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The impact of temperature on worker absenteeism in the Indian manufacturing sector.

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Abstract

Are salaried workers more likely to be absent on hotter days? Do cooling technologies reduce heat stress and lower worker absenteeism? In this paper, we answer these questions by analysing daily data on 274 employees across 86 locations. We find that higher temperatures lead to more absenteeism but only for workers without access to climate control technologies. Cooling technologies are therefore adaptive. We also find that higher night-time temperatures decrease the probability of missing work for workers with climate control. Given that absenteeism takes worker output to zero, our findings imply that firms can minimise output losses by investing in technologies that produce thermal comfort.

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1 Introduction

In India, the formal organised sector contributed almost 50% to Gross Value Added (GVA) in 2017-18 (Murthy, 2019). Although the the share of salaried workers in total employment in India stood at 22.8% in 2017-18, there has been a steady increase in formal sector employment in India overtime due to economic growth (Mehrotra et al., 2019). The share of regular wage workers increased from 14.3 per cent in 2004-5 to 22.8 percent in 2017-18 (Mehrotra et al., 2019). India is projected to continue to grow and as it does more and more workers will be employed by the formal sector in the future. Most climate models also predict an increase in the number of hot days at all land locations in this century (Lehner et al., 2018; Sillmann et al., 2013; Seneviratne et al., 2014; Trenberth, 2015; Perkins et al., 2012). These facts suggest that it is important to understand the impact of temperature on worker productivity in the formal sector that employs salaried workers.

Workers can respond to thermal discomfort in 2 ways, they are less productive at work and they miss work more often. The former channel has been extensively studied particularly in the physiology literature that concluded in as early as 1919 that higher temperatures reduced worker output. (Parsons, 2007) has a detailed survey of these studies. This literature uses wet bulb temperature to measure heat as it takes into account the effect of relative humidity on heat stress(Kjellstrom et al., 2009; Lemke and Kjellstrom, 2012; Parsons, 2007). Humans generate heat when working and this heat must be dissipated to maintain thermal comfort. The efficiency of the heat transfer mechanism depends not only on ambient temperature but also on relative humidity. But observational data on relative humidity is often missing in developing countries forcing researchers to use ambient measures of temperature such as maximum temperature and minimum temperature.

Prior evidence on temperature impacts on worker absenteeism is much more limited. Workers can miss work due to both or either higher maximum temperatures and higher minimum temperatures. Minimum temperatures are recorded at night and hotter nights may imply lower quality of sleep that may influence the decision to show up at work whereas higher maximum temperatures induce fatigue during the day. The impact of these two temperature measures on worker absenteeism is not perfectly understood. These impacts will also vary depending on whether workers have access to climate control technologies at work or at home.

(Somanathan et al., 2021; Adhvaryu et al., 2020) have analysed the impact of high temperatures on worker output and estimated temperature impacts on worker absenteeism in very few specifications. Given their primary focus is analysing worker output that is likely to be more impacted by higher daytime temperatures at the workplace, these studies do not examine the impact of minimum temperature on worker absenteeism. The samples are from a small number of locations and from industries where output per worker is observable. (Somanathan et al., 2021) use temperature bins of maximum temperature to model a non-linear relationship between worker absenteeism and temperature whereas (Adhvaryu et al., 2020) use reanalysis data to calculate wet bulb temperature and its impact on absenteeism in two specifications in their paper but do not analyse the impact of climate control technologies on worker absenteeism.

In this paper, we examine the impact of daily maximum temperature and daily minimum temperature on worker absenteeism in the formal sector in India. We focus on worker absenteeism because that is largely the only observable measure of worker productivity in the formal sector. We estimate separate models for workers with access to climate control technologies and workers without climate control at the workplace. The data on worker absenteeism is from a large welding company in India. We collect daily data on worker attendance that spans 86 locations (see Figure 1) across India. More than 200 workers in these locations are followed over a period of almost 3 years from 2016-2018. The workers employed by this company comprise mainly of engineers. They commute on a daily basis to offer assistance with the installation and use of welding equipment to their clients. This allows us to identify outdoor workers who are hit the hardest by high temperatures.

More studies from the formal sector in developing countries are needed to estimate the impact of temperature on worker absenteeism. Economic growth implies an expansion of the formal sector that employs salaried workers. Further, as the climate warms in the developing world, worker absenteeism is likely to increase. Since absenteeism takes output to zero, it has significant implications for industry-wide output and the economy. Knowledge of the impact of temperature on worker absenteeism is therefore needed to guide policy to adapt to rising temperatures.

We find that higher maximum temperatures increase the probability of missing work for workers without access to climate control technologies whereas higher minimum temperatures decrease the probability of missing work for workers with climate control. The latter finding is robust for majority of the regression models barring one specification. We also explore non-linear and lagged temperature impacts and our findings remain intact. For maximum temperature, we estimate contemporaneous impacts of about 4.7% relative to mean absenteeism and lagged impacts of about 5.8%. The estimated impacts for minimum temperature are slightly lower in magnitude with impacts of about 3-4% of mean absenteesim.

The findings above are based on regression models that control for worker fixed effects and time fixed effects i.e. year-month and day of the week fixed effects. All the models are estimated for two sub-samples in the data, workers with and without access to climate control technologies. The source of the identifying variation is the day-to-day variation in worker attendance and temperature that remains after we have removed the variation due to unchanging worker characteristics and seasonality due to day of the week and month and year.

The primary contribution of this study is to the literature on the relationship between worker absenteeism and temperature in the formal manufacturing sector that employs salaried workers. Prior two studies (Somanathan et al., 2021; Adhvaryu et al., 2020) in this area have largely focused on the impact of temperature on worker output in industries that record output. In many settings though worker output is not readily observable. The only observable measure of worker productivity is worker absenteeism. Estimates of the magnitude of the impact of higher temperature on worker productivity measured by worker absenteeism are important for two reasons. First, the formal manufacturing sector employs a substantial number of people even in developing countries. About 24% of India's workforce was made of regular salaried employees in 2018 (Initiative, 2020). Second, salaried employees have higher productivity than piece-rate employees (Bryson et al., 2011) and therefore their absenteeism leads to a larger decline in output.

2 Data

The following section describes the data sources.

2.1 Worker Data

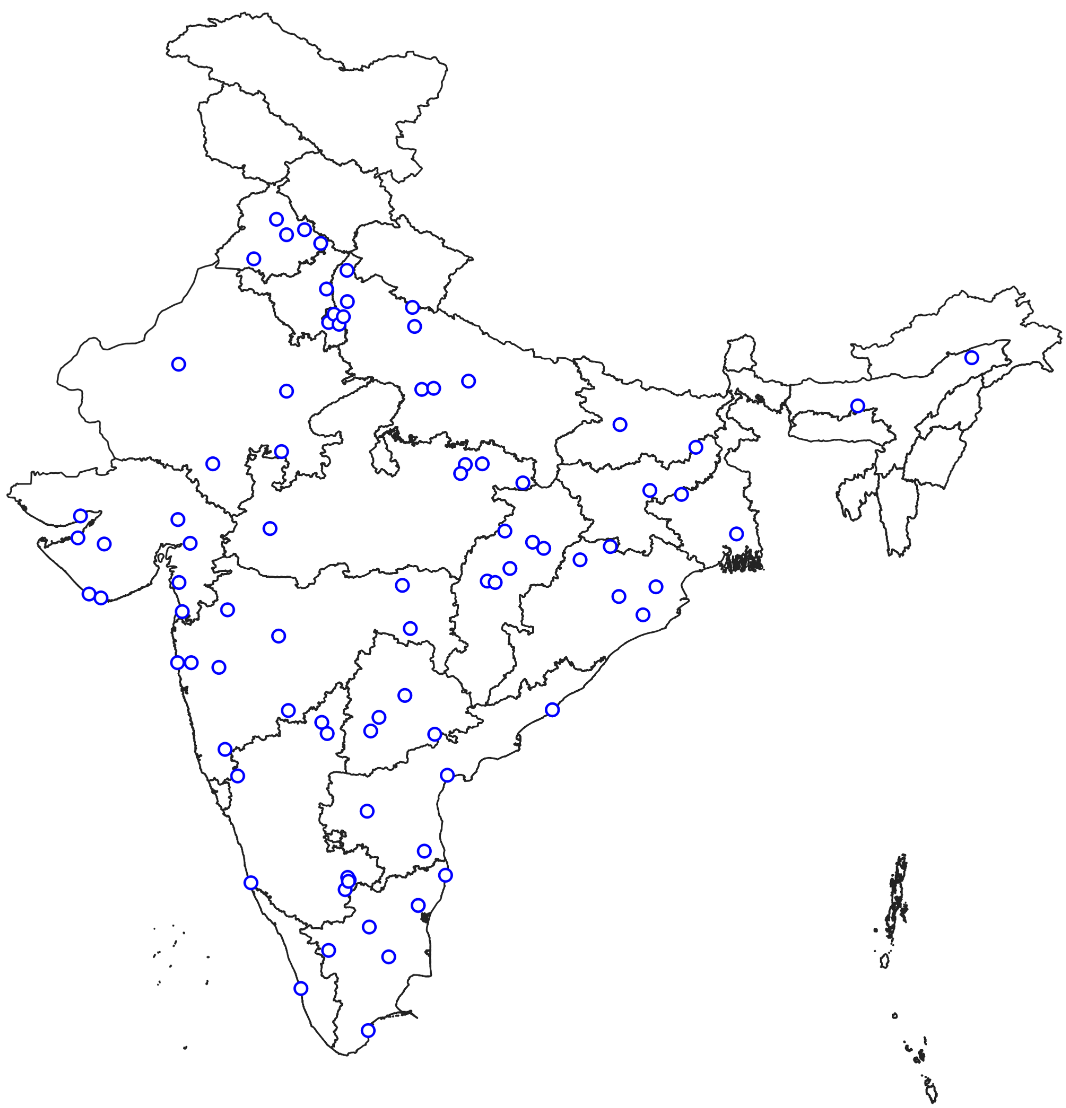
Daily data on worker attendance is taken from a large welding company in India. The company is one of the largest provider of high-quality welding equipment, consumables, automation solutions and training. It has offices in many locations nationally and internationally and has played a significant role in the post-independence industrialisation in India. Majority of their workers are sales workers that are engineers. Their primary job is to offer assistance to their clients with the use of welding equipment and promote sales. The workers are required to make visits to sites where the machinery is installed. Their main mode of transport is two-wheelers. The non-sales workers are stationed in offices and their task ranges from managing the company accounts to dealing with human resources. All employees are salaried and are entitled to a fixed monthly wage.

The company follows a six day working week with Sunday being a holiday. Employees can take a fixed amount of leave every year that varies depending on their location. We measure worker absenteeism by a dummy variable that takes the value1 if a worker was present on a working day and zero otherwise. We, therefore, exclude holidays and Sundays from the sample.

The sales workers do not have access to any climate control technologies when they are on site visits. On days that they are not performing site visits they work from their offices. The non-sales workers that comprise of accountants, human resource personnel etc., on the other hand, work in climate controlled environments. The data therefore has information on the type of climate control technology that is available to each worker.

The dataset includes daily data on more than 200 workers that are spread across 86 locations in India. The study covers the period from 2016-2018. The use of climate control technologies by a worker determines his heat exposure and in turn his productivity. Temperature impacts on absenteeism should be higher where climate control and cooling is likely to be limited. Hence, we split workers into two sub-samples depending on whether a worker had access to climate control technology.

Figure 1: Workplace Locations



2.2 Weather Data

Daily data on temperature were obtained from the Global Surface Summary of the Day (GSOD) data from the National Climatic Data Center, NESDIS, NOAA, U.S. Department of Commerce (NOAA, 2015). This database contains global daily station-level data on weather variables such as temperature and rainfall. We extract data on daily maximum temperature and daily minimum temperature and daily rainfall from this database to control for temperature. Data from the closest weather station to a factory location is assigned to all the workers in that location. This data allows us to estimate impacts of temperature on worker absenteeism for a larger sample as it contains data from weather stations all over India.

Table 1 and Figure 2 report summary statistics of the key variables of interest. The dependent variable absenteeism is defined as the number of days a worker is absent per 1000 days. It is binary and takes the value 1000 if a worker was absent on a working day and 0 otherwise. Figure 2 shows that worker absenteeism is highest during May, the hottest month in the data, followed by the month of December when business activity is low all over the world. The summary statistics in Table 1 are shown for the 2 sub-samples in the study i.e. workers with and without access to climate control technologies.

Figure 2: Worker attendance and Mean Temperature by month

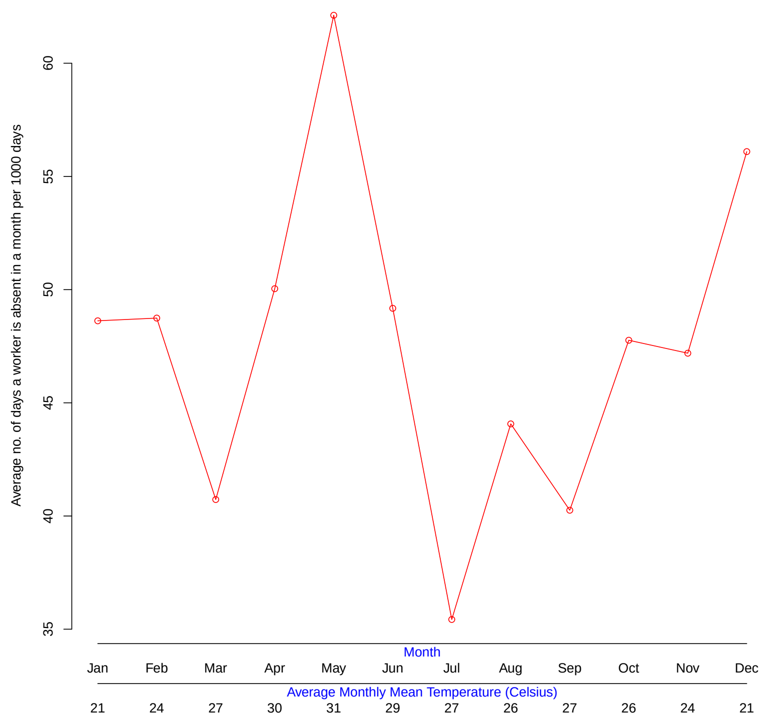


Table 1: Summary Statistics

	Mean	Standard Deviation	Min	Max	Count
Sample of Workers without Climate Control					
Absent (No. of days a worker is absent per 1000 days)	61.30	239.88	0	1000	93381
MaxT (Celsius)	31.84	4.28	13.22	47	91622
$MaxT_{3day}$	31.85	4.13	15.51	46	91255
$Weekly_{MaxT}$	31.87	4.08	15.86	45.56	91151
$L2_{MaxT}$ (No. of days MaxT was in Q2 (29.11, 31.61] in the week)	1.84	2.19	0	7	89709
$L3_{MaxT}$ (No. of days MaxT was in Q3 (31.72, 34.61] in the week)	1.66	2.18	0	7	89709
$L4_{MaxT}$ (No. of days MaxT was in Q4 (34.72, 50] in the week)	1.60	2.53	0	7	89709
MinT (Celsius)	20.52	4.58	0.72	34	91622
$MinT_{3day}$	20.52	4.48	4.11	33.15	91255
$Weekly_{MinT}$	20.54	4.42	5.21	31.38	91151
$L2_{MinT}$ (No. of days MinT was in Q2 (18.28, 20.29] in the week)	2.03	2.53	0	7	89709
$L3_{MinT}$ (No. of days MinT was in Q3 (21, 24.28] in the week)	1.75	2.29	0	7	89709
$L4_{MinT}$ (No. of days MinT was in Q4 (24.29, 36.39] in the week)	1.43	2.51	0	7	89709
Rainfall (mm)	3.23	13.83	0	361.95	87376
Sample of Workers with Climate Control					
Absent (No. of days a worker is absent per 1000 days)	44.11	205.34	0	1000	88783
MaxT (Celsius)	32.40	4.49	11	50	69472
$MaxT_{3day}$	32.40	4.33	13	48.50	69047
$Weekly_{MaxT}$	32.43	4.28	13.20	47.43	69127
$L2_{MaxT}$ (No. of days MaxT was in Q2 (29.11, 31.61] in the week)	1.66	2.07	0	7	66499
$L3_{MaxT}$ (No. of days MaxT was in Q3 (31.72, 34.61] in the week)	1.83	2.24	0	7	66499
$L4_{MaxT}$ (No. of days MaxT was in Q4 (34.72, 50] in the week)	1.89	2.74	0	7	66499
MinT (Celsius)	21.12	5.05	0.11	36.39	69469
$MinT_{3day}$	21.12	4.95	1.90	33.19	69046
$Weekly_{MinT}$	21.15	4.90	2.53	32.90	69122
$L2_{MinT}$ (No. of days MinT was in Q2 (18.28, 20.29] in the week)	1.37	2.19	0	7	66488
$L3_{MinT}$ (No. of days MinT was in Q3 (21, 24.28] in the week)	1.73	2.30	0	7	66488
$L4_{MinT}$ (No. of days MinT was in Q4 (24.29, 36.39] in the week)	2.13	2.88	0	7	66488
Rainfall (mm)	3.12	12.75	0	361.95	66748

3 Temperature Effects on Absenteeism

3.1 Linear Modelling of Temperature

Daily absenteeism was regressed on daily maximum temperature, daily minimum temperature, rainfall and a bunch of fixed effects.

The models are of the form

$$A_{id} = w_i + \alpha_D + \gamma_Y + \nu_M + \beta_1 \mathit{MaxT}_{id} + \beta_2 \mathit{MinT}_{id} + \delta \mathit{Rain}_{id} + u_{id} \tag{1}$$

where the subscripts i and d refer to worker and day respectively, $MaxT$ is the average daily maximum temperature and $MinT$ is the average daily minimum temperature. $Rain$ is the daily rainfall and u is the error term. w_i is a worker-specific intercept that controls for all worker-specific time-invariant factors. The coefficient on α_D accounts for seasonality due to the day of the week, γ_Y controls for year and ν_M for month specific seasonality. The β coefficients, therefore, capture the effect of deviations from mean maximum temperature and mean minimum temperature on deviations from mean absenteeism after removing the variation due to seasonality and fixed characteristics of workers and rainfall.

Residuals in these regressions could also be spatially correlated across workers in the same location and serially correlated over days. We addressed this issue by using Driscoll-Kraay standard errors (Driscoll and Kraay, 1998; Hoechle, 2007) that are robust to both cross-sectional dependence and temporal dependence when the time dimension becomes large. Since we have daily data on workers for almost 3 years, the time dimension is large.

Sustained high temperatures may lead to fatigue or illness. Following prior literature, we also estimate the impact of lagged temperature on absenteeism. This is done in 2 ways. We calculate the average temperature up to 3 working days prior and on the day the worker reported to work and the average temperature in the past 6 working days and on the same day. We modify Equation 1 and replace concurrent temperature with the average of lagged and current temperature.

The models are of the form

$$A_{id} = w_i + \alpha_D + \gamma_Y + \nu_M + \beta_1 \mathit{MaxT}_{3day} + \beta_2 \mathit{MinT}_{3day} + \delta \mathit{Rain}_{id} + S_{id} + u_{id} \tag{2}$$

$$A_{id} = w_i + \alpha_D + \gamma_Y + \nu_M + \beta_1 \textit{Weekly}_{MaxT} + \beta_2 \textit{Weekly}_{MinT} + \delta \textit{Rain}_{id} + S_{id} + u_{id} \tag{3}$$

The new temperature measures in Equation 2 are $MaxT_{3day}$ and $MinT_{3day}$ and in Equation 3 are $Weekly_{MaxT}$ and $Weekly_{MinT}$. These are the averages of lagged and current temperature with lags upto the last 3 working days and in the last 6 days.

4 Non-Linear Modeling of Temperature

We model temperature with indicator variables to capture potential nonlinear and lagged effects on absenteeism. We follow the approach of Schlenker and Roberts (2009); Somanathan et al. (2021) to create the indicator variables. The quartiles of temperature divide the data into bins and we calculate the number of days temperature fell in a particular bin in the six days preceding a work day and on the current day. The first quartile is the omitted category.

The bin lengths for maximum temperature and minimum temperature are given in Table 1. The regression equation that we estimate is as follows:

$$A_{id} = w_i + \alpha_D + \gamma_Y + \nu_M + \sum_{j=2}^{4} \omega_j \boldsymbol{L}^j_{MaxTid} + \sum_{j=2}^{4} \zeta_j \boldsymbol{L}^j_{MinTid} + \delta \textit{Rain}_{id} + S_{id} + u_{id} \tag{4}$$

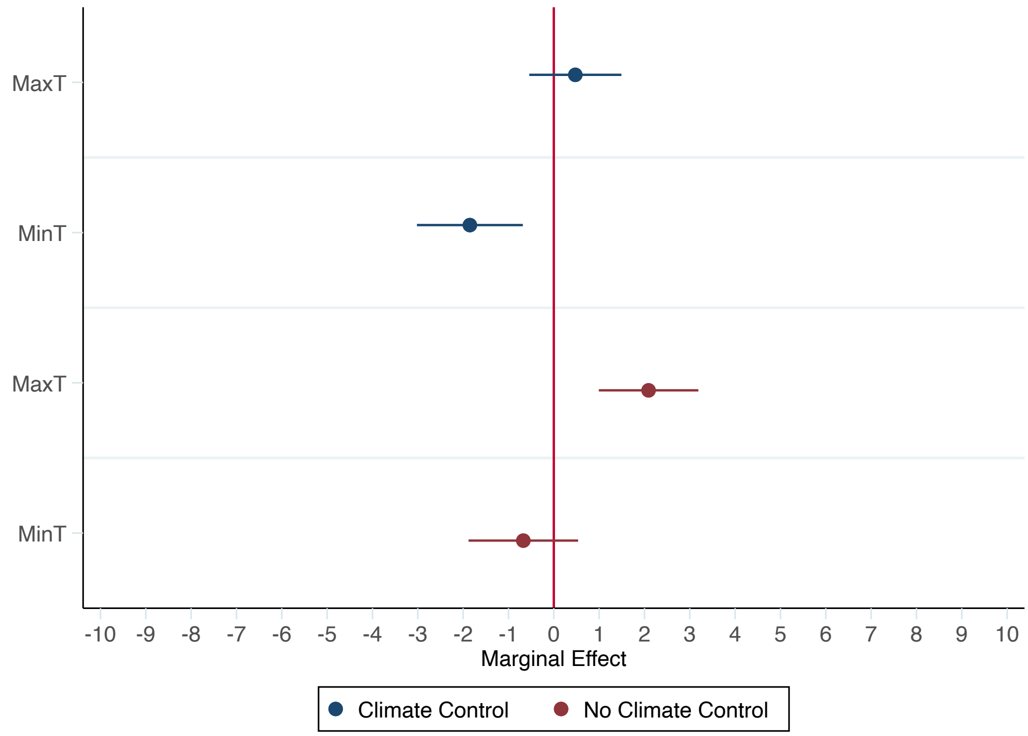
The temperature control in Equation 4 is L^j, a count of the number of days temperature was in Quartile j in the preceding 6 days and on the current day.

We also model temperature using restricted cubic splines. The Akaike Information Criterion (AIC) was used to decide on the number of knots to be used in the spline model. We looped over several choices for the number of knots and chose the value 4 since that minimised AIC. This was done for each sub-sample of the data i.e. workers with and without access to climate control technologies.

4.1 Results

Coefficient estimates of Equation 1 are shown in Figure 3. We find that as daily maximum temperature increases absenteeism increases for workers without climate control. Results from column (1) imply a 4.7% increase in the probability of missing work for a 1°C increase in maximum temperature relative to mean absenteeism in this sample. We find lower estimates for minimum temperature of about 3% and in the opposite direction for workers without climate control. For this sample, we find statistically significant impacts only for minimum temperature.

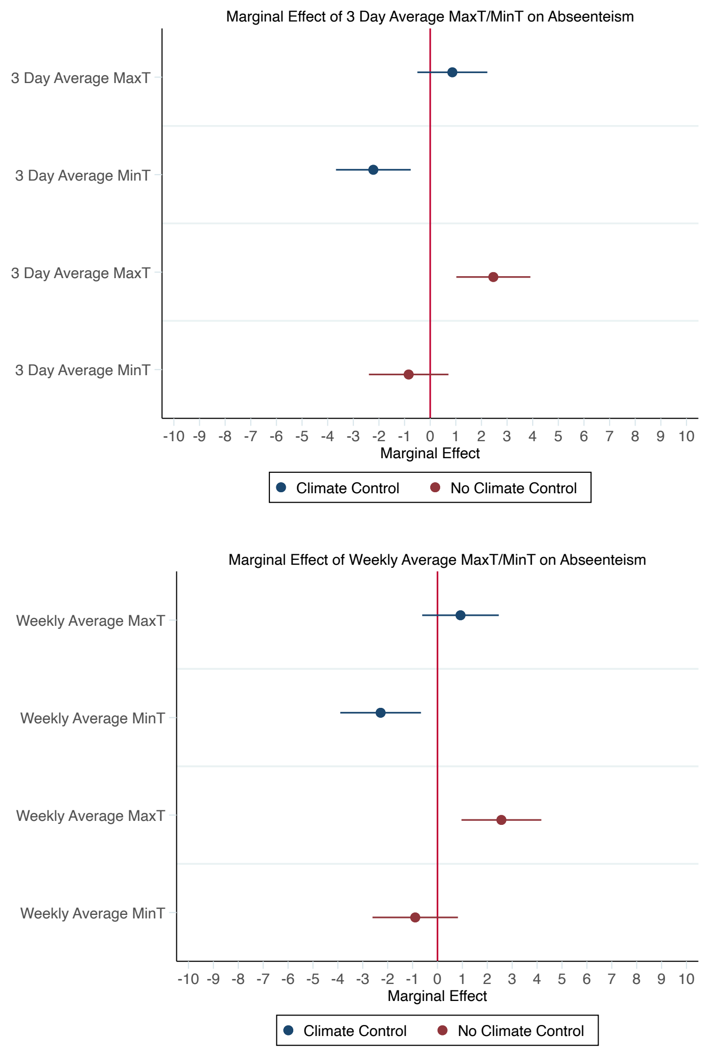
Figure 3: Linear Impact of Temperature on Absenteeism



Notes: The dependent variable is absent per 1000 days. Plots depict the β coefficients from Equation 1 with 95% confidence intervals computed using Driscoll-Kraay standard errors that are robust to cross-sectional and temporal dependence. Regression estimates are shown for both the sub-samples in the study i.e. workers with and without climate control. The regression uses 87,352 observations on 144 employees that have access to climate control technologies and 66,745 observations on 130 employees that did not have access to climate control technologies over the three year time span of the study. Year, month, and day-of-the-week fixed effects are included in the regression (Equation 1.

The impact of higher temperatures during the week on worker attendance i.e. estimates of Equation 2 and Equation 3 are shown in Figure 4. The results for the three day averaged temperatures are similar in direction and magnitude to the results from the model shown in Figure 3 that accounts for contemporaneous temperature. We find slightly higher estimates for average weekly temperatures. The probability of missing work due to a 1°C increase in average maximum temperature in the week increases to about 2.62 for workers without climate control. This corresponds to about 5.8% of the mean absenteeism in this sample.

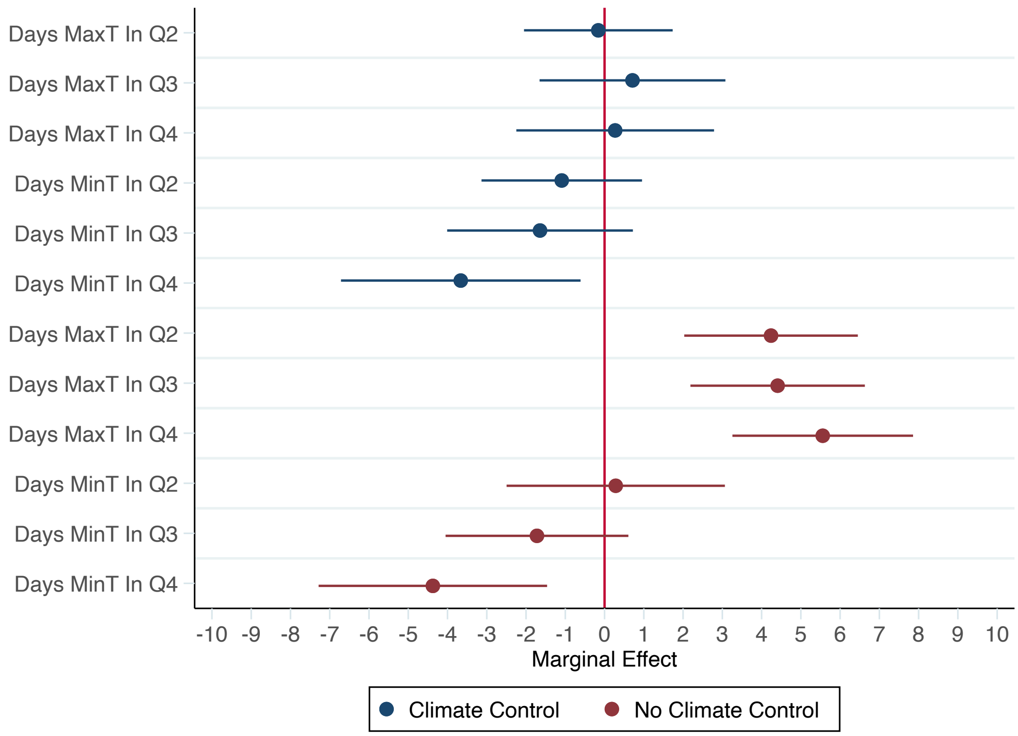
Figure 4: Impact of Average Weekly Temperature on Absenteeism



Notes: The dependent variable is absent per 1000 days. Plots depict the β coefficients from Equation 2 & Equation 3 with 95% confidence intervals computed using Driscoll-Kraay standard errors that are robust to cross-sectional and temporal dependence. Regression estimates are shown for both the sub-samples in the study i.e. workers with and without climate control. The regression uses 86,550 observations on 144 employees that have access to climate control technologies and 65,755 observations on 127 employees that did not have access to climate control technologies over the three year time span of the study. Year, month, and day-of-the-week fixed effects are included in the regression (Equation 2 & Equation 3).

The estimates from Equation 4 are shown in Figure 5. For workers without climate control, an additional day that maximum temperature is above $34.7°C$ in the six preceding days and on the current day relative to a day in the first quartile of maximum temperature causes an increase by 12% in the probability of missing work. This estimate decreases by half in magnitude for minimum temperature for the sample of workers that have access to climate control.

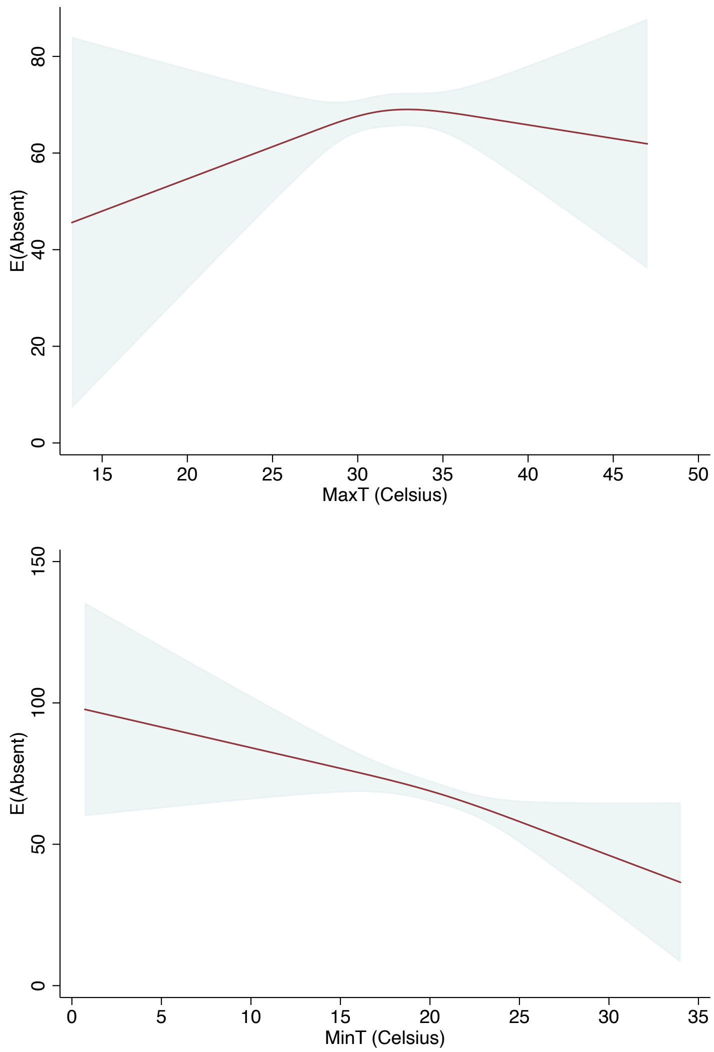
Figure 5: Impact of Sustained High Temperatures on Absenteeism



Notes: The dependent variable is absent per 1000 days. Plots depict the ω_j and ζ_j coefficients from Equation 4 with 95% confidence intervals computed using Driscoll-Kraay standard errors that are robust to cross-sectional and temporal dependence. Regression estimates are shown for both the sub-samples in the study i.e. workers with and without climate control. The regression uses 85,582 observations on 144 employees that have access to climate control technologies and 63.914 observations on 126 employees that did not have access to climate control technologies over the three year time span of the study. Year, month, and day-of-the-week fixed effects are included in the regression (Equation 4).

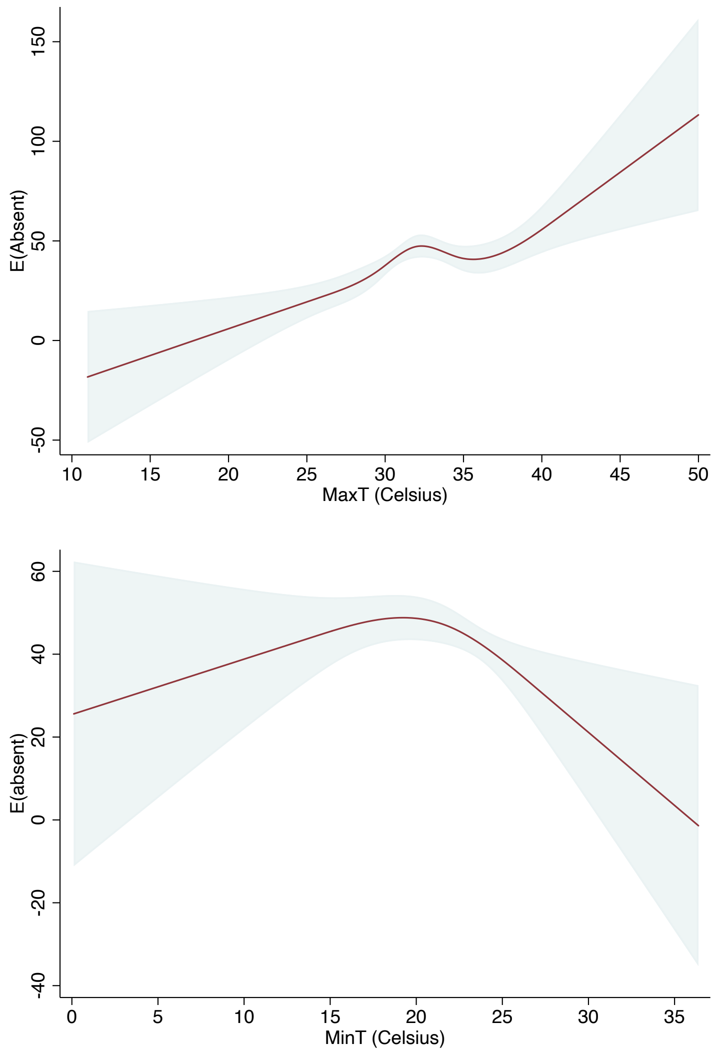
The results from the restricted cubic spline model are shown in Figure 6 and Figure 7. The results indicate that the relationship between temperature and worker absenteeism is largely linear for both the sub-samples in the study.

Figure 6: Non-Linear Impact of Temperature on Absenteeism: Workers with Climate Control



Notes: The dependent variable is absent per 1000 days. Plots depict 95% confidence intervals computed using standard errors that are clustered by worker. Year, month, and day-of-the-week fixed effects are included in the regression.

Figure 7: Non-Linear Impact of Temperature on Absenteeism: Workers without Climate Control



Notes: The dependent variable is absent per 1000 days. Plots depict 95% confidence intervals computed using standard errors that are clustered by worker. Year, month, and day-of-the-week fixed effects are included in the regression.

To sum-up the results from our models indicate that higher temperatures (both contemporaneous and lagged) impact worker absenteeism. We find that for workers without access to climate control higher day-time temperatures make it more likely that they will miss work. This finding is robust across specifications. We do not find that minimum temperature impacts this sub-sample of workers except in the regression model in Equation 4. The estimates from this model are shown in Figure 5. Here, we find that an additional day during the week at the very end of the distribution of minimum temperature may decrease the probability of missing work relative to a day in the first quartile of the distribution. But, this result does not hold when we model minimum temperature using other specifications such as three day averages and weekly averaged temperature.

Higher minimum temperatures influence the decision to show up at work for workers in climate controlled environments. This finding is also robust across specifications. This may be because higher minimum temperatures may imply lower quality of sleep and therefore cause workers to miss work. Given that we do not have data on climate control technologies available to workers other than the workplace, we cannot verify this hypothesis. As expected, for this sub-sample of workers higher maximum temperatures do not lead to worker absenteeism.

5 Discussion and Conclusions

In this paper we analyse the impact of daily maximum temperature and daily minimum temperature on worker absenteeism by analysing data from multiple locations across India. The sample consists of salaried workers that will in the near future constitute a larger and larger proportion of the Indian workforce due to economic growth. We estimate separate regressions for workers with climate control and for workers without climate control to determine whether climate control technologies are adaptive.

The results imply that higher day-time temperatures negatively impact worker absenteeism for workers without climate control. We find evidence of both concurrent and lagged impacts of maximum temperature on the probability of missing work for these workers. Another although less robust finding is that higher night-time temperatures make it more likely that workers with climate control at the workplace will go to work. We estimate impacts of about 6% for lagged maximum temperature and of about 4% for lagged minimum temperature.

Our findings conform to the economics literature (Somanathan et al., 2021; Adhvaryu et al., 2020) on estimates of temperature on worker absenteeism in developing countries. We are unable to compare our estimates with the estimates in (Somanathan et al., 2021; Adhvaryu et al., 2020) because of differing methodologies. (Somanathan et al., 2021) use two temperature bins in daily maximum temperature to estimate contemporaneous impacts and counts of the number of days maximum temperature was in each bin the preceding six days to estimate lagged impacts. Our preferred measure is daily maximum temperature and daily minimum temperature and the contemporaneous and lagged impacts of both these temperature variables in our paper are subsumed in one variable that is a count of the number of days temperature was in a bin on the same day and the preceding six days.

Knowledge of temperature impacts of worker absenteeism in the formal sector is important particularly for developing countries that already employ a large number of people in it. Further, as the data shows this number is likely to increase due to economic growth. If we assume that all workers are equally productive and a proportionate increase in absenteeism implies a proportionate reduction in worker output, then our estimates imply a 4.7% decline in output due to worker absenteeism for workers without climate control due to a 1°C increase in maximum temperature. These workers are more likely to be impacted by global warming.

References

Achyuta Adhvaryu, Namrata Kala, and Anant Nyshadham. The Light and the Heat: Productivity Co-benefits of Energy-Saving Technology. *Review of Economics and Statistics*, 102(4):779–792, 2020.

Alex Bryson, Babatunde Buraimo, and Rob Simmons. Do Salaries Improve Worker Performance? *Labour Economics*, 18(4):424–433, 2011.

John C Driscoll and Aart C Kraay. Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data. *Review of Economics and Statistics*, 80(4):549–560, 1998.

Daniel Hoechle. Robust Standard Errors for Panel Regressions with Cross-Sectional Dependence. *Stata Journal*, 7(3):281, 2007.

Accountability Initiative. A Comprehensive Overview: Defining and Measuring Informality in India's Labour Market. 2020.

Tord Kjellstrom, Ingvar Holmer, and Bruno Lemke. Workplace Heat Stress, Health and Productivity–an Increasing Challenge for Low and Middle-Income Countries During Climate Change. *Global Health Action*, 2(1):2047, 2009.

Flavio Lehner, Clara Deser, and Benjamin M Sanderson. Future Risk of Record-Breaking Summer Temperatures and its Mitigation. *Climatic change*, 146(3-4):363–375, 2018.

Bruno Lemke and Tord Kjellstrom. Calculating Workplace WBGT from Meteorological Data: a Tool for Climate Change Assessment. *Industrial Health*, 50(4):267–278, 2012.

Santosh Mehrotra et al. Informal employment trends in the indian economy: Persistent informality, but growing positive development. *ILO (working paper)*, 2019.

SV Ramana Murthy. Measuring informal economy in india: Indian experience. In *Seventh IMF Statistical Forum, Washington, DC*, 2019.

NESDIS NOAA. Global surface summary of the day. *U.S. Department of Commerce*, 2015.

Ken Parsons. *Human Thermal Environments: the Effects of Hot, Moderate, and Cold Environments on Human Health, Comfort and Performance*. CRC press, 2007.

SE Perkins, LV Alexander, and JR Nairn. Increasing Frequency, Intensity and Duration of Observed Global Heatwaves and Warm spells. *Geophysical Research Letters*, 39(20), 2012.

Wolfram Schlenker and Michael J Roberts. Nonlinear Temperature Effects Indicate Severe Damages to US Crop Yields under Climate Change. *Proceedings of the National Academy of Sciences*, 106(37):15594–15598, 2009.

Sonia I Seneviratne, Markus G Donat, Brigitte Mueller, and Lisa V Alexander. No Pause in the Increase of Hot Temperature Extremes. *Nature Climate Change*, 4(3):161, 2014.

Jana Sillmann, Viatcheslav V Kharin, FW Zwiers, Xuebin Zhang, and D Bronaugh. Climate Extremes Indices in the CMIP5 Multimodel Ensemble: Part 2. Future Climate Projections. *Journal of Geophysical Research: Atmospheres*, 118(6):2473–2493, 2013.

Eswaran Somanathan, Rohini Somanathan, Anant Sudarshan, and Meenu Tewari. The Impact of Temperature on Productivity and Labor Supply: Evidence from Indian Manufacturing. *Journal of Political Economy*, 129(6):1797–1827, 2021.

Kevin E Trenberth. Has There Been a Hiatus? *Science*, 349(6249):691–692, 2015.