heat effects separately for plants with and without climate control and for the two plants outside the NCR. Although this variation is not experimentally induced, the comparison of temperature-productivity relationships across these sites helps understand the ability of firms to mitigate temperature impacts by investing in 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 even when factory floor temperatures are effectively controlled.

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 building and infrastructural 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.[6] Workers are assigned to one of three teams which rotate across these shifts. For example, a team working in the morning shift one week, will move to the afternoon shift the next week and the night shift the following week. The median number of workers on the factory floor from each team is 66. We observe the team present for each shift as well as the number of blooms rolled, over all shifts on all working days in the period 1999-2008. Overall we obtain production data for 9172 shifts over 3339 working days and use this to examine temperature-productivity relationships. For a shorter time period, we also obtain personnel records which allow us to relate temperatures to plant level absenteeism. These cover the period between February 2000 snd March 2003 and we use these to obtain a daily count of unplanned absences for

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

the plant for 857 working days in this period.[7]

The bloom production process is highly mechanized and runs continuously with breaks when machinery needs repair or adjustment for a different size of rails or for switching to structural 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 may limit the effects of worker heat stress 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. Value added in these plants is however much higher than in the weaving units. Perhaps for this reason, diamond firms in Surat were found to have invested substantially, but selectively, in air-conditioning.

Diamond polishing can be broadly classified into five distinct operations: (i) sorting and grading, (ii) planning and marking, (iii) bruting, (iv) cutting, (v) polishing. While most firms do undertake all operations, the importance of each of these varies. For example, smaller firms do more sorting and cutting and transfer the stones to larger firms for final polishing. Mechanization and the intensity of labor also varies by unit and process. We asked each firm for information on the use of air-conditioning in each of the five operations listed above. 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 and specify the number of workers and the number of machines needed for each operation.

We were not able to obtain worker level productivity measures from diamond firms. However

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

we use this survey data to estimate the probability of climate control investments as a function of the characteristics of different manufacturing processes within the firm.

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.[8] The ASI provides annual information on output, working capital and input expenditures in broad categories, as well as numbers of skilled and unskilled workers employed. The format is similar to census data on manufacturing in many other countries.[9]

A drawback of the ASI from our perspective is that small manufacturing enterprises not registered under the Factories Act are excluded. These units contribute about 5% to Indian net domestic product and may have more limited means to adapt to temperature change.[10] The weaving units we study are an example. Plants surveyed in the ASI thus primarily inform us about temperature sensitivity within larger firms with presumably greater adaptive capacity.

We use ASI data for survey years between 1998-99 to 2007-08 to create a panel of 21,525 manufacturing plants matched to districts within India. Districts are the primary administrative sub-division of Indian states. There are occasional changes in district boundaries over time. There were 593 districts at the time of the 2001 Census and we place each plant within its 2001 district boundary. The final panel is unbalanced, with large firms appearing every year and smaller firms appearing in multiple years only if they are surveyed. In the Appendix we describe in greater detail the data cleaning operations and procedures used to

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

[9]See Berman, Somanathan, and Tan (2005) for a discussion of the variables and some of the measurement issues in the ASI.

[10]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.

construct the panel.

3.2 Meteorological Data

We match our daily micro-data from weaving, diamond and garment firms to local temperature, precipitation and humidity measures from public weather stations in the same city. We use these to compute daily WBGT using (1).

For the steel plant at Bhilai no public weather station data was available 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. We use annual averages of these daily measures and then use a spatial average over relevant points in the grid. 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 co-ordinates and average over grid points within the geographical boundaries of the district in which the plant is located.

A strength of this data is that it uses quality controlled ground-level monitors and not simulated measures from reanalysis models.[11] A limitation is that it cannot be used to estimate WBGT because it does not contain measures of relative humidity. In examining heat effects on output for the steel mill and for plants in the ASI panel, we therefore use only the dynamic variation in temperature and rainfall.[12]

[11] 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.

[12] 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.

4 Results

4.1 Temperature and Daily Worker Output

The physiological basis of heat stress suggests that 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.

Our primary specification is:

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

Y_{id} denotes output produced by worker, line or team i on day d. Fixed-effects for the i^{th} unit are α_i and $\gamma_M, \gamma_Y, \omega_W$ are indicators for month, year and day of the week, respectively. Together, these control for idiosyncratic worker productivity levels and temporal and seasonal shocks. R_{id} controls for rainfall experienced by the i^{th} unit. To capture non-linearities in the effects of heat-stress, we interact 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 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 control 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 1 presents our estimates for temperature effects on worker output. Column 1 is based on the rail mill data, columns 2-4 on garment manufacturing lines and columns 5-6 on cloth output from weaving units. Estimates from climate-controlled plants are shaded. Columns 2 and 3 offer a within-firm comparison of co-located production units belonging to the same firm but with different levels of climate control. This was possible because the roll-out of climate control technology took place during the period for which we collect data. Column 4 presents data from garment plants located in the milder climate of Hyderabad in South India and Chhindwara in Central India.[13] The most systematic productivity effects 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 over 8 percent for garment lines and weaving units without climate control. There is no apparent effect for units with climate control.

[Table 1 about here.]

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 1, although estimates are less precise.

[Figure 1 about here.]

The clearest evidence in support of the heat-stress hypothesis is obtained from the within-firm comparison of NCR garment manufacturing units, with differing levels of climate control. Production lines on floors without access to air-washers show a drop in output with

[13]The median wet bulb globe temperature within days in the highest bin is greater in the NCR garment plants (29.22 degrees) than in Hyderabad and Chhindwara (28.21 degrees).

increasing wet bulb globe temperatures especially in the highest temperature bins. This link is broken with climate control. Garment lines located in Hyderabad and Chhindwara - where air-washers were not installed - also show a drop in efficiency with increasing wet bulb temperatures but the estimated response is smaller, most likely due to the more moderate ambient temperatures in these areas relative to Delhi.

In small weaving units of Surat, a similar non-linear pattern of temperature impact on worker output is observed with negative impacts on days with high wet bulb temperatures. In contrast, in the highly mechanized rail mill, there is no evidence that output is affected by very high temperatures and our point estimates are small and often not statistically significant from zero. 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 seen in the rail mill.[14]

We also note that the output of weaving workers does not seem influenced by moderate temperatures while there is a more uniform temperature-output relationship for sewing lines in garment units without climate control. Although these two work environments differ on many dimensions, one possible explanation may be the nature of the wage contract. While garment workers are paid a monthly wage, weaving workers are paid per unit of cloth woven and therefore have a strong incentive to sustain high output if possible.

4.2 Worker Absenteeism

Recent evidence from the United States finds small reductions in time allocations to work on very hot days (Zivin and Neidell, 2014). Such changes in attendance could affect labor

[14] These estimates should be robust to any effects of power outages on output. 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 in our estimates by including day of week fixed effects.

input costs independently of actual workplace performance. In the hot temperature and low income environments we study, there are many channels through which temperatures could influence absenteeism. Sustained high temperatures may lead to fatigue or illness. Longer term seasonal variations could create differences in disease burden or influence occupation choice. These effects are likely to depend on both contemporaneous and lagged temperatures.

To investigate this possibility, we exploit the detailed histories of worker attendance that we collect for weaving plants in Surat, garment manufacture units in the NCR and the rail mill in Bhilai. For all three cases we construct a time series measure of the total number of worker absences every day.[15] These absence records span two years (2012 and 2013) for garment plants, three years (Feb 2000 to March 2003) for the rail mill and one year (April 2012 to March 2013) for Surat weaving units. This micro-data can be used to investigate the relationship between absenteeism and temperature.

As we have noted, exposure to heat may affect the decision to miss work through both contemporaneous and lagged temperatures. An exposure-response framework is thus a natural way to model this relationship. Denoting the number of absences in a cohort of workers observed on day t_0 by A_{t_0}, we can model

$$A_{t_0} = \alpha + \beta E_{t_0} + \gamma X_{t_0} + \epsilon_{t_0}$$

Here $E_{t_0} = f(W_{t_0}, \ldots, W_{t_0-K})$ is the accumulated heat exposure at time t_0 that depends on the history of all wet bulb globe temperatures experienced over the previous K days. γX_{t_0} denotes other covariates (such as festival seasons) that might change A_{t_0}. In general E_{t_0} will vary non-linearly with both the level of wet bulb globe temperatures, W_{t_0-k}, as well as the lag period k.

[15] In the case of the rail mill and garment plants an absence is defined as a recorded leave day. In the case of daily wage weaving workers an absence is defined as any day when no payments were recorded for a worker. Absences for garment workers are calculated for workers observed for at least 600 days over the two year period.

Different assumptions on how to model exposure lead to different models of varying generality. A simple specification is to assume that exposures are proportional only to contemporaneous temperatures so that $E = \beta W_{t_0}$. This assumes that lagged temperature histories do not have cumulative or sustained effects on the propensity to miss work. Because it is plausible that temperatures experienced in the recent past might influence absenteeism, we also estimate a second specification. We set exposures E equal to the mean wet bulb globe temperature experienced over the previous $k = 7$ days and allow for non-linearities in response by separately estimating β for different quartiles of observed $\mathbf{W^K_{t_0}}$. We report estimates from both models (setting $k = 7$) in Table 2, additionally controlling for month fixed effects, year fixed effects, day of week fixed effects and rainfall.

We find evidence that sustained high temperatures are associated with an increase in absenteeism for workers in the rail mill and garment plants. For the highest quartile of lagged weekly temperatures, a $1°C$ increase in the average weekly WBGT is associated with a 10 percentage point increase in absences for rail mill workers and a 6 percentage point increase for garment workers. In contrast, we do not see absenteeism effects for weaving workers, perhaps because of their very different wage contracts. Recall that in both garment and rail plants, workers are full-time employees paid a monthly wage, while in the weaving units they are daily wage workers who are not paid when they do not come to work. This means that the marginal cost of an additional absence is relatively high for weaving workers, while it may be small or zero in the other two cases.

Interestingly, increased worker absenteeism is visible even where the work-place itself uses climate control. These investments may thus allow only partial adaptation to the impact of temperature on labor. Although they mitigate temperature related productivity losses while at work, they may not be sufficient to prevent changes in attendance.

[Table 2 about here.]

Modeling exposure using average weekly temperatures involves some restrictive assumptions. Temperatures at different lag periods may not contribute equally to the propensity to miss work. Also weeks with similar average temperatures may have very different impacts upon workers depending on the levels of daily temperatures within the week. It is possible to estimate a more flexible model that relaxes these assumptions and also gives us more insight into how absenteeism is affected by both the levels of ambient temperatures and the length of time for which a hot spell continues. Both these factors may be changing as a function of anthropogenic forces. Anthropogenic climate change is expected to lead to a significant increase in the probability of extreme temperature days (Fischer and Knutti, 2015). Urban heat islands have already led to sustained warming in hotspots within many cities (Mohan et al., 2012; Zhao et al., 2014).

Rather than specifying upfront how temperatures contribute to exposure, the exposure-response relationship can be flexibly modeled using a non-linear distributed lag model (Gasparrini, 2013). Distributed lag models represent E_{t_0} as a weighted sum of lagged wet bulb globe 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 related to each other by some flexible function whose parameters can be estimated from the data[16]. A non-linear DLM extends this idea by allowing the contribution of temperature to total exposure to vary with both lag durations (k) as well as temperature levels W.[17] We follow the procedure in Gasparrini (2013), using two independent third order polynomials to describe how the levels and lag period of ambient temperatures contribute to cumulative exposure E_{t_0} at time t_0 and estimate the parameters of this model.

We can now use this model to simulate predicted changes in absenteeism under different

[16] In the weekly average model, these weights are 1 for $K <= 7$ and 0 for $K > 7$. More generally we could let $\tau_k = g(k)$.

[17] The net exposure can then be described by a bidimensional function $E(W, k) = \sum_0^K f \cdot g(W_{t_0-k}, k)$ where f describes the effect of temperature levels W on exposure and g describes the effect of lag period k. Gasparrini (2013) shows how this can be represented as the product of temperature histories with a cross-basis matrix linear in parameters for different choices of functions f and g and thus estimated using least squares.

specified histories of WBGT exposures. Figure 2 displays two cross-sections. 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 (k ranging from 1 to 10). For workers with long term contracts - rail mill (Panel A) and garment firms (Panel B) - absences increase approximately linearly with every additional day of elevated temperatures at the rate of approximately 1 to 2 percent per day. We interpret this response curve to suggest that as the duration of hot spells is increased, the probability of absenteeism rises steadily. In the right column, we simulate the variation in absenteeism for a fixed exposure duration (10 days) at varying levels of temperature. We see clear evidence that temperatures above 25 degrees drive the absenteeism response. As with the simpler linear models of Table 2, we see no effect on daily wage workers.

Our analysis here is restricted to short-run (10-day) responses of attendance to temperature shocks. Although our data does not support a detailed investigation of longer run responses, Figure A.3 in the Appendix suggests there are seasonal reductions in the availability of daily wage workers (but not full-time contracted workers) during high temperature months. This may reflect the fact that daily wage workers have greater flexibility to shift occupations relative to workers on full time contracts.

[Figure 2 about here.]

4.3 Adaptation and Investments in Climate Control

An indirect way of testing the heat-stress mechanism is by observing the way in which plants make investments in climate control technologies. We would expect that plants that are concerned about heat impacts on workers would preferentially invest in cooling for production activities that are high value and labor intensive.

Our survey of diamond polishing units reveals frequent investments in air-conditioning but also substantial variation in the deployment of this climate control across different production areas within the same plant. We use our survey data to estimate a logit model of the probability of plants using air-conditioning for any stage in their production process as a function of (i) the share of workers employed in the process (worker intensity), (ii) the share of machines used within a process (mechanization intensity) and (iii) the self-reported importance of the process in determining stone quality (a proxy for value addition). We control for the total number of workers (a proxy for firm size) and the years since the first air-conditioning investment.[18]

Figure 3 summarizes our results. We find that diamond polishing units in Surat are significantly more likely to use air-conditioning for production tasks they consider important in determining product quality and for tasks that are labor-intensive. These patterns are consistent with a model of adaptive investments where firms choose to preferentially cool high value and labor intensive processes.[19]

[Figure 3 about here.]

4.4 Annual Manufacturing Output

In Section 4.1 we directly investigated the relationship between temperature and worker output. The effect sizes we identify are similar to those documented in the literature investigating changes in country level economic output with temperature. But do these temperature effects remain when we examine output data over longer periods and aggregated over an entire manufacturing unit rather than a single worker or group of workers?

[18]We also estimate a model with firm fixed effects, identified only using within plant variation across process areas, and find that our results remain similar.

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

To answer this, we examine the relationship between district temperatures and annual output in our nation-wide panel of manufacturing plants. We focus on testing for non-linearities in output response since our hypothesized mechanism of heat stress should depend mostly on exposure to high temperatures.

In the ASI panel we observe annual - as opposed to daily - plant output. However we do observe temperatures for every day within the year. Suppose $V(T_d)$, is the monetary value of plant output as a function of daily temperature, T_d. If we assume that the non-linear response of output to temperature can be approximated using a stepwise linear function of production in temperature we can write:

$$\bar{V}(T_d) = \bar{V}(T_0) + \sum_{k=1}^{N} \beta_k D_k(T_d). \tag{3}$$

$D_k(T_d)$ is the number of degree days within a given temperature bin and its coefficient measures the linear effect of a one degree change in temperature on output, within the kth temperature bin. Aggregating this daily output as a function of daily degree days over all days in the year suggests the model in Equation 4 which can be taken to the data.

$$V_{it} = \alpha_i + \gamma_t + \omega K_{it} + \sum_{k=1}^{N} \beta_k D_{itk} + \phi W_{it} + \theta R_{it} + \epsilon_{it}, \tag{4}$$

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. 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.[20] We use three temperature

[20] Degree days are commonly used to summarize the annual temperature distribution and carry units of temperature (Jones and Olken, 2010). A day with a mean temperature of 23 degrees contributes 20 degrees to the lowest temperature bin and 3 degrees to the [20,25) degree bin.

bins with $T \leq 20°C, T \in [20°, 25°), T \geq 25°C$. β_k is the output effect of a one degree rise in temperature within bin k. 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 use daily mean temperatures in our specifications.[21]

We use working capital available to the plant at the start of the financial year as an input control because it determines resources available for purchasing inputs and is also plausibly exogenous to temperatures experienced during the year and to realized labor productivity. This would not be true of actual labor, energy or raw material expenditures during the year because lower labor productivity due to temperature changes may also reduce the wage bill under piece rate contracts and be accompanied by lower raw material use.

We estimate (4) using both absolute output as well as log output as outcome variables. When using the former, coefficients are expressed as proportions of the average output level. Results are in Table 3. Columns (1) and (3) contain estimates from our base specification. Columns (2) and (4) control for the reported total number of workers W_{it} on the right hand side. These are not our preferred estimates because employment data is both less complete and may contain measurement errors.[22]

The results provide clear evidence of a non-linear effect of temperature on output. Output declined by between 3 and 7 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 2.8 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

[21] 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.

[22] 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 more workers.

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.

[Table 3 about here.]

Heterogeneity in Temperature Response

Heat stress on labour should generate greater production declines in manufacturing plants with a high labor share of output and limited climate control. To investigate whether temperature has heterogeneous effects on productivity based on these characteristics, we calculate for each plant in our dataset the ratio of wages paid over every year to output in that year and also the ratio of electricity expenditures to total cash on hand at the start of the year (our measure of capital). Electricity consumption in this instance is used as an imperfect proxy for climate control, which is typically quite electricity intensive, since we do not observe such investments directly in the annual survey data.[23]

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 (5) separately for labor shares and electricity quartiles to examine whether temperature effects are heterogeneous in the manner we expect.

$$V_{it} = \alpha_i + \gamma_t + \omega K_{it} + \beta T_{it} \times Q_i + \theta R_{it} + \epsilon_{it} \tag{5}$$

We find that output from plants with higher labor shares is indeed more strongly affected by temperature and that those with greater electricity consumption appear less vulnerable

[23] Section 4.1 provides more robust evidence since we observe the climate control technologies that are actually adopted.

(Table 4).

[Table 4 about here.]

Robustness Checks: Price Shocks and Power Outages

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.

Although most of these 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 (4). 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.

A second confounding factor in the ASI data is the reliability of power supply. It is possible that power supply to a plant might be influenced by local temperature shocks. 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 average mean temperatures and degree days above $> 25°C$ and find that between the five year period from 1971-1975 and 2005-2009, temperatures have risen by an average of about 0.91 degrees across India. Combining this with the estimated mean effect of temperature on output from the nation-wide ASI panel (3.3 percent reduction per degree from Column 5 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.

To the extent that this estimate ignores adaptive costs already incurred, it may be an underestimate of the full costs imposed by temperature changes in recent years. Adaptive actions might 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). Many of these measures are neither easy nor costless.

These measures of warming may also underestimate the impact of urban heat island effects. Heat island effects in urban areas have already led to local temperature hotspots that can be more than five degrees warmer than surrounding areas (Mohan et al., 2012; Zhao et al., 2014). Since many manufacturing units are located in urban hotspots, this source of surface warming may be very significant to 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 (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 (Chaturvedi et al., 2012).

6 Conclusions

We use primary micro-data collected from various work environments to show that elevated local temperatures can have a significant negative impact on worker productivity and labor supply. Our data come from settings that do not necessarily involve heavy physical labor or outdoor exposures and the effects we identify remain visible on both daily and annual time-scales, at both the individual worker and manufacturing plant level. This suggests that the impact of temperature on labor may be widely pervasive. In many settings high temperatures may operate as a tax on labor and may therefore directly influence long run rates of economic growth.

Climate change projections for India, under business-as-usual scenarios (between 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. 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 lower crop yields(Lobell, Schlenker, and Costa-Roberts, 2011; Schlenker and Roberts, 2009; Mendelsohn and Dinar, 1999; Auffhammer, Ramanathan, and Vincent, 2006). Indeed 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 evidence shows that gradual temperature change may impose costs in the manufacturing sector, either via its effect on labor productivity or the energy costs of adaptation technologies. Moreover, climate change is not the only reason to be concerned about temperature change. Although scientists have documented the role of urbanization in generating significant local warming(Zhao et al., 2014), relatively little attention has been paid to the economic implications of this phenomenon. Satellite based studies in India's NCR show the presence of urban hotspots with temperature elevations of greater than five degrees celsius (Mohan et al., 2012). Our results suggest that these heat islands may have economically significant negative effects on productivity, especially since manufacturing activity is generally located in urbanizing areas. These costs may be both large today and growing quickly in developing countries which are also urbanizing at rapid rates.

The net economic costs due to heat stress will depend on how much adaptation takes place and the variable and fixed costs of adaptation. We show that climate control appears effective in breaking the relationship between ambient temperatures and workplace productivity (although not necessarily between temperature and absenteeism). However we also document variable adoption of climate control across sectors, firms and even within firms (from our survey of diamond cutting units in Surat). Since adaptation is costly, we should expect selective adoption. An important area of future research involves understanding the determinants of investment in adaptation, quantifying the productivity effects of technologies that influence workplace temperatures (Adhvaryu, Kala, and Nyshadham, 2014), and evaluating the potential of adaptive investments beyond air-conditioning (urban design, cool roofs and building codes, developing urban water bodies and green areas and so on).

Lastly, while our study has examined only manufacturing in India, temperature impacts on worker productivity may be even more pronounced in the agricultural sector. 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.

References

Adhvaryu, Achyuta, Namrata Kala, and Anant Nyshadham. 2014. "The Light and the Heat: Productivity Co-benefits of Energy-saving Technology."

Adiga, Arvind. 2015. "Uncommon Brilliance." *Time* .

Allcott, Hunt, Allan Collard-Wexler, and Stephen O'Connell. 2014. "How Do Electricity Shortages Affect Productivity? Evidence from India."

Arellano, M. 1987. "Computing Robust Standard Errors for Within-Group Estimators." *Oxford Bulletin of Economics and Statistics* 49:431–434.

Auffhammer, M., S. M. Hsiang, W. Schlenker, and A. Sobel. 2013. "Using Weather Data and Climate Model Output in Economic Analyses of Climate Change." *Review of Environmental Economics and Policy* 7 (2):181–198. URL `http://dx.doi.org/10.1093/reep/ret016`.

Auffhammer, M, V Ramanathan, and J R Vincent. 2006. "From the Cover: Integrated model shows that atmospheric brown clouds and greenhouse gases have reduced rice harvests in India." *Proceedings of the National Academy of Sciences* 103 (52):19668–19672. URL `http://dx.doi.org/10.1073/pnas.0609584104`.

Berman, Eli, Rohini Somanathan, and Hong W Tan. 2005. "Is Skill-biased Technological Change Here Yet?: Evidence from Indian Manufacturing in the 1990's." *Annals of Economics and Statistics* 79-80 (299-321).

Burgess, Robin, Olivier Deschenes, Dave Donaldson, and Michael Greenstone. 2011. "Weather and Death in India."

Chaturvedi, Rajiv K, Jaideep Joshi, Mathangi Jayaram, G. Bala, and N.H. Ravindranath. 2012. "Multi-model climate change projections for India under Representative Concentration Pathways." *Current Science* 103 (7):791–802.

Das, Sanghamitra, Kala Krishna, Sergey Lychagin, and Rohini Somanathan. 2013. "Back on the Rails: Competition and Productivity in State-Owned Industry." *American Economic Journal: Applied Economics* 5 (1):136–162. URL http://dx.doi.org/10.1257/app.5.1.136.

Dell, Melissa, Benjamin F Jones, and Benjamin A Olken. 2012. "Temperature Shocks and Economic Growth: Evidence from the Last Half Century." *American Economic Journal: Macroeconomics* 4 (3):66–95. URL http://dx.doi.org/10.1257/mac.4.3.66.

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken. 2014. "What Do We Learn from the Weather? The New Climate-Economy Literature." *Journal of Economic Literature* 52 (3):740–798. URL http://dx.doi.org/10.1257/jel.52.3.740.

Field, CB, V Barros, K Mach, and M Mastrandrea. 2014. "Climate Change 2014: Impacts, Adaptation, and Vulnerability."

Fischer, E. M. and R. Knutti. 2015. "Anthropogenic contribution to global occurrence of heavy-precipitation and high-temperature extremes." *Nature Climate change* URL http://dx.doi.org/10.1038/nclimate2617.

Gasparrini, Antonio. 2013. "Modeling exposure-lag-response associations with distributed lag non-linear models." *Statistics in Medicine* 33 (5):881–899. URL http://dx.doi.org/10.1002/sim.5963.

Hsiang, Solomon M. 2010. "Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America." *Proceedings of the National Academy of Sciences of the United States of America* 107 (35):15367–72.

IMD. 2015. "Indian Meterological Department: Annual And Seasonal Mean Temperature Of India." URL https://data.gov.in/catalog/annual-and-seasonal-mean-temperature-india.

ISO. 1989. "Hot environments – Estimation of the heat stress on working man, based on the WBGT-index (wet bulb globe temperature)." Tech. rep., International Standards Organization.

Jones, Benjamin F and Benjamin A Olken. 2010. "Climate Shocks and Exports." *American Economic Review* 100 (2):454–459. URL `http://dx.doi.org/10.1257/aer.100.2.454`.

Kjellstrom, Tord, Ingvar Holmer, and Bruno Lemke. 2009. "Workplace heat stress, health and productivity: An increasing challenge for low and middle-income countries during climate change." *Global Health Action* 2: Special Volume:46–51.

Lemke, Bruno, Bruno and Tord Kjellstrom, Tord. 2012. "Calculating Workplace WBGT from Meteorological Data: A Tool for Climate Change Assessment." *Industrial Health* 50 (4):267–278. URL `http://dx.doi.org/10.2486/indhealth.MS1352`.

Lobell, David B, Wolfram Schlenker, and Justin Costa-Roberts. 2011. "Climate trends and global crop production since 1980." *Science* 333 (6042):616–620.

Mendelsohn, R and A Dinar. 1999. "Climate Change, Agriculture, and Developing Countries: Does Adaptation Matter?" *The World Bank Research Observer* 14 (2):277–293. URL `http://dx.doi.org/10.1093/wbro/14.2.277`.

Mohan, Manju, Yukihiro Kikegawa, B. R. Gurjar, Shweta Bhati, and Narendra Reddy Kolli. 2012. "Assessment of urban heat island effect for different land use-land cover from micrometeorological measurements and remote sensing data for megacity Delhi." *Theoretical and Applied Climatology* 112 (3-4):647–658. URL `http://dx.doi.org/10.1007/s00704-012-0758-z`.

Parsons, K C. 1993. *Human Thermal Environments*. Informa UK (Routledge). URL `http://dx.doi.org/10.4324/9780203302620`.

Schlenker, W. and Michael Roberts. 2009. "Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change." *Proceedings of the National Academy of Sciences* 106 (37):15594–15598.

Seppanen, Olli, William J. Fisk, and David Faulkner. 2003. "Cost Benefit Analysis of the Night-Time Ventilative Cooling in Office Building." Tech. rep., Lawrence Berkeley National Laboratory.

Seppanen, Olli, William J. Fisk, and Q.H. Lei. 2006. "Effect of Temperature on Task Performance in Office Environment." Tech. rep., Lawrence Berkeley National Laboratory.

Sharma, Rajiv and Sunita Chitkara. 2006. "Expert Group on Informal Sector Statistics (Delhi Group)." .

Sherwood, Steven C. and Matthew Huber. 2010. "An adaptability limit to climate change due to heat stress." *Proceedings of the National Academy of Sciences* :1–4.

Wyndham, C.H. 1969. "Adaptation to heat and cold." *Environmental Research* 2:442–469.

Zhao, Lei, Xuhui Lee, Ronald B. Smith, and Keith Oleson. 2014. "Strong contributions of local background climate to urban heat islands." *Nature* 511 (7508):216–219. URL `http://dx.doi.org/10.1038/nature13462`.

Zivin, Joshua Graff and Matthew Neidell. 2012. "The Impact of Pollution on Worker Productivity." *American Economic Review* 102 (7):3652–3673. URL `http://dx.doi.org/10.1257/aer.102.7.3652`.

———. 2014. "Temperature and the Allocation of Time: Implications for Climate Change." *Journal of Labor Economics* 32 (1):1–26. URL `http://dx.doi.org/10.1086/671766`.

Table 1: Effect of Wet Bulb Globe Temperature on Daily Worker 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	0.462
	(0.003)	(0.004)	(0.007)	(0.097)	(0.009)	(0.998)
(4) WBGT:[20-25)	-0.0002	-0.014^{**}	-0.064^{***}	-0.004	0.006	1.627^{*}
	(0.005)	(0.007)	(0.020)	(0.009)	(0.009)	(0.835)
(5) WBGT:[25-27)	0.011^{*}	0.029^{**}	-0.149^{***}	0.004	-0.014	-0.492
	(0.006)	(0.014)	(0.026)	(0.020)	(0.014)	(1.125)
(6) WBGT:[≥27]	0.016	0.001	-0.087^{***}	-0.037^{**}	-0.085^{**}	-7.131^{**}
	(0.011)	(0.007)	(0.024)	(0.016)	(0.038)	(2.923)
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 (use of AC or airwashers); 2. Observations refers to the total number of worker-days (weaving), line-days (garments) or shift-days (steel); 3. Robust standard errors correcting for serial correlation and heteroskedasticity (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 2: Effect of Temperature on Worker 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. Robust standard errors correcting for serial correlation and hetero-skedasticity (Arellano, 1987); 3. Q1-Q4 refer to quartiles of weekly WBGT; 4. Rainfall in models 1,2,5,6 measured in mm and rainfall in models 3,4 measured in fraction of hours with recorded precipitation event; 5. *p<0.1; **p<0.05; ***p<0.01

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

	Dependent variable:			
	Plant Output Value		Log Plant Output	
	(1)	(2)	(3)	(4)
Below 20°C	0.029	0.029	−0.014	−0.014
	(0.025)	(0.024)	(0.023)	(0.022)
20°C to 25°C	−0.044*	−0.041*	−0.051**	−0.047**
	(0.026)	(0.024)	(0.022)	(0.021)
Above 25°C	−0.068***	−0.056***	−0.040***	−0.033**
	(0.015)	(0.015)	(0.013)	(0.013)
rainfall	0.005*	0.002	0.001	0.001
	(0.002)	(0.003)	(0.002)	(0.002)
capital	0.382***	0.342***		
	(0.010)	(0.009)		
log(capital)			0.383***	0.304***
			(0.007)	(0.006)
workers		0.002***		
		(0.0001)		
log(workers)				0.417***
				(0.008)
Worker Controls	N	Y	N	Y
Units	21,525	21,525	21,525	21,525
R^2	0.249	0.291	0.196	0.272

Notes: 1. All models include plant, year fixed effects, capital controls and quartile dummies; 2. Robust standard errors correcting for serial correlation and heteroskedasticity (Arellano, 1987); 3. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 4: 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	−0.037***	−0.062***
	(0.013)	(0.013)
Mean Temperature X		
Quartile 2	−0.007	0.019***
	(0.006)	(0.005)
Quartile 3	−0.022***	0.031***
	(0.007)	(0.007)
Quartile 4	−0.028***	0.032***
	(0.008)	(0.008)
Number of Units	21,525	21,525
Mean Obs. per Unit	4.8	4.8
R^2	0.302	0.260

Notes: 1. All models include plant and year fixed effects and capital controls; 2. Robust standard errors correcting for serial correlation and heteroskedasticity (Arellano, 1987); 3. *p<0.1; **p<0.05; ***p<0.01

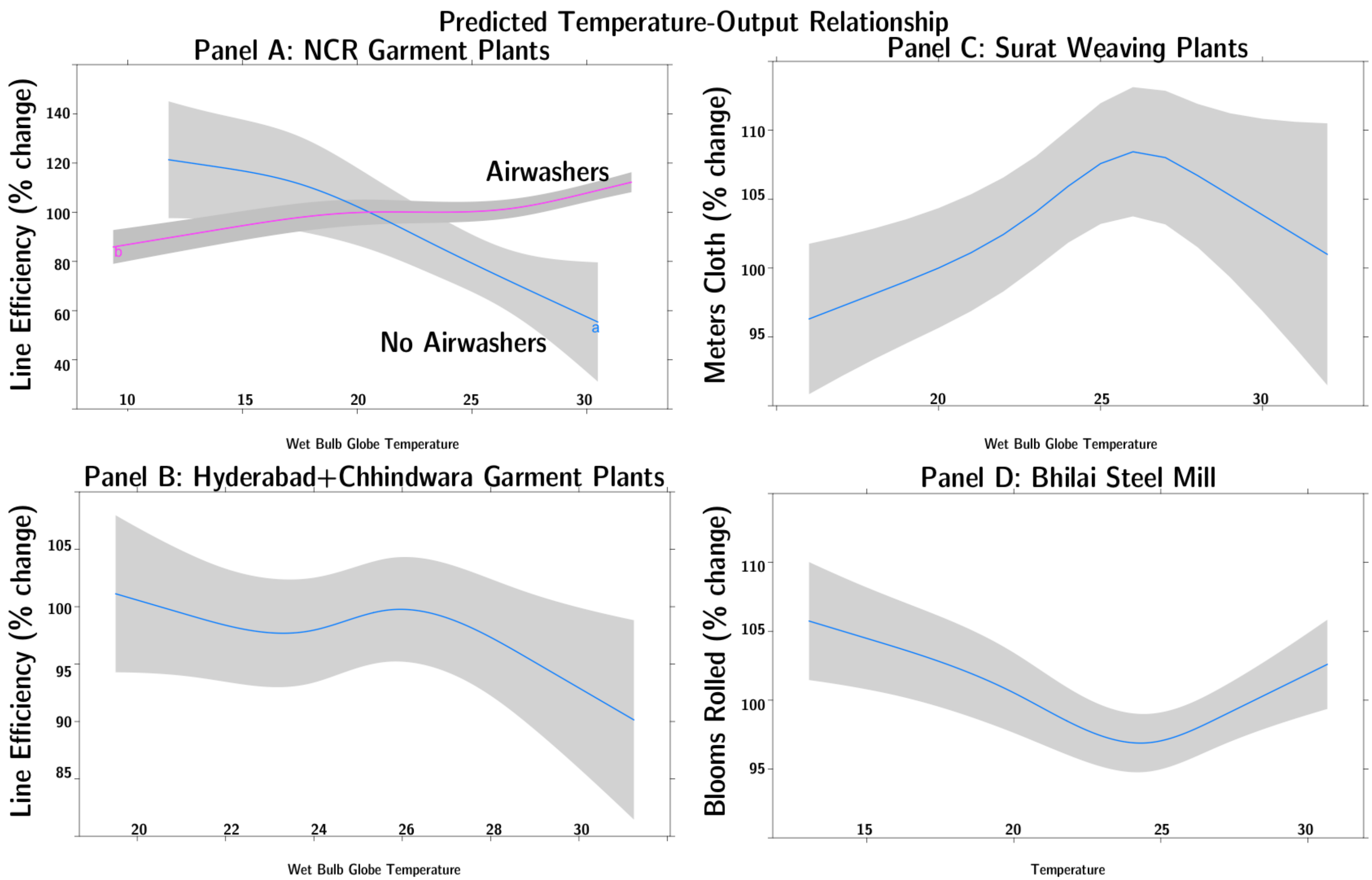

Figure 1: Restricted cubic spline models of the impact of temperature on output measures. Panel A: Logged efficiency in garment plants in NCR with airwashers (5 plants) and without airwashers (1 plant). Panel B: Logged efficiency for garment plant in Hyderabad and Chhindwara without airwashers. Panel 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.

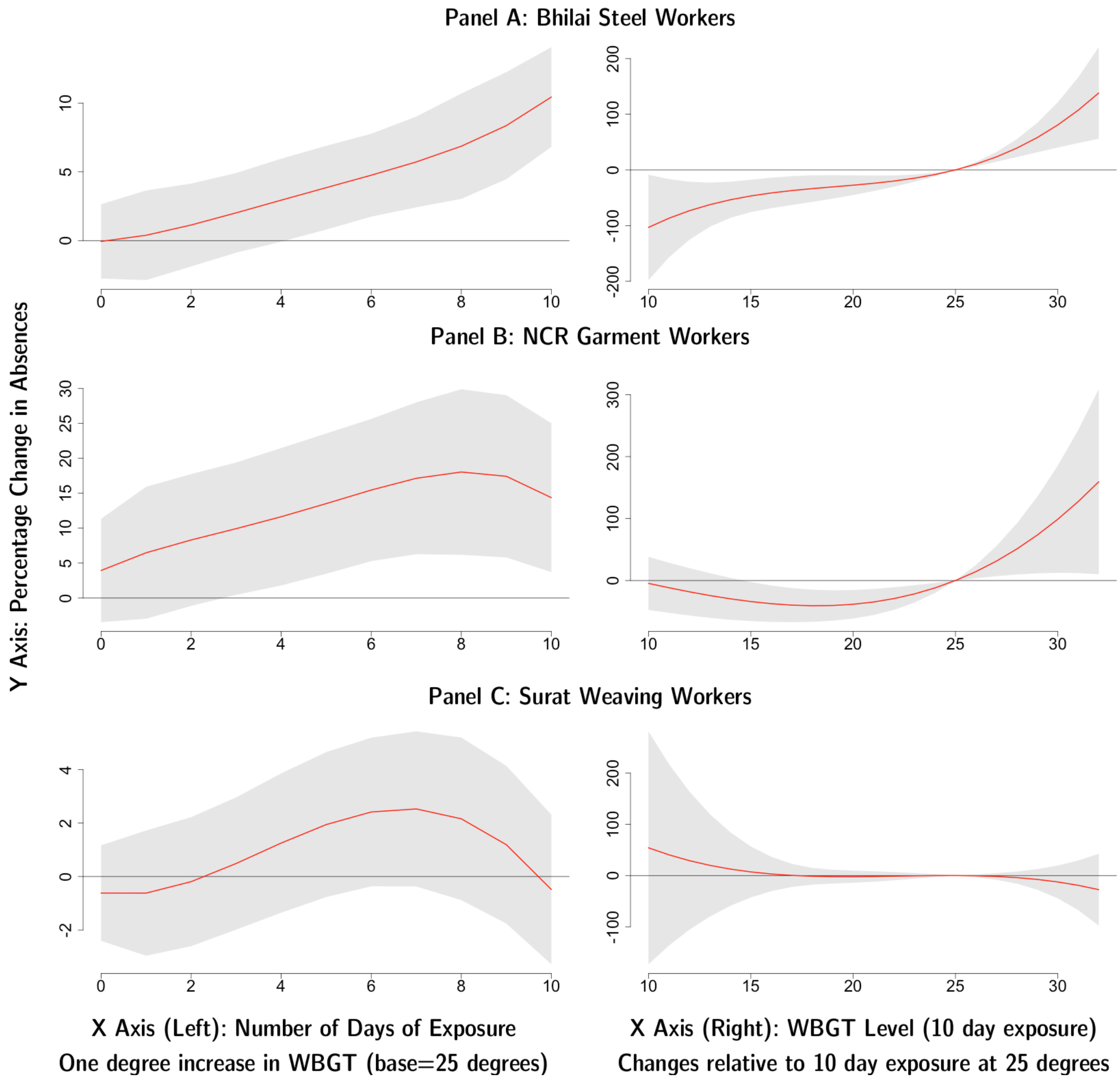

Figure 2: Predicted impact of wet bulb globe temperature on attendance measures for rail mill workers (Panel A), garment workers (Panel B) and workers in weaving firms (Panel C). Left column plots predicted percentage change in absenteeism under a one degree temperature increase sustained for varying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

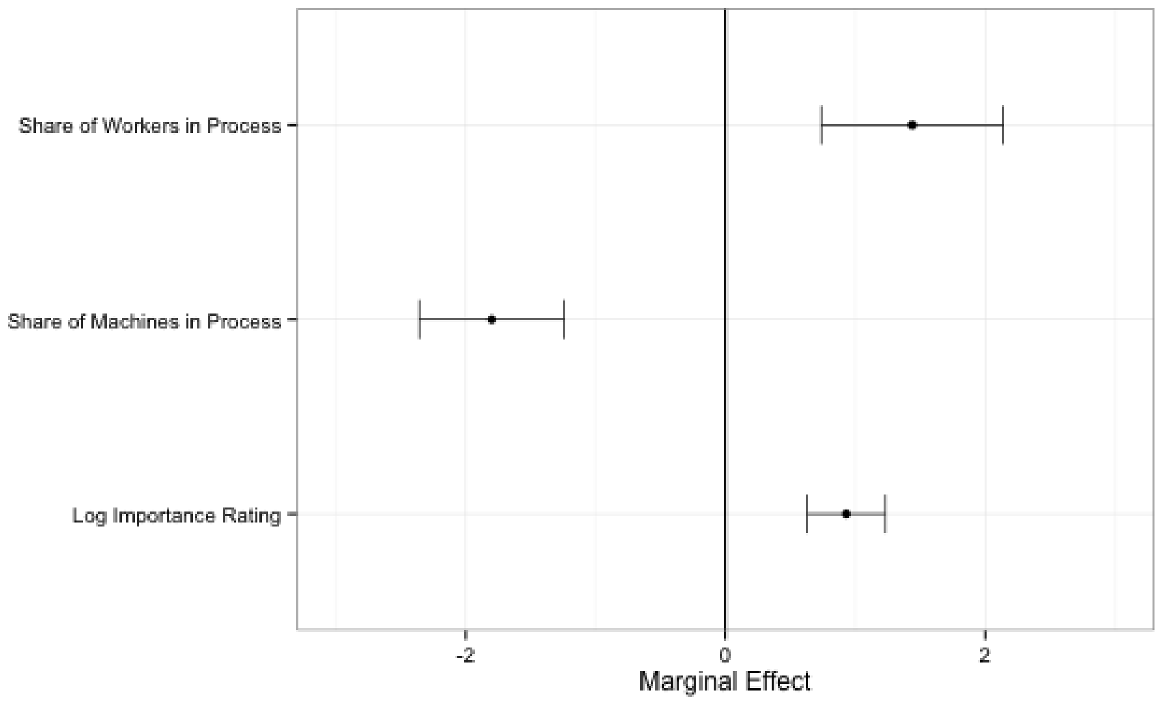

Figure 3: Marginal effect of covariates on probability of seeing climate control for a single process within the diamond production line. Bootstrapped robust standard errors. Estimated using data on 750 processes across 150 firms.

Appendix: For Online Publication

A.1 Annual Survey of Industry Data Cleaning

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 variant 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. We dropped units that appear less than three times in the panel and performed additional data cleaning operations described below to eliminate outliers and possible data errors. Our final sample has 21,525 manufacturing units distributed all over India and spanning all major manufacturing sectors (Figure A.1).

The following data-cleaning operations are performed on the 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 trim the top 2.5 percent and bottom 2.5 percent of the distribution of observations by output value, total workers, 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 plants with zero or negative values of output, capital, workers or raw materials used.

5. We drop units that appear less than three times during our study period.

6. We drop plants where district locations change over the panel duration.

[Figure 4 about here.]

[Figure 5 about here.]

A.2 Additional Results

Annual Average Temperature and Manufacturing Output

The model in Equation 4 allowed 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:

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

where T_{it} is the average temperature during the financial year t (so that a year is calculated from April 1 through March 31) and the other variables are as in (4). Estimates are in Table

A.1.

[Table 5 about here.]

Using estimated WBGT with the ASI panel

The impact of temperature degree days on output in Table 3 used temperature data rather than WBGT because measures of relative humidity are not available across all districts and over the ten year period covered by our manufacturing plant panel. An alternative is to approximate 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.

[Table 6 about here.]

Price Shocks and Power Outages

In this section we report results investigating the robustness of the non-linear response of output to temperature (reported in Table 3) to the inclusion of controls for power outage probabilities. We also test to see whether local input prices can be shown to respond to local temperature shocks to any significant degree. 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 6.

$$P_{it} = \alpha_i + \gamma_t + \omega K_{it} + \sum_{k=1}^{N} \beta_k D_k + \phi W_{it} + R_{it} + \epsilon_{it} \tag{7}$$

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 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 4. As Table A.3, Column 2 makes clear, our temperature response estimates seem robust to the addition of the outages control.

[Table 7 about here.]

Seasonal Patterns in Absenteeism

In interviews with weaving firm managers in Surat a frequent complaint related to the difficulty of hiring daily wage workers for industrial work during the summer months. 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 reported that they were actively considering the possibility of combating this preference for less taxing work by temporarily raising wages through a summer attendance bonus. However small scale weaving units operate on very tight profit margins and do not necessarily have the ability to raise wages very easily.

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.

[Figure 6 about here.]

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. 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 3 (column 2). 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 7 about here.]

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	$-.046^{***}$	-0.044^{***}	-0.038^{***}	-0.038^{***}	-0.033^{***}
	(0.012)	(0.011)	(0.011)	(0.010)	(0.010)
rainfall	0.006^{**}	0.004^{***}	0.006^{***}	0.001	0.001
	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
capital		0.382^{***}	0.342^{***}	0.383^{***}	0.304^{***}
		(0.010)	(0.010)	(0.007)	(0.006)
Capital Controls	N	Y	Y	Y	Y
Worker Controls	N	N	Y	N	Y
Units	21,525	21,525	21,525	21,525	21,525
R^2	0.0076	0.4615	0.4876	0.6705	0.6595

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

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	$-.050^{***}$	-0.049^{***}	-0.040^{***}	-0.041^{***}	-0.034^{**}
	(0.015)	(0.014)	(0.013)	(0.013)	(0.012)
rainfall	0.006^{**}	0.004^{*}	0.003	0.001	0.001
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
capital		0.382^{***}	0.342^{***}	0.383^{***}	0.304^{***}
		(0.010)	(0.009)	(0.007)	(0.006)
Capital Controls	N	Y	Y	Y	Y
Worker Controls	N	N	Y	N	Y
Units	21,525	21,525	21,525	21,525	21,525
R^2	0.0076	0.4615	0.4876	0.6705	0.6595

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

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	−0.007
	(0.085)	(0.025)
20°C to 25°C	0.125	−0.039
	(0.078)	(0.025)
Above 25°C	0.066	−0.032*
	(0.048)	(0.017)
rainfall	0.004	0.002
	(0.006)	(0.002)
power outages		−0.091
		(0.087)
Number of Units	21,525	21,525
Mean Obs. per Unit	4.8	4.8
R^2	0.685	0.202

Notes: 1. All models include plant and year fixed effects and capital controls; 2. Robust standard errors correcting for serial correlation and heteroskedasticity (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

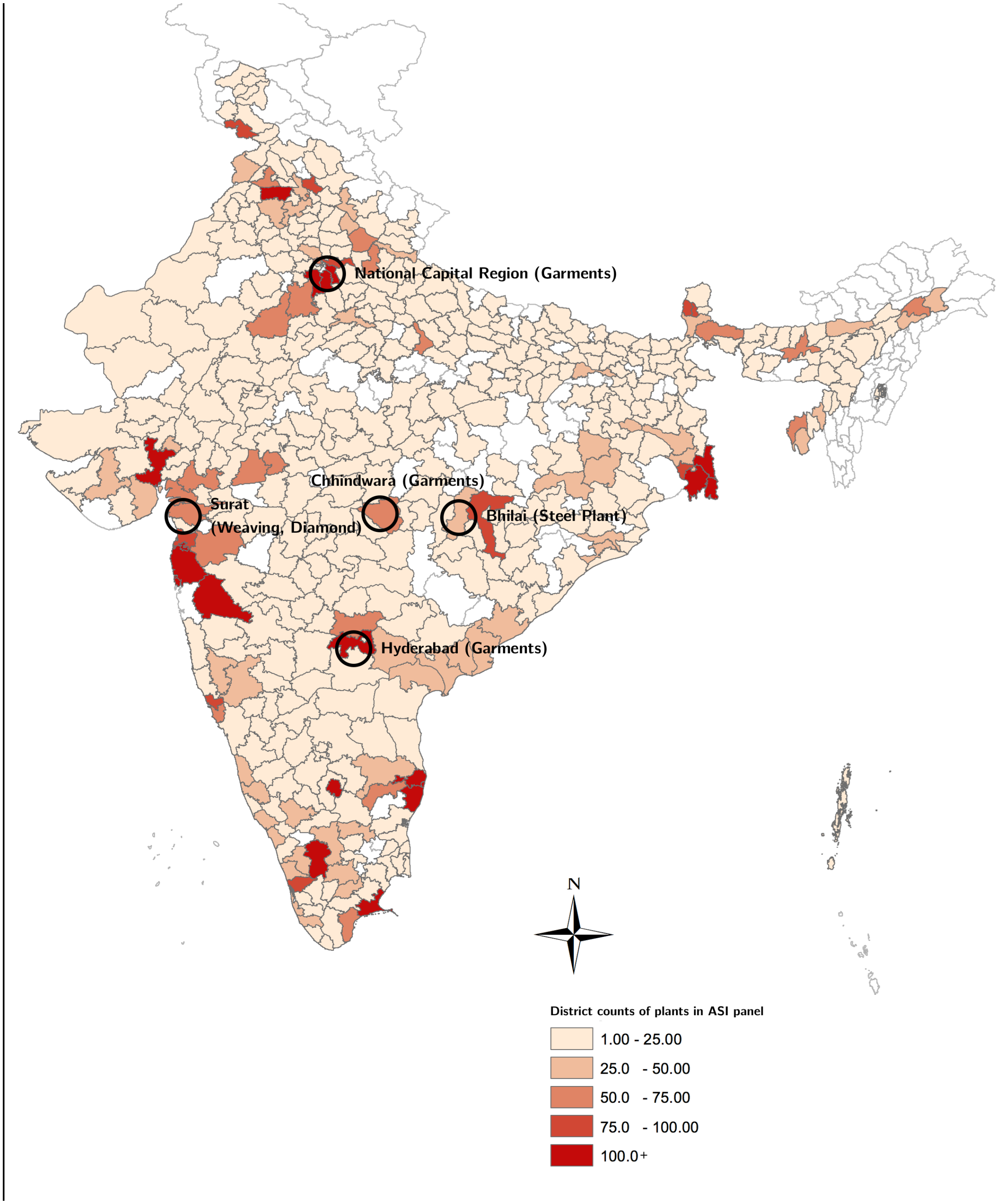

Figure A.1: Distribution of ASI plants over Indian districts and location of micro-data sites

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

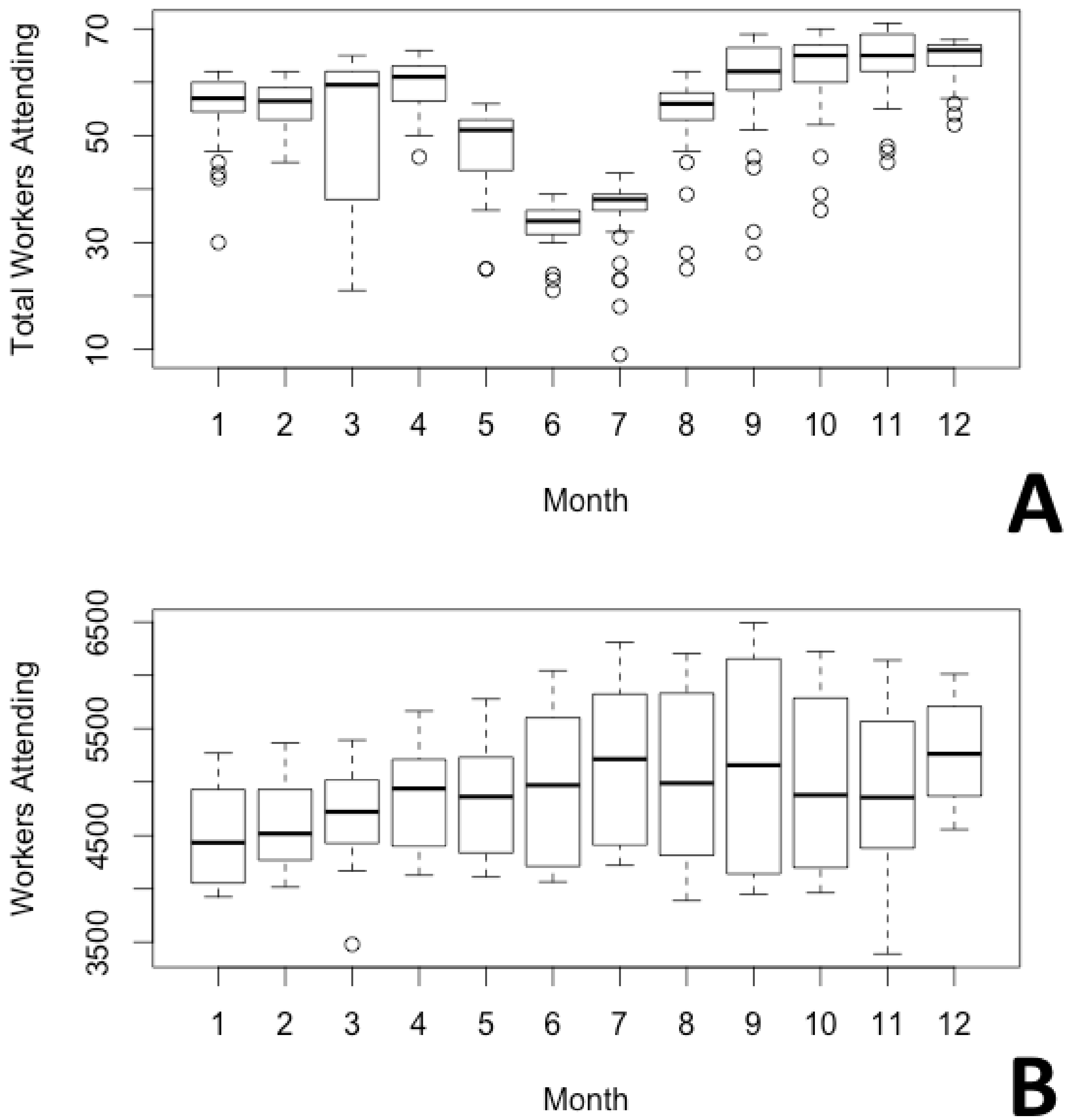

Figure A.3: Boxplots of worker attendance by month for daily wage workers in weaving units (Panel A) and regular workers in garment manufacture units (Panel B)

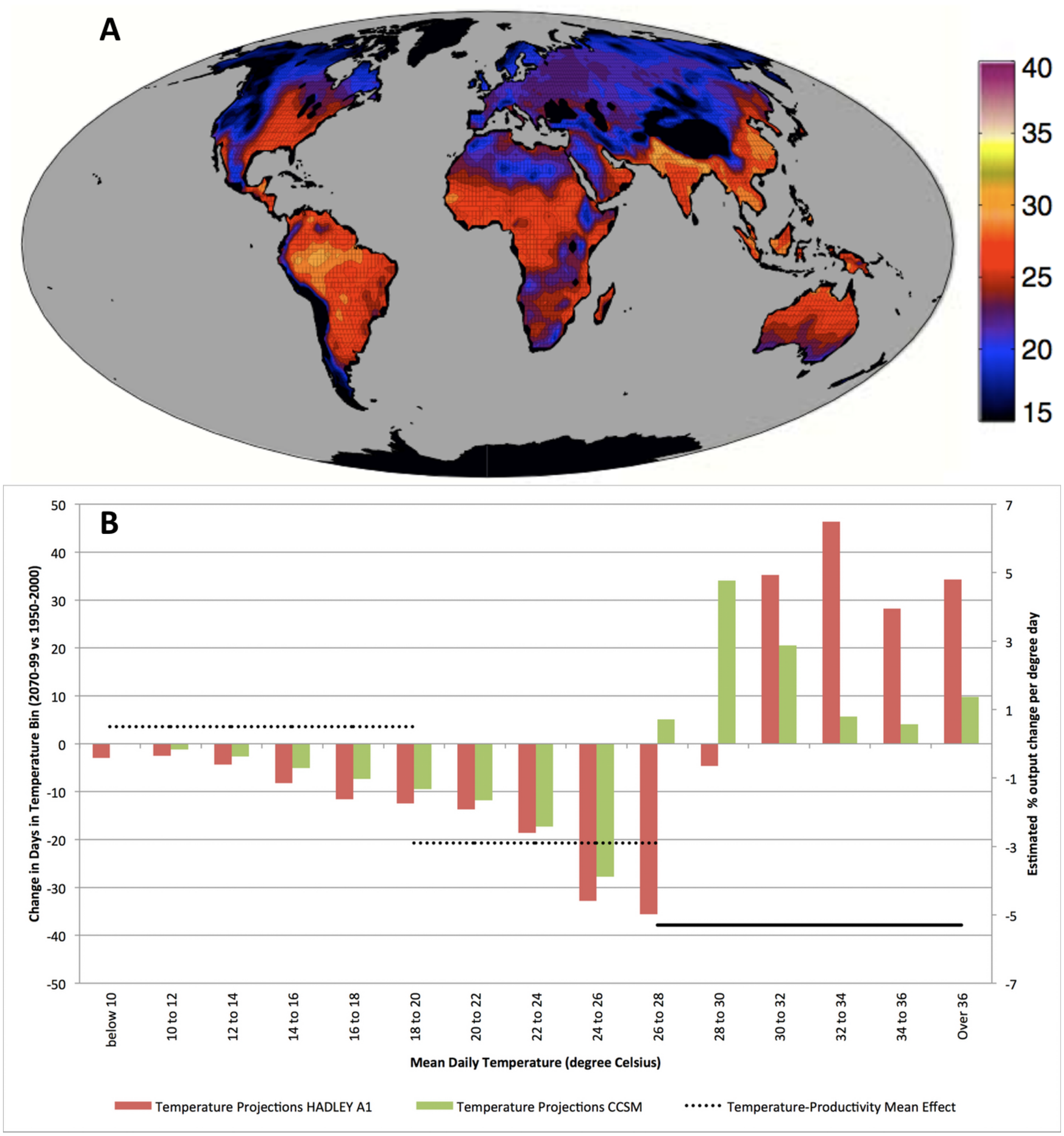

Figure A.4: Panel A: Estimated annual wet bulb globe temperature maxima, 1999-2008. Source: Sherwood and Huber (2010). Panel B: Projected temperatures under a business as usual climate change scenario for India. Source: Burgess et al. (2011). Overplotted lines denote estimated productivity impacts of temperature from Table 3, Column 3. Solid segments imply statistically significant effects