The Impact of Temperature on Manufacturing Worker Productivity: Evidence from Personnel Data*

Xiqian Cai†, Yi Lu‡, Jin Wang§

This Version: May, 2016

Abstract

This paper presents evidence on the impact of temperature on daily indoor worker productivity in a non-climate-controlled manufacturing environment. Combining individual worker productivity data from personnel records in China with weather data, this paper documents an inverted-U shaped relationship between temperature and labor productivity. Workers do not increase avoidance behavior in response to heat. There is also suggestive evidence of better adaptation to higher temperatures among local workers compared with those from elsewhere. The findings suggest that the economic loss from reduced labor productivity in manufacturing due to ambient temperature is quantitatively important, providing new insights on the biological effects of climate factor in affecting human labor.

Keywords: Climate; Temperature; Thermal Stress; Manufacturing; Labor Productivity

JEL Classification: J22, J24, Q54

*We thank Graff Zivin Joshua, James Fenske and Alberto Salvo for their valuable comments. All errors remain our own.

†Xiqian Cai, Institute of Economics, School of Economics and Wang Yanan Institute for Studies in Economics, Xiamen University, Xiamen 361005, China. Email: caixiqian@gmail.com.

‡Yi Lu, Department of Economics, National University of Sinagapore, 1 Arts Link, Singapore 117570. Email: ecsluyi@nus.edu.sg.

§Jin Wang, Division of Social Science, Hong Kong University of Science and Technology, Clear Water Bay, Hong Kong. Email: sojinwang@ust.hk.

1 Introduction

Economists have long debated the role of climate factors in economic development (Sachs, 2003; Acemoglu, Johnson, and Robinson, 2002). A voluminous recent literature has empirically established a causal link between weather and economically relevant outcomes (Dell, Jones and Olken, 2014). Considerable progress has been made in estimating the agriculture sector's vulnerability to high temperature with less attention paid to industrial sectors (Deschenes and Greenstone, 2007; Schlenker and Roberts, 2009). However, agriculture may account for only a small fraction of the economic impact of local temperature. The remaining impact would be in industries that have been omitted from existing estimates of the impact of climate change (Hsiang, 2010).

According to the International Labor Organization (ILO), there are about 80 million indoor workers employed in a wide range of high-risk manufacturing sectors (ILO, 2012). They are usually exposed to high temperatures in low and middle economies because of inadequately climate-controlled working conditions. Of special interest is China because it has become the world's largest manufacturer and carbon dioxide emitter, accounting for 29 percent of global value added, 24 percent of world employment and 29 percent of total emissions (World Bank, 2013). Understanding how temperature impacts industrial sectors in general and how heat stress affects labor in countries like China in particular may, therefore, have economic significance. Yet evidence on this important topic remains scarce.

Motivated by the geographical and sectoral gaps in the literature, this study sets out to use novel evidence from a Chinese manufacturing firm to evaluate the impact of temperature on the daily productivity of indoor workers in an uncontrolled thermal environment. One could argue that hot days might lead to changes in productivity as a result of changes in the composition of production–for example, workers might decide not to work or to cut working hours on such days; on-the-job task productivity declines. To shed light on this central issue, our analyses touch on extensive and intensive margins. In particular, we start by estimating the response of labor supply to temperature. We then investigate the impact of temperature on worker productivity and identify the underlying mechanism. We also explore impact heterogeneity across worker characteristics such as gender, age and place of origin.

The firm we study is a leading producer of double-wall paper cups in China. The workers' main tasks are to operate molding machines which seal the cup's body to the bottom, and then wrapping machines, which bind up sleeves of cups. In this firm workers rotate daily among teams, products and machines for the sake of fairness. They are paid through a two-tier piece rate scheme based on their daily output and specified target levels that differ among products. These two important features have beneficial implications for the study. First, the quasi-random rotation largely eliminates any confounders correlated with temperature. Then, the piece-rates are effective in inducing effort, thus substantially reducing any bias involved in using output as a proxy for productivity (Bandiera et al., 2005; 2010). Taken together, these factors allow estimating the temperature effect more precisely with a more accurate measure of outcomes.

The analysis draws on comprehensive daily administrative data from the firm, which contains information on worker-level output and machine conditions for each workday from October, 2012 to February, 2014, as well as on weather data from the national climate data center. The administrative data are objectively measured. They include detailed information on worker characteristics such as age, gender, province of origin, the number of hours worked, and their night shift schedule. To take in air pollution and other climate factors, daily air quality data are also collected from the city's environmental monitoring station along with precipitation, humidity, wind speed, air pressure and visibility. In order to make it comparable across products, the main outcome measure—worker productivity—is expressed as a percentage of one's output over the specified product's target.

To identify the effect of temperature, we use the framework applied by Graff Zivin and Neidell (2012), Chang et al. (forthcoming) and Graff Zivin and Neidell (2014), which are the closest predecessors to this investigation. They document the potential impacts of pollution on the productivity of outdoor agricultural labor and indoor factory workers, and that of temperature on time allocation in the US. Building on their work, this study proceeds to examine temperature and industrial labor productivity. Specifically, we exploit the daily variation in the maximum temperature, which is exogenous to workers. We allow for the possibility of a nonlinear relationship between daily maximum temperature and worker productivity. To isolate the temperature effect, we properly control for various worker characteristics, environmental factors and seasonality that may potentially correlate with temperature. We further conduct a variety of robustness checks to address the possibility of omitted variables such as the allocation of teams, machines and products, machine breakdowns, typhoons and alternative pollution indicators which might influence productivity. Like all studies using detailed data from one particular firm, there is a delicate trade-off between precision and generality (Bandiera et al., 2009). To investigate the external validity of the findings, we compare the estimates with those from the US and India.

The analysis yields three classes of results. First, no absenteeism in response to temperature or pollution is observed, indicating a lack of direct avoidance behavior. There is also no impact on the number of working hours for those who went to work, suggesting no significant behavioral effects of temperature.

Second, an inverted U-shaped relationship between the daily maximum temperature and worker productivity is detected. To elaborate, productivity at temperature below $60°F$ is about 11% less than that at $75 - 79°F$, and it steadily increases over that range. The productivity then decreases to about 6.7% less above $95°F$. The annual income losses due to deviations from the most productive level ($78°F$) are around ¥400 per worker (US$61.5), i.e., 0.7% of a worker's income at $78°F$. Assuming that the estimate of the effect of temperature on labor productivity applies to all secondary workers within the same city, maintaining the temperature at the optimal level $78°F$ would translate into a $64.6 million increase in total worker earnings.

After accounting for worker, manager, machine and city-level factors, a strong impact of temperature on labor productivity remains. Only the current temperature is found to predict worker productivity, not future or past temperatures, supporting the hypothesis that thermal stress during the production process is driving losses–the biological effects of temperature. The non-linear productivity response to temperature and the optimal zone observed are largely consistent with the findings of Graff Zivin and Neidell (2014) in the US and those of Adhvaryu, Kala and Nyshadham (2015) in India. The similar patterns in China suggest that the mechanism is rather general, increasing confidence in the external validity of the findings.

Third, no significant gender or age differences in the effects of temperature on productivity are found. The effects are, however, substantially larger among non-local workers. Indeed, almost no effect is observed among local workers. The local workers are perhaps better adapted to the local temperature environment than non-local ones. This would agree with the findings of a growing number of studies on adaptation to negative climate or environment shocks (Deschênes et al., 2011).

This paper makes contact with several strands of literature. It fits into a growing body of work seeking to identify the effect of temperature on labor supply and labor productivity, driven largely by extreme heat stress. Several recent studies have shown a strong relationship between the indoor temperature and the productivity of call center workers and bank workers (Niemelä et al., 2002; Fisk et al., 2002). Cachon, Gallino and Olivares (2012) have documented at the plant level a negative effect of weather on automobile production in the United States. Adhvaryu, Kala and Nyshadham (2015) have also observed a negative, non-linear productivity-temperature gradient in the garment sector in India. As in that work, our analyses focus on labor productivity, but the novel daily worker productivity data in this study are highly disaggregated, enabling the analysis of much finer variation within a firm, which distinguish the biological from the behavioral effects of temperature stress (Heal and Park, 2015).

In a closely related paper, Sudarshan et al. (2015) use worker-level data from three industries (cloth weaving, garment and rail production) in India to examine the impact of temperature on labor supply and productivity. In addition to differences in the countries studied, the current paper departs from that work in two key aspects. First, in contrast to our findings, that paper has observed significant labor supply response to temperature, i.e., worker absenteeism increases on hot days. Such self-selection could introduce a potential bias in productivity estimates because the results are valid only for the sample of workers that chose to work.[1] This probably also explains why output reductions are only found for temperatures above $27°C$ in that paper. Second, besides temperature, pollution is an important factor in affecting worker productivity particularly in developing countries, which we have controlled for in the empirical setting while the other work did not.

This study also relates to the micro-level studies on the causal impacts of environmental conditions on health and human capital. A number of inquiries have related extreme weather and other environmental shocks to an increase in mortality in the United States (Deschênes and Moretti, 2009; Deschênes and Greenstone, 2011), Indonesia (Maccini and Yang, 2009), and Africa (Kudamatsu et al., 2012; Adhvaryu et al., 2016). Graff Zivin, Hsiang and Neidell (2015) establish a negative relationship between ambient heat and human capital. This work moves beyond examining the impact of temperature on human capital, which is an important input of the production function, to directly estimating its productivity effect.

The micro-level observations also contribute to a deeper understanding of the impacts of temperature on long-term GDP and sectoral outputs. Hsiang (2010) emphasizes the role of themal stress in causing temperature-related losses in non-agricultural industries in 28 Caribbean-basin countries. In a similar vein, Jones and Olken (2010) find that temperature affects not only agricultural exports, but also manufactured goods. Dell, Jones, and Olken (2012) have shown large and negative effects of higher temperatures on economic growth and aggregate industrial output in poor countries. The findings of this study corroborate the findings of that line of research by providing micro-level evidence that extreme temperature retards worker productivity in a manufacturing setting without climate control. The evidence also offers an account of how temperature could slow down economic progress at the sectoral level in developing countries, as prior studies have suggested.

This paper is structured as follows. Section 2 summarizes the relationship between temperature and thermal stress. Section 3 provides an introduction to the institutional context of this study and describes the daily worker productivity and environmental data, followed by econometric models. Section 4 presents the empirical results, and section 5 offers concluding remarks.

[1] See Chang et al. (forthcoming) for detailed discussions on the importance of addressing self-selection in estimating the effects of environmental factors on productivity.

2 Background

This study investigates the relationship between temperature and labor productivity. One important issue based on which such a link might be established and interpreted is the pathway at play. That temperature stress affects human economic activity is well supported by works in ergonomics and physiology. Humans are affected by their surrounding environment. Thermal conditions produce physiological and psychological strain on the person, which consequently leads to changes in health, cognition and performance (Graff Zivin et al., 2014).

The connection between exposure to high temperature and endurance and fatigue has been extensively documented (Nielsen et al. 1993; Galloway and Maughan 1997; Gonzalez-Alonso et al. 1999). Other authors have shown that temperature is an important factor in determining cognitive performance (Epstein et al., 1980; Ramsey, 1995; Hancock and Vasmatzidis, 2003). Operating through these channels, thermal stress could be expected to retard the productivity of workers (Graff Zivin et al., 2012).

According to evidence cited by Hsiang (2010), extensive laboratory and observational ergonomic studies have established an association between temperature stress and reduced human performance (Ramsey and Morrissey, 1978; Wyon, 2001; Pilcher, Nadler, and Busch, 2002; Seppäen et al., 2003; Seppäen et al. 2006; Hancock, Ross, and Szalma, 2007). Most forms of human performance deteriorate with thermal stress beyond a threshold (Hsiang, 2010), but not always linearly. There is little performance loss in moderate temperature regimes (Hancock and Warm, 1989). Heat stress leads to a decline in productivity beginning at moderate deviations from the optimal zone $27°C$ $(80°F)$ (Heal and Park, 2015).

Individuals vary in their responses to heat. Inherent characteristics including body size, gender, ethnicity and age and acquired characteristics such as physical fitness, heat acclimatization, obesity, medical conditions and self-induced stress all influence responses to heat (Nunneley, 1998). Early laboratory studies seemed to detect significant group differences in heat tolerance between males and females as well as between younger and older persons. Women were found to be less heat-tolerant than men. Older persons also on average exhibit less heat tolerance: industrial populations generally show a gradual decline in heat tolerance after age 50. However, recent research has viewed such group differences as driven by aerobic capacity and heat acclimatization rather than gender, race or age (Kenney et al., 1992).

Maximal aerobic capacity (VO2 max) has been found to be a very important predictor of individual responses to heat stress. Persons exposed repeatedly to heat will tolerate the heat better after even a few days. They become acclimatized (Nielsen, 1998). By contrast, less frequent exposure to heat has a much weaker effect in building heat acclimatization and subjects' heat tolerance may gradually decay (Nunneley, 1998).

3 Methods

3.1 Institutional Context

Established in 2003 at Xiamen in Fujian Province, the company has become a major supplier of paper cups for the food and beverage industry. In 2011, it accounted for about 15% of the national market. By 2013, it had total assets of US$7 million, annual revenue of $5 million, and about 300 employees. Xiamen is a major city on the southeast coast of China, and Xiamen's weather is mild during much of the year except from July to September (the typhoon season). The average temperature is about $21°C$ (about $70°F$). The factory is in the Xiamen Xiang'an industrial district. The factory has an administrative area, a production area, a warehouse, a dormitory, a dining-room and a basketball court. The workshop covers an area of 10,000 square metres. The corporate structure is illustrated in Figure 1.

[Insert Figure 1 here]

Double-walled paper cup production is segmented into four stages—laminating, printing and cutting, molding and wrapping. The data collection focused on the production workers in the molding and wrapping departments, who operate the molding and wrapping machines. Workers are hired from both within and outside Fujian Province. Each day, they are divided into day and night shifts, each of 12 hours. Within a shift, each worker is assigned a machine and a product to work on. A machine can generally be configured for multiple types of products, and production efficiency may differ among products depending on the production processes involved.

Workers rotate jobs regularly in terms of which machine they operate and which product they produce. Specifically, at the start of the workday, workers are informed of their teams, with each team manager supervising four or five workers. Team composition was determined by the deputy general manager in charge of production one day before. It varies by day, and is normally unknown to the team managers and workers until they arrive at the site. Team managers determine who operates each machine for each product category. Workers do not themselves decide which product or machine they work on, nor do they decide which team to work with. Once the assignment has been made, they cannot change either the machine or the product. The only choice a worker has is how much effort to exert into running the machine and processing material for the next production stage. The nominally random rotation in fact takes into account fairness concerns, as the deputy general manager explained. It also partially reflects the fact that there is little heterogeneity in the workers' skill by design they have equal chances to acquire skills, competence and expertise through the jobs assigned.

Once production begins, team managers prepare boxes labeled with the workers' names and products, and (if needed) help facilitate operations. Given the production technique, a worker's output strongly depends on the normal functioning of the machine. If a machine breaks down, the worker calls the team manager or maintenance staff to repair it. Team managers record the duration of the breakdown and repair. During that period the worker is not allowed to change to a different machine or to leave the workplace, which means that his (or her) production is completely interrupted until the machine is fixed.

Team managers are paid a flat rate, while workers are paid a two-tier piece rate based on their daily output and specified target levels determined by the deputy general manager in charge of production. The targets $\bar{Q}_p$ differ across products with an average value of 20,000 pieces. The target will be adjusted downward if a machine breakdown occurs. When meeting the target, workers are paid a piece rate (denoted α_1) per unit of output. After their output exceeds the target, a higher rate α_2 will be applied to each unit above the target. If a worker fails to meet the threshold, the unfulfilled units are deducted at the same rate α_2. The piece rate of the first tier α_1 varies between ¥0.005 and 0.007; and that of the second tier is set as $\alpha_2 = \alpha_1 + \delta$ with $\delta \in [0.002, 0.004]$. Formally, a worker's daily salary w_{id} is determined by $\alpha_1 \bar{Q}_p + \alpha_2 (Q_{id} - \bar{Q}_p)$, where Q indicates output, p indicates product, i indicates worker and d indicates day.

3.2 Estimation Specification

To examine the effect of temperature, we follow the identification framework used in the literature (e.g., Graff Zivin and Neidell, 2009 and 2014),

$$y_{id} = f_1(temp_d) + \mathbf{X}_d' \boldsymbol{\eta} + \mathbf{D}_i' \theta + \varepsilon_{id}, \tag{1}$$

The dependent variable is the outcome y of worker i on day d. We begin by examining the impact of temperature on labor supply. Specifically, two outcome variables are constructed: a dummy variable indicating whether or not worker i went to work on day d to measure the labor supply response at the extensive margin, and a variable of working hours for worker i who went to work on day d to measure the labor supply response at the intensive margin. We then investigate the effect of temperature on worker productivity, the key outcome of interest. In particular, to account for the variation in product type, the outcome variable—worker productivity—is defined as worker i's over-target percentage of output; specifically,

$y_{id} \equiv \left(Q_{id} - \bar{Q}_p\right) / \bar{Q}_p * 100$. As the workers' compensation is completely based on their daily output, both the firm and workers take care to record productivity precisely, suggesting minimal measurement errors.

The core regressor of interest is the daily maximum temperature, controlling for the minimum temperature following the lead of Graff Zivin and Neidell (2014). No information on indoor temperature was recorded, so the outdoor temperature were used. The indoor and outdoor temperatures should be highly correlated as the workshop had no heating or air conditioning.[2] The $f_1(temp_d)$ term allows for a possible non-linear relationship between daily maximum temperature and worker productivity. Specifically a second-order polynomial function is assumed in the baseline analysis. A non-parametric estimation using a series of indicator variables for every $5°F$ and a two-segment estimation as used by Adhvaryu, Kala and Nyshadham (2015) are also tested.

The analysis controls for a series of daily and worker characteristics which may potentially correlate with temperature. Specifically, the vectors of daily controls $\mathbf{X}_d$ include precipitation, humidity, wind speed, air pressure and air pollution index (API). The vectors of worker characteristics D_i take in age, gender, an indicator of whether or not a worker is local, and an indicator for the night shift. To further control for seasonality, day-of-week dummy variables and year-month dummies are also included.

Standard errors are two-way clustered by day because the regressor of interest varies daily and by worker to control for any serial correlation in worker productivity (Cameron, Gelbach and Miller, 2011).

3.3 Data

Xiamen's meteorological data are extracted from the National Climate Data Center's "Global Surface Summary of the Day" file. They are collected by the weather stations under China's Meteorological Administration. The primary data elements extracted are the daily maximum and minimum temperatures, dew point, precipitation, barometric pressure, visibility and wind speed. All of the variables except for the temperatures are the mean daily values, which are based on the hours of operation of the station.

Air quality is known to have an impact on worker productivity (Graff Zivin and Neidell, 2012), making it a potential confounder. Xiamen's air pollution data are extracted from the database of China's National Environmental Monitoring Center (CNEMC), which is under the Ministry of Environmental Protection. The CNEMC has been monitoring daily pollution levels in 86 major cities since 2008, and it develops an API for each city based on

[2] Adhvaryu, Kala, and Nyshadham (2015) show that indoor and outdoor temperatures are highly correlated for a large garment firm in India (i.e., the correlation is roughly 0.79).

the levels of sulfur dioxide, nitrogen dioxide and suspended particulates less than 10 μm in diameter (PM_{10}) measured at the monitoring stations in that city. The API is calculated based on average daily concentrations of the pollutants. An individual score is assigned to the level of each pollutant. And the largest of the three is published as the city's API. China's national API scale ranges from 0 to more than 300. It is further divided into five ranges—0–50, 51–100, 101–200, 201–300 and >300—which are categorized as excellent, good, slightly polluted, heavily polluted and hazardous, respectively. It is noteworthy that the scale for each pollutant and the final daily API value are non-linear. As a result, an API value of 100 does not imply that the pollution is twice as serious as that at an API of 50, nor does it indicate that it is twice as harmful.

Xiamen's APIs from October 2012 to January 2014 are used in the analysis. A slight drawback of such data is that actual pollutant concentrations are not reported. There are also concerns that the air quality data reported by Chinese cities may suffer from data manipulation. However, using rigorous approaches, Ghanem and Zhang (2014) have suggested that the pollution data for Xiamen are not manipulated. Nevertheless, visibility is tested as a proxy for the API to assess whether measurement error could explain away the results. Visibility is usually defined as "the greatest distance at which an observer can just see a black object viewed against the horizon sky" (Malm, 1999). Because the visibility is recorded by weather stations, which are presumably much less subject to political interference, the data should be fairly accurate.

The daily productivity data contain detailed worker-level output and machine conditions for each workday from October 2012 to February 2014. Data for 61 workers, 77 machines, 23 products, and 473 workdays are recorded in total. Table 1 reports summary statistics for worker productivity, individual characteristics and environmental indicators with a breakdown of the sample size. The average productivity is 23.11, which means that 23.11% of the output is over-target ouput, on average.

The average daily maximum temperature is about $78°F$, with a standard deviation of $11°F$, a maximum of $99°F$ and a minimum of $55°F$. Overall, Xiamen has good air quality throughout the year. The mean API is 54 and the maximum API score is 99, implying that on average the air quality meets the requirement for a blue-sky day.

[Insert Table 1 here]

For a deeper look at labor productivity, Figure 2 plots the distribution of average output by product and for all products, with a line drawn at the rate that corresponds with the target output level. A large proportion of the distributions crosses the thresholds, indicating most production exceeds the targets, and the variation in productivity is very significant. This is crucial in getting precise estimates of the impact of temperature. Figure 3 plots the distribution of average output by job tasks and for all tasks, also showing a large variation across different tasks.

[Insert Figure 2 here]

[Insert Figure 3 here]

Relatedly, Figures 4 and 5 present the considerable variation in productivity by workers and across workers. Each individual's average daily productivity over time is plotted in figure 4. The average daily productivity of all workers by day is plotted in figure 5. These two figures suggest that both individual ability and environment factors could be important predictors of variations in productivity.

[Insert Figure 4 here]

[Insert Figure 5 here]

To illustrate the relationship between temperature and API, Figure 6 plots the demeaned average daily temperature and API for the sample period, which are obtained by subtracting the average yearly temperature (API) from the daily temperature (API). It shows sizable variation in both variables over time. Since the temperature and API seem correlated, API is included as a control to ensure that the estimates of productivity's relationship with temperature are not confounded by the correlation.

[Insert Figure 6 here]

4 Empirical Findings

4.1 Labor Supply Response

Estimation results relating labor supply and temperature are reported in Table 2. Column 1 suggests that there is no significant response of labor supply to temperature in terms of the decision to work. Neither the daily maximum temperature nor its square is statistically significant. These results hold when worker characteristics are replaced with worker fixed effects in column 2. Columns 3 and 4 further show that temperature has no significant predictive power for the number of working hours of those who choose to work.

[Insert Table 2 here]

Taken together, these results suggest that there is no significant avoidance behavior related to temperature in this context. Given that there is no effect of temperature on the decision to work, the following analyses of worker productivity will not be contaminated by the sample selection (for example, only the sample of workers who went to work is used), enabling unbiased estimates of productivity in response to temperature.

4.2 Productivity Response

To explore the relationship between temperature and worker productivity, a nonparametric estimation in which the daily maximum temperature is divided into $5°F$ increments is used. The lowest temperature bin, $0° - 60°F$ is omitted, so the estimates can be interpreted as the change in productivity relative to that at $60°F-$.

The estimated coefficients are plotted in Figure 7. It is clear that there is an almost symmetric inversed-U shaped relationship between daily maximum temperature and productivity. Specifically, worker productivity at $60°F-$ is about 11% less than at $75° - 79°F$, and it steadily increases until $75°F - 79°F$. The productivity then decreases to yield about a 6.7% reduction at $95°F+$. These findings corroborate the estimates of non-linear temperature effects on time allocation by Graff Zivin and Neidell (2014) and on production efficiency by Adhvaryu, Kala and Nyshadham (2015).

[Insert Figure 7 here]

Table 3 shows the main results regarding the relationship between temperature and worker productivity. Column 1 uses a linear model as in equation (1). A positive and statistically significant effect for the daily maximum temperature, but a negative and statistically significant effect for its squared term are found. These results imply that temperature significantly affects worker productivity, but in an inverse U shape with the optimal temperature being around $78°F$ $(= 0.5741/(2 * 0.0037))$. Such findings are consistent with those reported in the literature. For example, in a survey of experimental studies, Seppänen, Fisk and Faulkner (2003) find that productivity loss starts at temperatures over $25°C$ ($\sim 77°F$). The results under this study are also consistent with the fact that a maximum temperature at $80°F$ is the most productive temperature for industrial tasks (Heal and Park, 2015).

[Insert Table 3 here]

The key outcome variable, worker productivity, is bounded from the below (that is, it cannot be less than -1). The results of a Type I Tobit model in column 2 show similar effects in terms of both statistical significance and magnitude.

Column 3 shows the results using a two-segment specification following the practice of Adhvaryu, Kala and Nyshadham (2015) in which the variations of temperature below $78°F$ and above $78°F$ are explored separately. Specifically, two new regressors of interests are constructed: *Max Temperature*$<$*78* is measured as the maximum temperature up to $78°F$, above which it is recorded as a constant $78°F$. *Max Temperature*$>$*78* is defined as maximum temperature minus $78°F$ in which the negatives are recorded as 0. The estimation results suggest that the temperature has a positive effect on worker productivity up to $78°F$, from which point the effect becomes negative, further confirming the pattern of non-linearity.

Economic Magnitude. The coefficients in column 3 of Table 3 can be used to gauge the economic magnitude of the temperature effects. Below $78°F$, an increase of $10°F$ in maximum temperature is associated with a 1.1 percentage point increase in the over-target percentage of output, or 5 percent relative to the sample mean. Above $78°F$, an increase of $10°F$ in maximum temperature is associated with a 0.15 percentage point decrease in the over-target percentage of output.

Note that a worker's income is determined by $w_{id} = \alpha_1 \bar{Q}_p + \alpha_2 (Q_{id} - \bar{Q}_p) = \bar{Q}_p [\alpha_1 + \alpha_2 y_{id}]$. To illustrate the income losses due to the temperature fluctuation, the benchmark levels $\bar{Q}_p = 20,000$, $\alpha_1 = 0.006$ and $\alpha_2 = 0.009$ are used. The estimates show that an increase of $10°F$ in maximum temperature below $78°F$ leads to a change of over-target output by a 1.1 percent increase, i.e., $\triangle y_{id} = 1.1\%$. As a result, $\triangle w_{id} = \bar{Q}_p \alpha_2 \triangle y_{id} = 1.98$. Similarly, an increase of $10°F$ in the maximum temperature above $78°F$ leads to $\triangle w_{id} = -0.27$. To calculate the income losses for the year, the distribution of daily maximum temperature in 2013 is used. When the daily maximum temperature deviates from the most productive level ($78°F$), the daily losses per worker are calculated (Appendix Table 1). Adding up the daily counts, the annual income losses are around ¥400 per worker (US\$61.5), i.e., 0.7% of a worker's income at $78°F$. Following the lead of Chang et al. (forthcoming), we assume that the estimate of the effect of temperature on labor productivity applies to all secondary workers in the city of Xiamen. According to Xiamen Municipal Statistical Bureau, the secondary sector employs a total of 1.05 million workers in 2013. If the temperature could be maintained at the optimal level $78°F$, this would translate into a \$64.6 million increase in worker earnings. We caution, however, that the temperature distribution varies across regions, making it difficult to apply Xiamen's estimates to calculating the aggregate labor savings for the entire secondary sector in China (231.7 million workers).

A meta-analysis by Seppänen, Fisk, and Lei (2006) finds that increasing temperature from $23°C$ ($\sim 73°F$) to $30°C$ ($\sim 86°F$) decreases labor productivity by around 9 percent. Using the estimates in Figure 6, moving from the $75°F - 79°F$ to the $80°F - 84°F$ range causes worker productivity to fall by about 6 percent. Therefore, the estimates of this study compare well with those of previous scholarly work. With the lack of technical protection against heat in developing countries' industrial sectors, these findings imply that the productivity loss resulting from excessive heat exposures could be very costly. They also have implications for the design of an effective adaptation policy, such as implementing preventive measures to reduce heat stress in the workplace.

4.3 Robustness Checks

In this subsection, we provide a battery of checks on the aforementioned results. Estimation results are reported in Table 4. The baseline estimates are included in column 1 for comparison.

[Insert Table 4 here]

To examine whether the estimates are biased due to any omitted variables in column 2, the worker controls are replaced by worker fixed effects (which essentially control for all worker characteristics but at the cost of substantially less variation). In column 3, no worker control variables are included. A consistent pattern of the temperature effects on worker productivity is evident. The proximity of the estimates in those two extreme cases (i.e., with all worker level controls and without any worker controls) compared to the baseline coefficients suggests that omitted variables at the worker level are not a major concern in this setting.

Second, the deputy general manager in charge of production may have adjusted the product mix in response to temperature. Because different products involve different production complexity, the estimates would not then capture the temperature effect on worker productivity but its effect on the product mix. To address this concern, a control variable is added indicating whether the same products are produced by workers on both day d and $d-1$. Any variation in productivity between day d and $d-1$ cannot then be explained by the variations in the product mix on different days. As reported in column 4, the results show that the estimates are robust to that additional control, which largely rules out concerns about changes in the product mix.

The deputy general manager might have assigned different machines on different days according to the daily maximum temperature, resulting in the estimates capturing the changes in production machines instead of worker productivity. To address this issue, in column 5 a control has been added indicating whether the same machines are used by workers on days d and $d-1$. Similar results are again found, implying that the estimated temperature effect is not purely driven by changes in production machines.

Machine breakdowns also affect worker productivity. If high temperatures caused more machines to break down, the estimates may in fact reflect machine reliability. An indicator of machine breakdowns is therefore included in column 6. Similar results suggest that machine breakdown is not a serious confounder of the temperature-productivity linkage.

Xiamen usually experiences typhoons between May and August. To alleviate any concern that the temperature effects may be confounded by the typhoon shocks, an indicator for typhoons is added. In column 7, the main finding remains robust to this additional control variable, suggesting that typhoons do not contaminate the temperature effect.

The API is also replaced with an alternative measure of air pollution—the visibility index. The estimation results in column 8 confirm the same pattern, suggesting that the results are not sensitive to the pollution indicator used.

Finally, lagging and leading indicators of temperature are included in column 9. The coefficients of the lag and lead temperatures are all small, and the coefficients of the main temperature terms are barely changed in magnitude. These results imply that only the current temperature is associated with worker productivity, not future or past temperatures, further supporting the hypothesis that thermal stress during the production process is driving losses (Hsiang, 2010).

4.4 Worker and Impact Heterogeneity

Differences among workers may have led to heterogeneity in the response of labor productivity to heat stress. Specifically, males versus females, young versus old workers, and local versus non-local workers (in which the province of origin is used as a proxy for local heat acclimatization) are considered. The estimation results are presented in Table 5.

[Insert Table 5 here]

In columns 1 and 2, the sample is divided into female and male groups, respectively. The estimates are quite similar between these two groups, despite some lose statistical significance, presumably due to the smaller samples. These results imply that there is not much difference in the temperature effects on worker productivity by gender. This is indeed supported by physiological studies: women and men are essentially similar in their responses to heat stress once controlling for important intergender population differences in physical fitness and heat acclimatization state (Kenney et al., 1992).

Columns 3 and 4 show the results with the sample divided into two groups aged above and below the sample's median age. Similar effects are apparent for the two groups, suggesting that there is not much age effect. Note that the entire sample is fairly young, with an average

age of 32 and only one worker with the maximum age of 50. This result is largely in line with the observations of studies that industrial populations generally show a gradual decline in heat tolerance after age 50 (Nunneley, 1998).

The non-local and local workers are distinguished in columns 5 and 6, respectively. Interestingly, there are significant and substantial effects of temperature for non-local workers, but almost no effects for local workers. One possible explanation is that local workers are more adapted to the local temperature environment than the non-local ones. They are more likely to have been exposed repeatedly to heat, building heat acclimatization. This might explain their lack of sensitivity to temperature.

5 Conclusion

This study has examined the impact of temperature on daily indoor worker productivity in a leading Chinese manufacturing firm. To do so, novel data on individual worker's productivity from personnel records is combined with high-frequency weather data. The primary contribution is to provide among the first evidence on temperature and manufacturing labor productivity in the largest developing country: China. We find that worker absenteeism and working hours did not change on hot days. There is an inverted-U shaped relationship between temperature and manufacturing labor productivity. These effects are substantially larger among non-local workers. Among local workers, there is almost no effect, indicating their adaptation in response to heat.

These findings suggest that the economic loss due to reduced labor productivity in manufacturing in response to ambient temperature is sizeable. They have important policy implications. Governments in poor countries may gain from investing in air-conditioning, fans or other cooling systems in workplaces. The high spatial density of human and physical capital in manufacturing makes such investments more practical and cost effective than in outdoor agriculture (Hsiang and Narita, 2012). For firms, heat acclimation training also promises to improve labor productivity.

According to a recent report by the world bank, the world may still be 4° Celsius warmer this century even if all countries fulfill their emissions-reduction pledges (World Bank. 2014). Global warming may also cause extreme weather shocks such as heat waves, droughts, and floods, by which poor countries are disproportionately more affected than wealthy ones, further inhibiting poverty reduction. In light of this global challenge, these empirical findings underscore the importance of the labor productivity impacts of increasing heat exposure. They should be incorporated into cost-benefit calculations relating to climate change. There will be additional productivity benefits from concerted international action to strengthen carbon emission regulations, a dimension that has received relatively little attention in the current policy debate (Tol, 2009). This is particularly true for China, the world's largest emitter of greenhouse gases, whose efforts are indispensable to successfully realising any global climate goal.

While the findings of this study confirm the importance of temperature in affecting labor productivity, much remains to be done. Because of different adaptive capacities, there might be substantial heterogeneity in the environmental sensitivities of various countries, industries and individuals (Deryugina and Hsiang, 2014). Investigations of involving a variety of geographic and sectoral contexts remain an exciting and promising area for future research.

References

[1] Acemoglu, Daron, Simon Johnson, and James A. Robinson (2002). Reversal of Fortune: Geography and Institutions in the Making of the Modern World Income Distribution. Quarterly Journal of Economics, 117(4): 1231–1294.

[2] Adhvaryu, Achyuta, Namrata Kala, and Anant Nyshadham (2015). The Light and the Heat: Productivity Co-benefits of Energy-saving Technology. Working paper, University of Michigan.

[3] Adhvaryu, Achyuta, Prashant Bharadwaj, James Fenske, Anant Nyshadham, and Richard Stanley (2016). Dust and Death: Evidence from the West African Harmattan. The Centre for the Study of African Economies Working Paper, WPS/2016-03, University of Oxford.

[4] Bandiera, Oriana, Iwan Barankay, and Imran Rasul (2005). Social Preferences and the Response to Incentives: Evidence from Personnel Data. Quarterly Journal of Economics, 120(3): 917–62.

[5] Bandiera, Oriana, Iwan Barankay, and Imran Rasul (2010). Social Incentives in the Workplace. Review of Economic Studies, 77(2): 417–58.

[6] Bandiera, Oriana, Iwan Barankay, and Imran Rasul (2009). Social Connections and Incentives in the Workplace: Evidence From Personnel Data. Econometrica, 77(4): 1047–1094.

[7] Cachon, Gerard P., Santiago Gallino, and Marcelo Olivares (2012). Severe Weather and Automobile Assembly Productivity. http://opim.wharton.upenn.edu/~cachon/pdf/weather_1015.pdf.

[8] Cameron, A. Colin, Jonah Gelbach, and Douglas Miller (2011). Robust Inference with Multi-way Clustering. Journal of Business and Economic Statistics, 29(2), 238–249.

[9] Chang, Tom, Joshua S. Graff Zivin, Tal Gross, and Matthew J. Neidell. Particulate Pollution and the Productivity of Pear Packers. American Economic Journal: Economic Policy. Forthcoming.

[10] 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.

[11] Deryugina, Tatyana, and Solomon M. Hsiang (2014). Does the Environment Still Matter? Daily Temperature and Income in the United States. NBER Working Paper No. 20750.

[12] Deschênes, Olivier, and Michael Greenstone (2007). The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather. American Economic Review, 97(1): 354–85.

[13] Deschênes, Olivier, and Enrico Moretti (2009). Extreme Weather Events, Mortality, and Migration. The Review of Economics and Statistics, 91(4): 659–681.

[14] Deschênes, Olivier, and Michael Greenstone (2011). Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US. American Economic Journal: Applied Economics, 3(4): 152–85.

[15] Epstein Y, Keren G, Moisseiev J, Gasko O, and Yachin S. (1980). Psychomotor Deterioration during Exposure to Heat. Aviation, Space, and Environmental Medicine, 51(6): 607–10.

[16] Fisk, W. J., Price, P., Faulkner, D., Sullivan, D., Dibartolomeo, D., Federspiel, C., ... & Lahiff, M. (2002). Worker Productivity and Ventilation Rate in a Call Center: Analyses of Time-series Data for a Group of Workers. Lawrence Berkeley National Laboratory.

[17] Galloway, S. D., and R. J. Maughan (1997). Effects of Ambient Temperature on the Capacity to Perform Prolonged Cycle Exercise in Man. Medicine and Science in Sports and Exercise, 29(9): 1240–49.

[18] Ghanema, D., and Junjie Zhang (2014). 'Effortless Perfection:' Do Chinese Cities Manipulate Air Pollution Data? Journal of Environmental Economics and Management, 68(2): 203–225.

[19] González-Alonso, José Christina Teller, Signe L. Andersen, Frank B. Jensen, Tino Hyldig, and Bodil Nielsen (1999). Influence of Body Temperature on the Development of Fatigue during Prolonged Exercise in the Heat. Journal of Applied Physiology, 86(3): 1032–39.

[20] Graff Zivin, Joshua, and Matthew Neidell (2012). The Impact of Pollution on Worker Productivity. American Economic Review, 102(7): 3652–73.

[21] Graff Zivin, Joshua, and Matthew Neidell (2014). Temperature and the Allocation of Time: Implications for Climate Change. Journal of Labor Economics 32(1): 1–26.

[22] Graff Zivin, Joshua, Solomon M. Hsiang, and Matthew Neidell (2015). Temperature and Human Capital in the Short- and Long-Run. NBER Working Paper No. 21157.

[23] Hancock, Peter, and Joel Warm (1989). A Dynamic Model of Stress and Sustained Attention. Human Factors, 31(5): 519–37.

[24] Hancock, P.A., and I. Vasmatzidis (2003). Effects of Heat Stress on Cognitive Performance: The Current State of Knowledge. International Journal of Hyperthermia, 19(3): 355–372.

[25] Hancock, P.A., Jennifer M. Ross, and James L. Szalma (2007). A Meta-analysis of Performance Response under Thermal Stressors. Human Factors 49(5): 851–877.

[26] Heal, Geoffrey and Jisung Park (2015). Goldilocks Economies? Temperature Stress and the Direct Impacts of Climate Change. NBER Working Paper No. 21119.

[27] Houser, Trevor, Robert Kopp, Solomon M. Hsiang, Michael Delgado, Amir Jina, Kate Larsen, Michael Mastrandrea, Shashank Mohan, Robert Muir-Wood, DJ Rasmussen, James Rising, and Paul Wilson (forthcoming). *American Climate Prospectus: Economic Risks in the United States*. Columbia University Press.

[28] 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, 107(35): 15367–72.

[29] International Labor Organization (2012). Sectoral Activities Department (SECTOR).

[30] Kenney, W. Larry, Dion H. Zappe, and George W. Bell (1992). Individual Characteristics and Response to Heat Stress. Proceedings of The Fifth International Conference on Environmental Ergonomics, Laboratory for Human Performance Research, The Pennsylvania State University, University Park, PA.

[31] Maccini, S. and Yang, D. (2009). Under the Weather: Health, Schooling, and Economic Consequences of Early-life Rainfall. American Economic Review, 99(3): 1006–1026.

[32] Malm, William C. (1999). Introduction to Visibility. Air Resources Division, National Park Service. Cooperative Institute for Research in the Atmosphere (CIRA), Colorado State University, Fort Collins, CO.

[33] Nielsen, B., J. R. Hales, S. Strange, N. J. Christensen, J. Warberg, and B. Saltin (1993). Human Circulatory and Thermoregulatory Adaptations with Heat Acclimation and Exercise in a Hot, Dry Environment. Journal of Physiology, 460(January): 467–85.

[34] Nielsen, B. (1998). Effects of Heat Stress and Work in the Heat. Chapter 42 Heat and Cold, in the ILO Encyclopaedia of Occupational Health and Safety.

[35] Niemelä Raimo, Mika Hannula, Sari Rautio, Kari Reijula, and Jorma Railio. (2002). The effect of air temperature on labour productivity in call centres—a case study. Energy and Buildings 34, no. 8: 759-764.

[36] Nunneley, Sarah A. 1998. Prevention of Heat Stress. Chapter 42 Heat and Cold, in the ILO Encyclopaedia of Occupational health and Safety.

[37] Pilcher, June J., Eric Nadler, and Caroline Busch (2002). Effects of Hot and Cold Temperature Exposure on Performance: A Meta-analytic Review. Ergonomics, 45(10): 682–698.

[38] Ramsey, J.D., and S.J. Morrissey (1978). Isodecrement Curves for Task Performance in Hot Environments. Applied Ergonomics, 9(2): 66–72.

[39] Ramsey J.D. (1995). Task Performance in Heat: A Review. Ergonomics, 38(1): 154–65.

[40] Sachs, Jeffrey D. (2003). Institutions Don't Rule: Direct Effects of Geography on Per Capita Income. National Bureau of Economic Research Working Paper 9490.

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

[42] Seppänen, O., W.J. Fisk, and D. Faulkner (2003). Cost Benefit Analysis of the Nighttime Ventilative Cooling in Office Building. *Proceedings of the Healthy Buildings 2003 Conference*, Singapore.

[43] Seppänen, O., W.J. Fisk, and QH Lei (2006). Effect of Temperature on Task Performance in Office Environment. Lawrence Berkeley National Laboratory.

[44] Somanathan, E., Rohini Somanathan, Anant Sudarshan and Meenu Tewari (2015). The Impact of Temperature on Productivity and Labor Supply: Evidence from Indian Manufacturing. Delhi: Indian Statistical Institute.

[45] Tol, Richard SJ. (2009). The Economic Effects of Climate Change. The Journal of Economic Perspectives, 23(2): 29–51.

[46] Wyon, DP (2001). Thermal Effects on Performance. Indoor Air Quality Handbook, McGraw-Hill, New York, pp.16.1–16.16.

[47] World Bank (2013). http://www.theglobaleconomy.com/rankings/.

[48] World Bank (2014). Turn Down the Heat: Confronting the New Climate Normal. Washington, DC: World Bank.

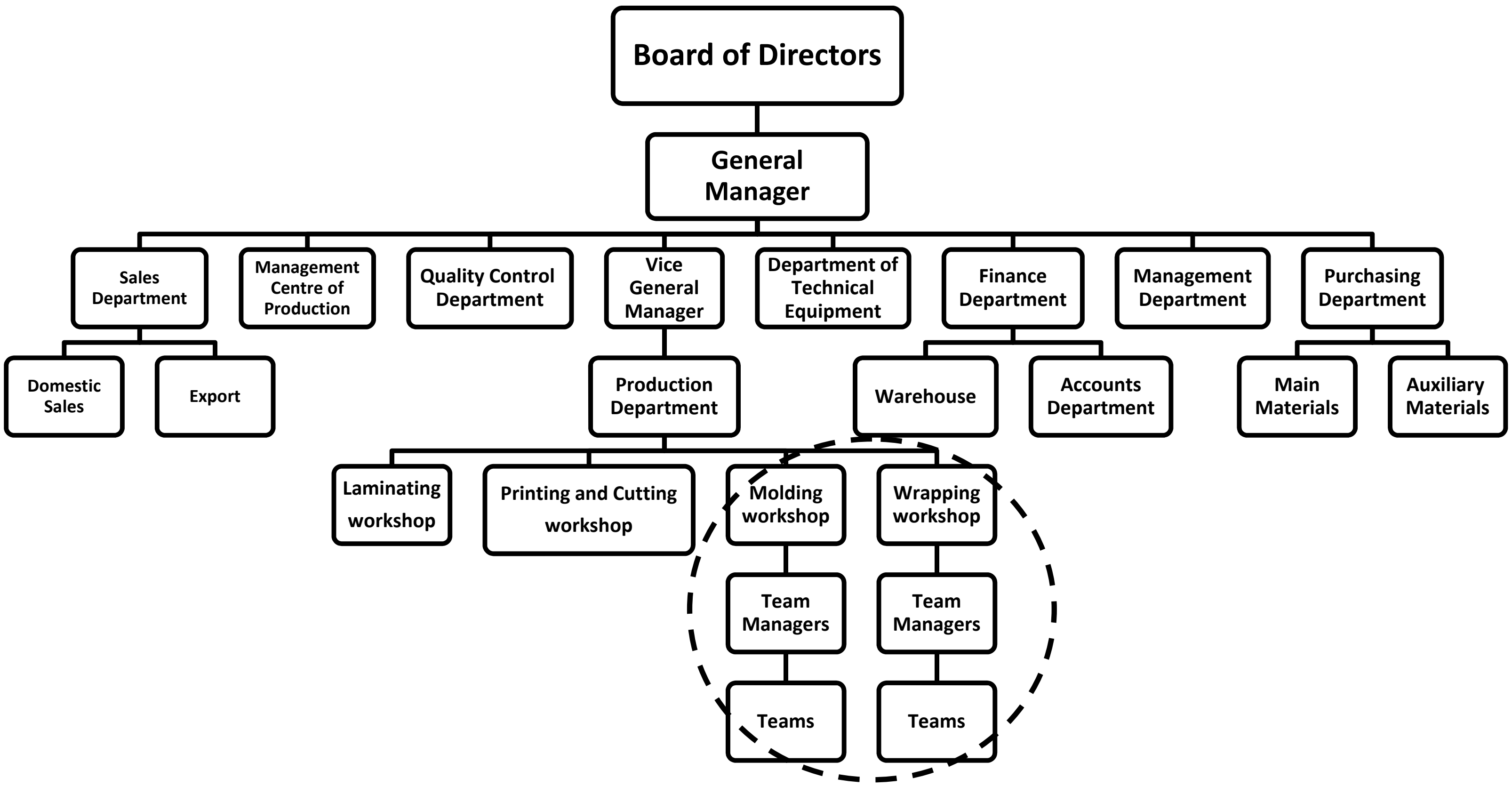

Figure 1. The Corporate Hierarchy

Note: The data focus on production workers in the molding and wrapping workshops which are marked in the dotted line circle.

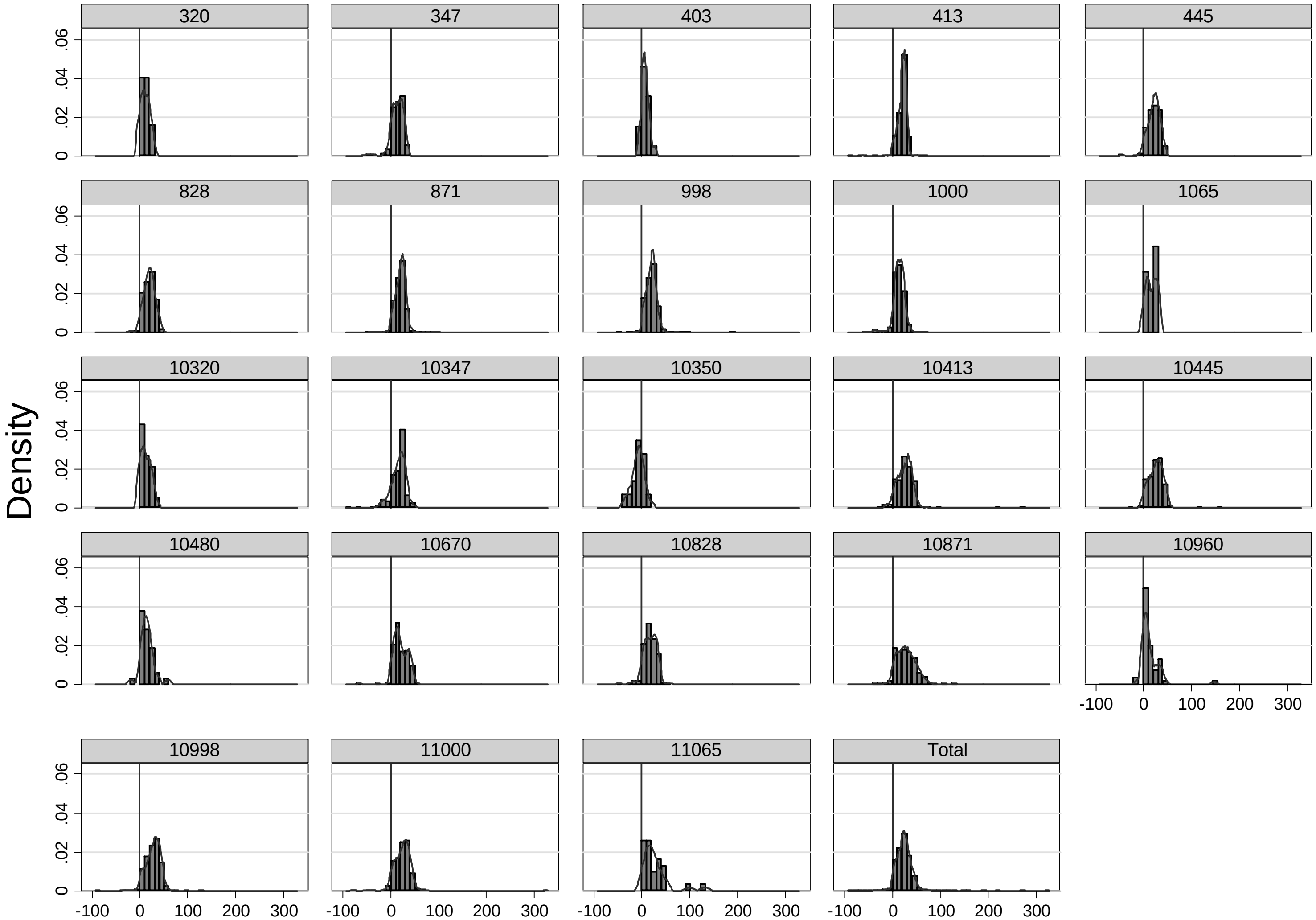

Figure 2: Over-target Percentage of Output by Product and for All Products

Note: This figure plots the over-target percentage of output for each of the products and for all products. The vertical line is the threshold for crossing from the minimum wage to the higher piece-rate regime, which is zero for all products.

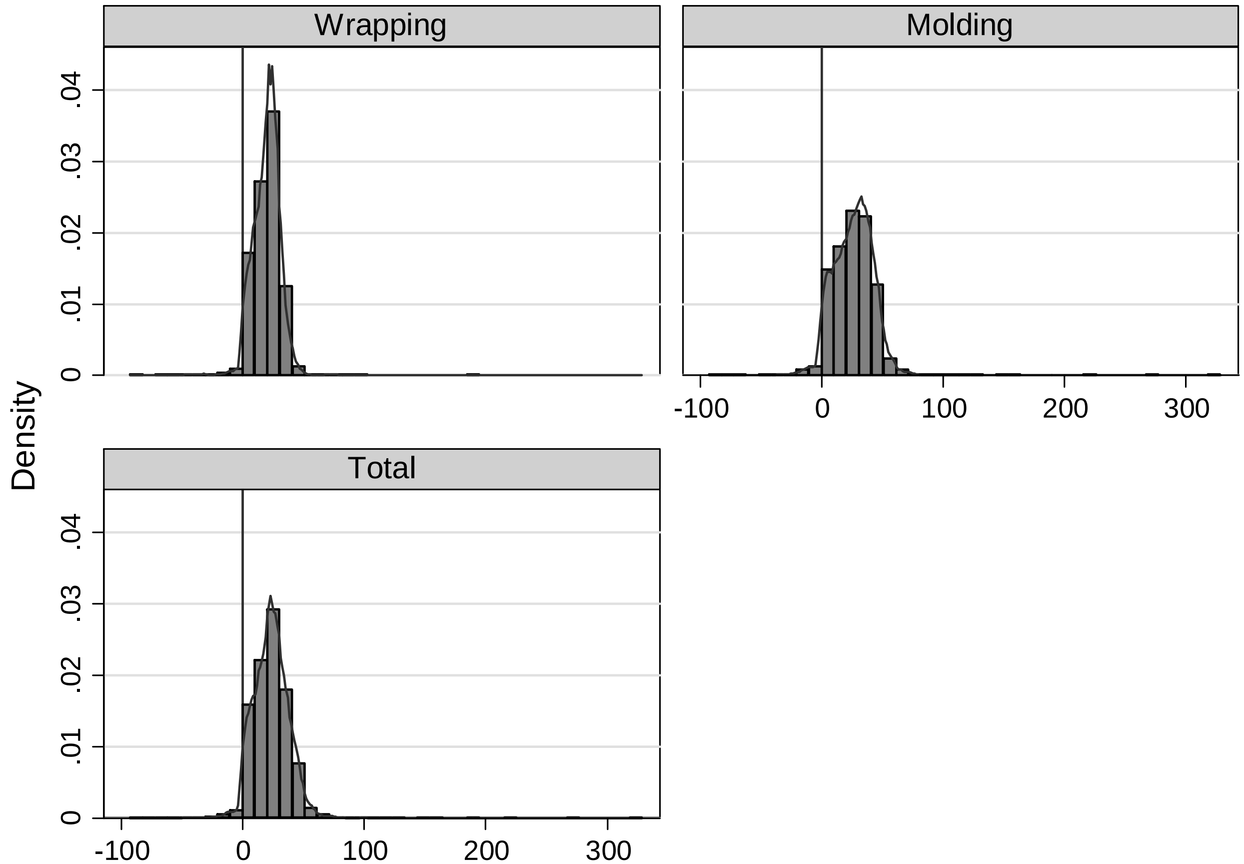

Figure 3: Over-target Percentage of Output by Task and for All Tasks

Note: This figure plots the over-target percentage of output for each of the two tasks and all tasks. The vertical line is the threshold for crossing from the minimum wage to the higher piece-rate regime, which is zero for all crops.

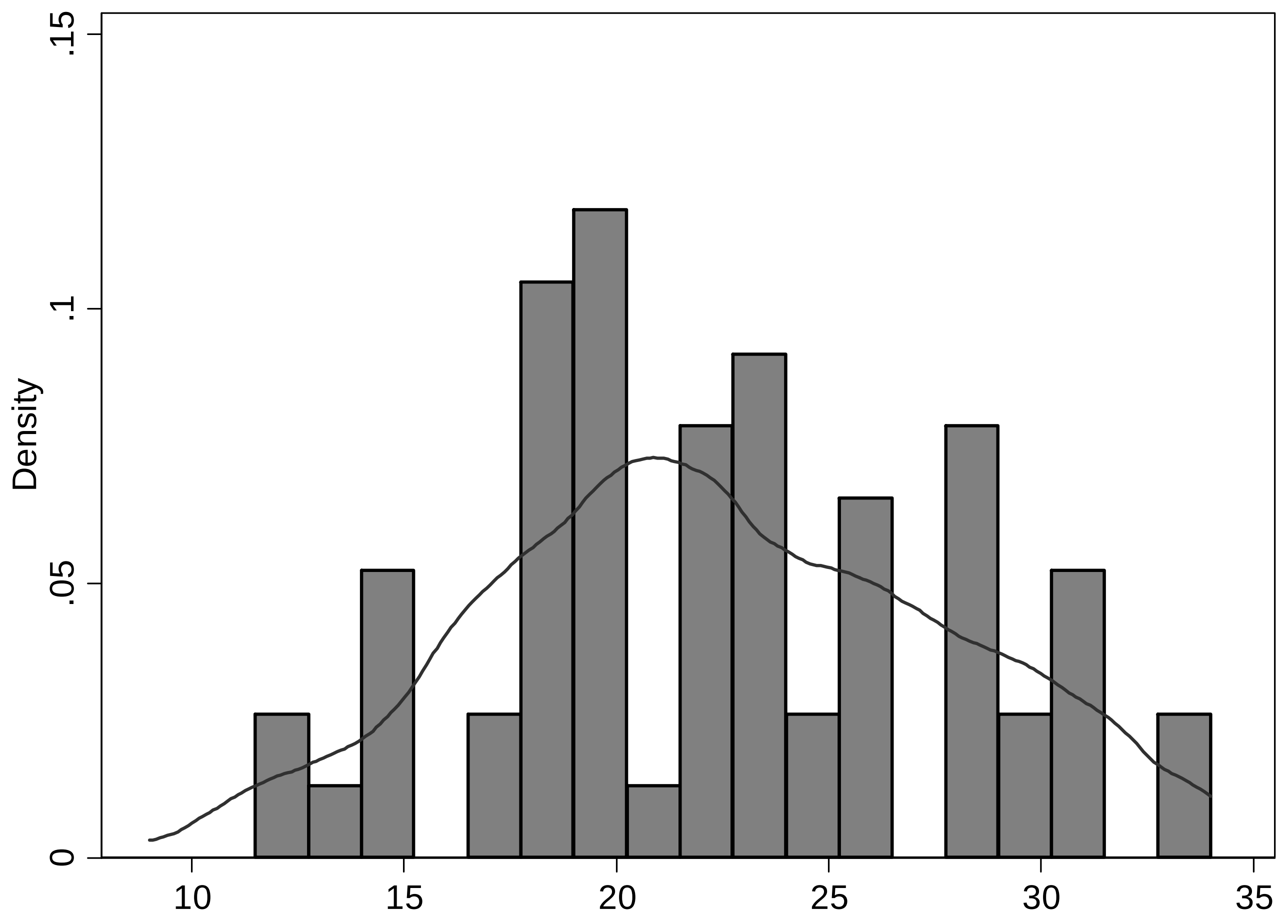

Figure 4. Variation in Productivity by Worker, All Products

Note: This figure plots the over-target percentage of output for all products by worker.

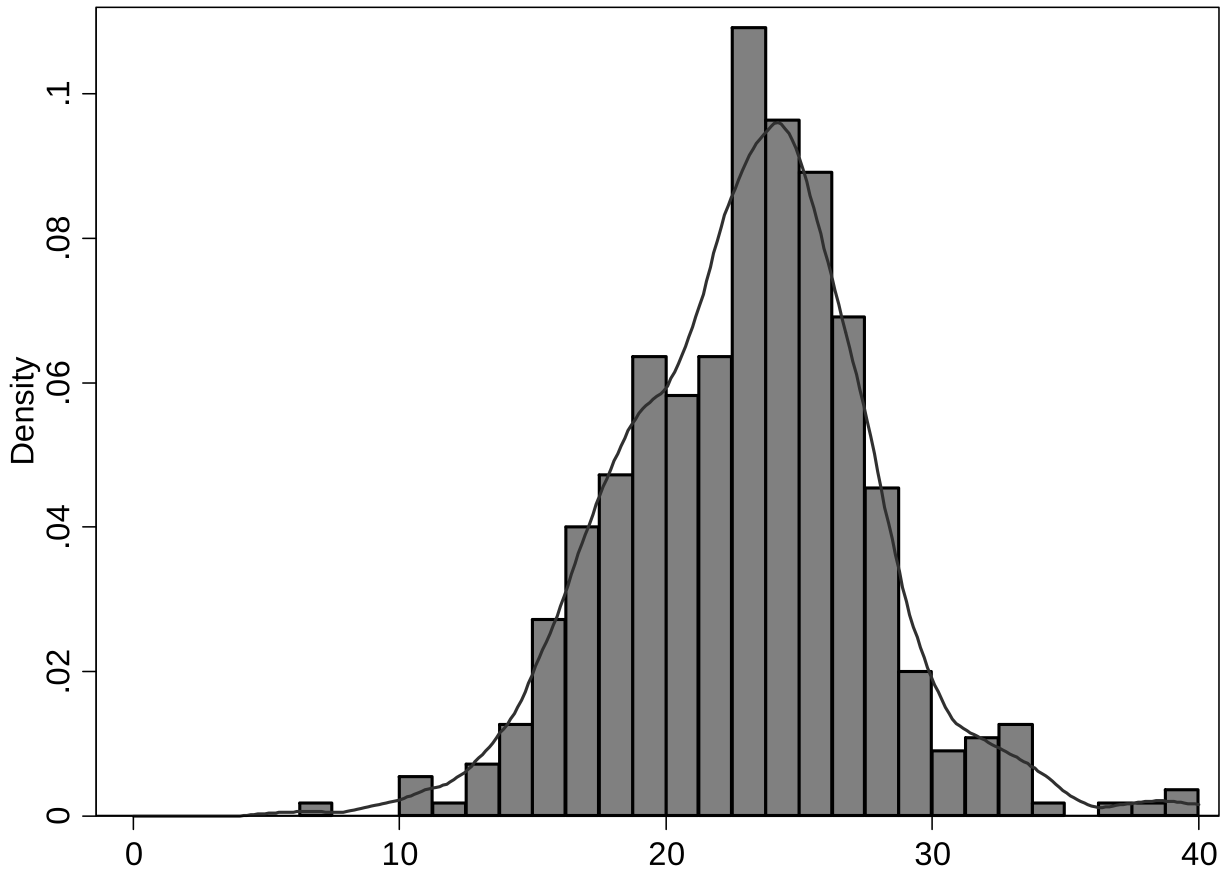

Figure 5. Variation of Productivity by Day, All Products

Note: This figure plots the over-target percentage of output for all products by day.

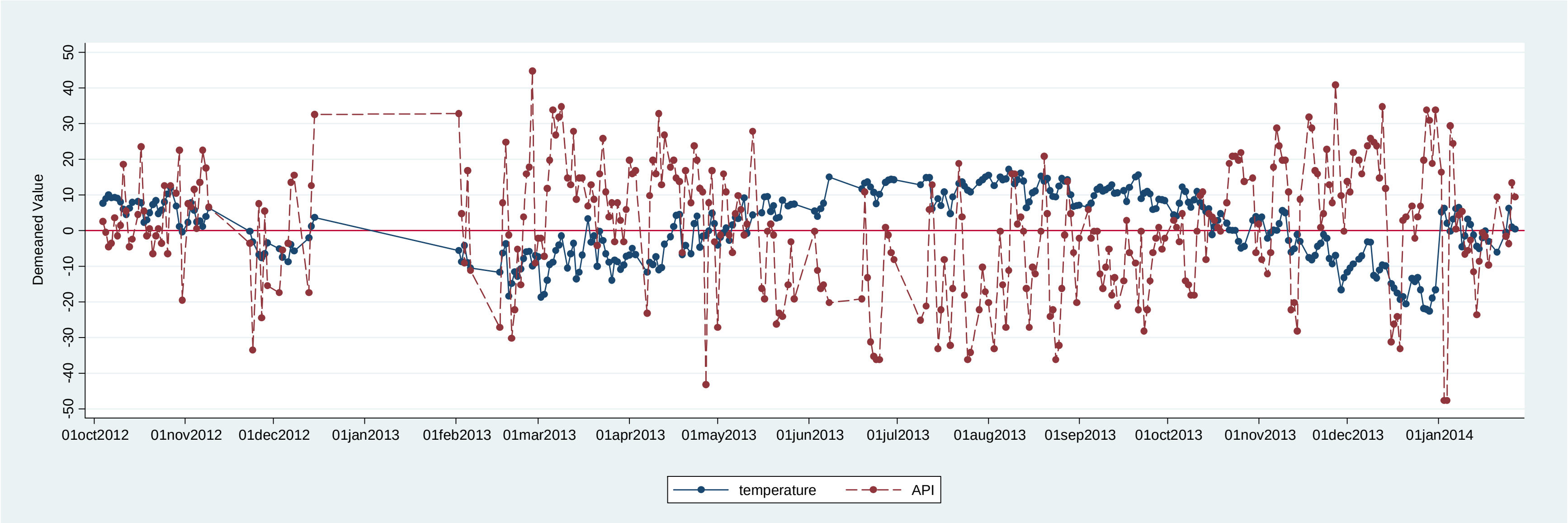

Figure 6. Average Demeaned Daily Temperature and API

Note: This figure plots demeaned temperature and API by day, which are obtained by subtracting the average yearly temperature (API) from the daily temperature (API).

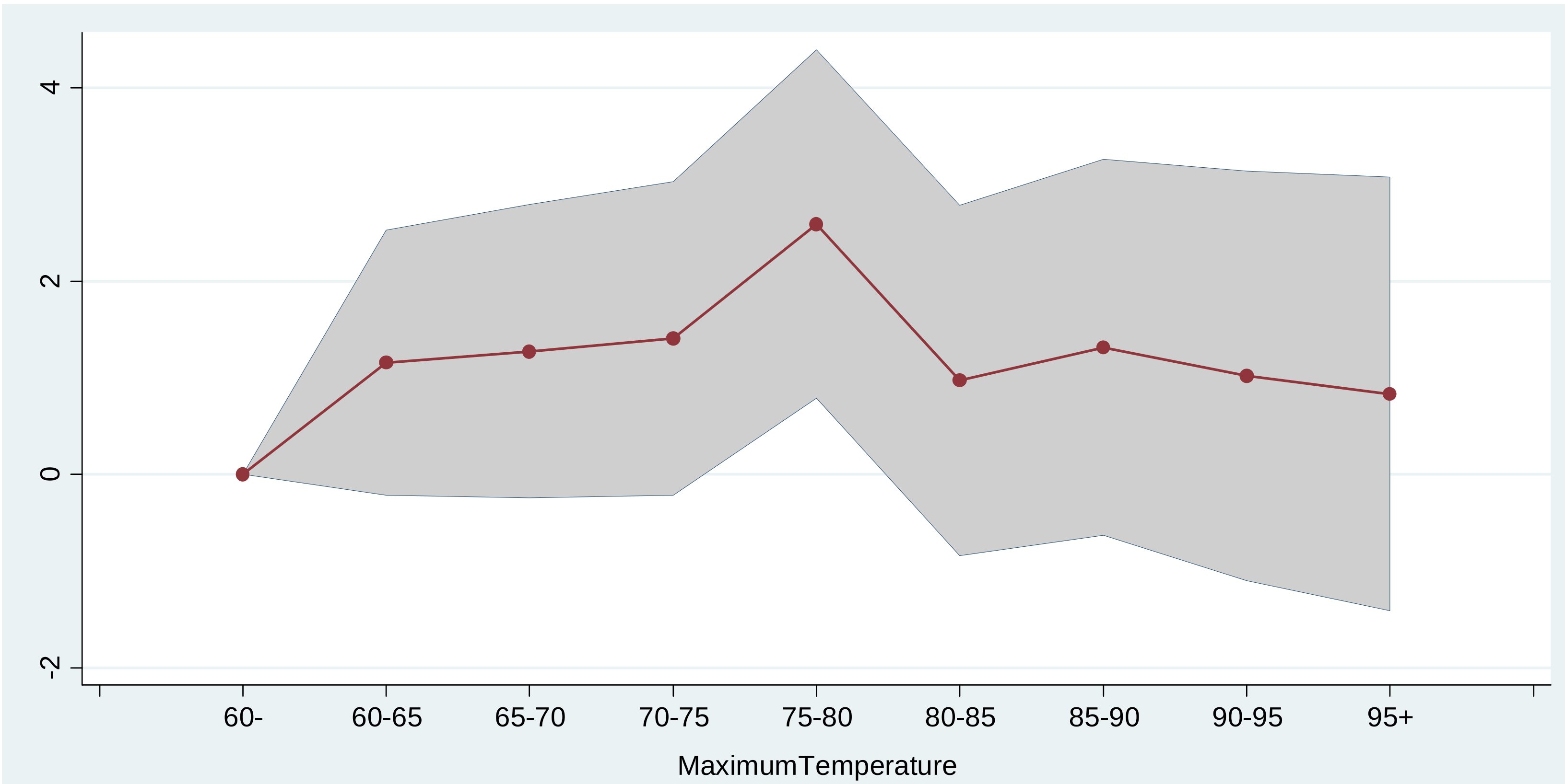

Figure 7. Relationship between Maximum Temperature and Productivity for All Individuals.

Note: The 95% confidence interval is shaded in gray. Covariates include gender, the local worker dummy, age, minimum temperature, minimum temperature squared, air pressure, wind speed, dew point, precipitation, API, day of the week dummies, month × year dummies, and a night shift dummy.

Table 1 Summary Statistics

	Observations	Mean	SD	Min	Max
Panel A. Productivity variables					
Productivity	14128	23.11	15.40	-92.86	328.57
Hour worked	14128	11.27	1.95	0.2	16
Night shift	14128	0.51	0.50	0	1
Worker characteristics					
Male	14128	0.39	0.49	0	1
Local worker	14128	0.37	0.48	0	1
Age	14128	32.08	8.71	17	50
Panel B. Environmental variables					
Maximum temperature (F)	473	78.42	10.80	55.4	98.6
Minimum temperature (F)	473	64.44	10.59	39.7	82.8
Precipitation (0.01 inches)	473	0.16	0.53	0	7.69
Dew point (F)	473	61.23	12.57	27.7	78.6
Wind speed (0.1 knots)	473	6.41	2.35	2	22
Station pressure (0.1 mb)	473	998.55	6.13	976.5	1011.9
API	473	53.84	17.42	10	99
Visibility (0.1 miles)	473	7.03	2.10	0.8	15.5
Panel C. Sample					
Number of days	473				
Number of employees	61				

Notes: The sample size in panel A refers to worker-days, while the sample size in panel B refers to the number of days. SD: Standard deviation.

Table 2 Temperature and Labor Supply

Variables	Extensive margin: probability of working		Intensive margin: hours worked	
	(1)	(2)	(3)	(4)
Max temperature	0.0059	0.0056	-0.0103	-0.0164
	(0.022)	(0.022)	(0.052)	(0.052)
Max temperature squared	-0.0001	-0.0001	-0.00002	0.00002
	(0.000)	(0.000)	(0.000)	(0.000)
worker FE	NO	YES	NO	YES
year-month FE	YES	YES	YES	YES
day of week FE	YES	YES	YES	YES
Observations	19,922	20,388	14,128	14,453
R-squared	0.079	0.110	0.022	0.034

Notes: Standard errors clustered on date and worker are shown in brackets. Hours worked is conditional upon working. All regressions include controls for maximum temperature, maximum temperature squared, minimum temperature, minimum temperature squared, air pressure, wind speed, dew point, precipitation, API, day of the week dummies, month × year dummies, and a night shift dummy. Columns 1 and 3 also include controls for gender, local worker status and age. Columns 2 and 4 also include the worker status dummies. All environmental variables, except for the temperature, are the mean value.

Table 3: Temperature and Worker Productivity

	(1)	(2)	(3)
Model	Linear	Tobit	Parametric Spline
Max temperature	0.5741**	0.6094**	
	(0.287)	(0.280)	
Max temperature squared	-0.0037*	-0.0039**	
	(0.002)	(0.002)	
Max temperature<78			0.1149**
			(0.052)
Max temperature >78			-0.0150***
			(0.005)
year-month FE	YES	YES	YES
day of week FE	YES	YES	YES
Observations	14,128	14,128	14,128
R-squared	0.045		0.045

Notes: Standard errors clustered on date and worker are reported in brackets. The dependent variable is the fraction of over-target output. Max temperature<78 is the maximum temperature up to 78º, above which it is recorded as a constant 78º. Max temperature>78 is defined as the maximum temperature minus 78º in which any negatives are recorded at a constant 0. All regressions include controls for gender, the local worker dummy, age, minimum temperature, minimum temperature squared, air pressure, wind speed, dew point, precipitation, API, day of the week dummies, month × year dummies, and a night shift dummy. All environmental variables, except for the temperatures, are the mean values. *** denotes significance at 1%, ** at 5%, and * at 10%.

Table 4: Sensitivity of the Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Max temperature	0.5741**	0.5403*	0.5879**	0.4515*	0.4626*	0.6160**	0.5743**	0.4969*	0.6115*
	(0.287)	(0.291)	(0.288)	(0.268)	(0.268)	(0.285)	(0.286)	(0.281)	(0.318)
Max temperature squared	-0.0037*	-0.0035*	-0.0038**	-0.0028	-0.0029*	-0.0038**	-0.0037*	-0.0032*	-0.0039*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Max temperature d+1									0.0586
									(0.307)
Max temperature d+1 squared									-0.0008
									(0.002)
Max temperature d-1									-0.0534
									(0.359)
Max temperature d-1 squared									0.0005
									(0.002)
Model	Baseline	Worker fixed effect	Exclude worker controls	Same product at d and d-1	Same machine at d and d-1	Include machine breakdown	Include typhoon	Visibility	Include Lag and Lead Temperature
year-month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
day of week FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	14,128	14,453	14,453	14,128	14,128	14,128	14,128	14,892	14,040
R-squared	0.045	0.165	0.037	0.074	0.074	0.133	0.045	0.046	0.047

Notes: Standard errors clustered on date and worker are reported in brackets. The dependent variable is the fraction of over-target output. All regressions include controls for gender, a local worker dummy, age, maximum temperature, maximum temperature squared, minimum temperature, minimum temperature squared, air pressure, wind speed, dew point, precipitation, API, day of the week dummies, month × year dummies, and a night shift dummy. All environmental variables, except for the temperatures, are the mean values. *** denotes significance at 1%, ** at 5%, and * at 10%.

Table 5: Impact Heterogeneity by Worker Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
Max temperature	0.5523*	0.5836	0.6893	0.4293	0.9484**	0.0009
	(0.311)	(0.437)	(0.459)	(0.275)	(0.357)	(0.350)
Max temperature squared	-0.0035	-0.0039	-0.0045	-0.0027	-0.0060**	-0.0002
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
Subsample	Female	Male	Below median age	Above median age	Non-local	Local
year-month FE	YES	YES	YES	YES	YES	YES
day of week FE	YES	YES	YES	YES	YES	YES
Observations	8,667	5,461	6,816	7,312	8,860	5,268
R-squared	0.082	0.027	0.045	0.048	0.058	0.042

Notes: Standard errors clustered on date and worker are reported in brackets. The dependent variable is the fraction of over-target output. All regressions include controls for gender, a local worker dummy, age, maximum temperature, maximum temperature squared, minimum temperature, minimum temperature squared, air pressure, wind speed, dew point, precipitation, API, day of the week dummies, month × year dummies, and a night shift dummy. Columns 1 and 2 include local worker dummy and age. Columns 3 and 4 include gender and local worker dummy. Columns 5 and 6 include gender and age. All environmental variables, except for the temperatures, are the mean values. *** denotes significance at 1%, ** at 5%, and * at 10%.

Appendix Table A1：Annual Losses Per Worker

Temperature	Frequency	Daily losses	losses*Frequency
51	1	-5.58	-5.58
57	10	-4.34	-43.43
59	8	-3.93	-31.44
60	7	-3.72	-26.06
62	12	-3.31	-39.71
63	1	-3.10	-3.10
64	15	-2.90	-43.43
65	3	-2.69	-8.07
66	15	-2.48	-37.23
67	4	-2.28	-9.10
68	16	-2.07	-33.09
69	11	-1.86	-20.48
70	4	-1.65	-6.62
71	12	-1.45	-17.37
72	3	-1.24	-3.72
73	13	-1.03	-13.44
75	11	-0.62	-6.83
77	18	-0.21	-3.72
78	15	0.00	0.00
79	1	-0.03	-0.03
80	12	-0.05	-0.65
81	4	-0.08	-0.32
82	23	-0.11	-2.48
84	24	-0.16	-3.89
86	18	-0.22	-3.89
87	17	-0.24	-4.13
88	19	-0.27	-5.13
90	1	-0.32	-0.32
91	27	-0.35	-9.48
92	1	-0.38	-0.38
93	22	-0.41	-8.91
95	14	-0.46	-6.43
96	2	-0.49	-0.97
98	1	-0.54	-0.54
Annual losses (¥)			-399.97

Note：If temperature is below $78°F$, Daily losses equal 20000*0.009*0.01149*(Temperature-78)%. If temperature is above $78°F$, Daily losses equal 20000*0.009*0.015*(78-Temperature)%.