

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

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## Abstract

This paper presents novel evidence on the impact of temperature on daily indoor worker productivity in a non-climate-controlled manufacturing environment of China. Combining individual worker productivity data from personnel records with weather data, it documents an inverted-U shaped relationship between temperature and labor productivity. Workers do not increase avoidance behavior. The findings suggest that the economic loss from reduced manufacturing labor productivity due to ambient temperature is quantitatively important, providing new insights on the biological effects of climate factor in affecting human labor. Further, back-of-the envelope calculations indicate that the estimated benefits of labor savings from mitigating warming are substantial.

**Keywords:** climate, temperature, thermal stress, manufacturing, labor productivity

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# 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 extreme temperatures (Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009; Burke and Emerick, 2016; Iyigun, Nunn and Qian, 2016). 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 China in particular may, therefore, have economic significance. These are the subject of this paper.

More precisely, this article provides 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. (2016), 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 temper-

ature 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 previous scholarly work and discuss the key characteristics of this specific setting.

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. These results echo Zhang et al. (2016)'s, who find that temperatures exert limited impacts on labor inputs of Chinese manufacturing firms.

Second, an inverted U-shaped relationship between the daily maximum temperature and worker productivity is detected. To elaborate, productivity at temperature below  $60^{\circ}F$  is about 11% less than that at  $75 - 79^{\circ}F$ , and it steadily increases over that range. The productivity then decreases to about 6.7% less above  $95^{\circ}F$ . The annual income losses due to deviations from the most productive level ( $78^{\circ}F$ ) are around ¥400 per worker (US\$61.5), i.e., 0.7% of a worker's income at  $78^{\circ}F$ . 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  $78^{\circ}F$  would translate into a \$64.6 million increase in total worker earnings. This also underscores the importance of implementing preventive measures

in the workplace, both in the short-term and in the face of long-run climate change (Kahn, 2016).

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, those of Adhvaryu, Kala and Nyshadham (2015) in India and of Zhang et al. (2016) in China. The similar patterns suggest that the mechanism is rather general, increasing confidence in the external validity of the findings.

Third, the effects of temperature on worker productivity are fairly homogeneous among the populations. Specifically, there are no significant differential effects between males and females, between young and old, or between migrants and local workers.

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 Indian garment sector. Also in India, Colmer (2016) has combined worker, firm and district-level data with high-resolution meteorological data to understand the effects of weather on agricultural productivity, industrial production and local labour markets. As in that work, our analyses focus on labor productivity. But using high-quality personnel data, this is among the first pieces of empirical analysis to establish a robust connection between temperature and worker productivity in China.

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.<sup>1</sup> This probably also explains why output reductions are only found for temperatures above  $27^{\circ}C$  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.

In parallel and independently of our analysis, a recent paper by Zhang et al. (2016) uses the Chinese manufacturing firm surveys 1998-2007 to examine the relationship between temperature and four components in a standard Cobb-Douglas production function: output, total factor productivity, labor, and capital inputs. They rely on year-to-year variation in a firm's exposure to the distribution of daily temperatures. Our paper exploits novel daily worker productivity and temperature data, which are highly disaggregated and precisely measured. We also distinguish the biological (i.e., the intensive margin) from the behavioral (i.e., the extensive margin) effects of temperature stress (Heal and Park, 2015).

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

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<sup>1</sup>See Chang et al. (2016) for detailed discussions on the importance of addressing self-selection in estimating the effects of environmental factors on productivity.

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 thermal 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.

The rest of the paper proceeds as follows. Section 2 summarizes the relationship between temperature and thermal stress. Section 3 introduces the institutional context of this study, followed by a description of the empirical strategy and data. Section 4 presents the empirical results. The last section concludes.

## 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 Vasmatazidis, 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; Seppänen et al., 2003; Seppänen 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  $27^{\circ}C$  ( $80^{\circ}F$ ) (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 ( $VO_2$  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  $21^{\circ}C$  (about  $70^{\circ}F$ ). The factory locates in the Xiamen Xiang’an Yinlu industry park. Because the industry park is far from the downtown area, the factory built dormitories and canteens for the workers. And all migrants and local workers eat and live together in the factory. Besides that, the factory has an administrative area, a production area, a warehouse 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. Each team produces the same product (to ensure fairness across workers within the team), and team managers determine who operates which machine, with the available machines to the team determined by the deputy general manager one day before. 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  $\alpha_1$ ) per unit of output. After their output exceeds the target, a higher rate  $\alpha_2$  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  $\alpha_2$ . The piece

rate of the first tier  $\alpha_1$  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 apply the commonly used framework with daily production data in the literature (e.g., Graff Zivin and Neidell, 2009 and 2014),

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

where  $i$  and  $d$  represent worker and day, respectively; and  $\varepsilon_{id}$  is the error term. 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).

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,  $y_{id} \equiv (Q_{id} - \bar{Q}_p) / \bar{Q}_p * 100$ . Note that the targeted output for each product  $\bar{Q}_p$  is fixed, the daily variation in  $y_{id}$ , therefore, comes from workers’ daily output  $Q_{id}$ . Meanwhile, because the workers’ compensation is solely based on their daily output, both the firm and workers carefully record productivity in meticulous detail, 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 was used. The indoor and outdoor temperatures should be highly correlated as the workshop had no heating or air conditioning. In particular, 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  $f_1(temp_d)$  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  $5^\circ F$  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.

### 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 the levels of sulfur dioxide, nitrogen dioxide and suspended particulates less than 10  $\mu m$  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 break-

down of the sample size. The average productivity is 23.11, which means that 23.11% of the output is over-target output, on average.

The average daily maximum temperature is about  $78^{\circ}F$ , with a standard deviation of  $11^{\circ}F$ , a maximum of  $99^{\circ}F$  and a minimum of  $55^{\circ}F$ . 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 environmental 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  $5^\circ F$  increments is used. The lowest temperature bin,  $0^\circ - 60^\circ F$  is omitted, so the estimates can be interpreted as the change in productivity relative to that at  $60^\circ F-$ .

The estimated coefficients are plotted in Figure 7. It is clear that there is an almost symmetric inverted-U shaped relationship between daily maximum temperature and productivity. Specifically, worker productivity at  $60^\circ F-$  is about 11% less than at  $75^\circ - 79^\circ F$ , and it steadily increases until  $75^\circ F - 79^\circ F$ . The productivity then decreases to yield about a 6.7% reduction at  $95^\circ F+$ . 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 is found. These results imply that temperature significantly affects worker productivity, but in an inverse U shape with the optimal temperature being around  $78^\circ F$  ( $= 0.5741/(2 * 0.0037)$ ). 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  $25^\circ C$  ( $\sim 77^\circ F$ ). The results under this study are also consistent with the fact that a maximum temperature at  $80^\circ F$  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  $78^{\circ}F$  and above  $78^{\circ}F$  are explored separately. Specifically, two new regressors of interests are constructed: *Max Temperature* $<78$  is measured as the maximum temperature up to  $78^{\circ}F$ , above which it is recorded as a constant  $78^{\circ}F$ . *Max Temperature* $>78$  is defined as maximum temperature minus  $78^{\circ}F$  in which the negatives are recorded as 0. The estimation results suggest that the temperature has a positive effect on worker productivity up to  $78^{\circ}F$ , from which point the effect becomes negative, further confirming the pattern of non-linearity.

### 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]

*Worker heterogeneity.* 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.

*Task assignment.* There is a concern that assignment of workers to tasks could respond

endogeneously to temperature changes, which may then confound our estimates. As elaborated in Section 3.1, the organization of production is wholly planned by the deputy general manager, who is in charge of production every day, including the production team formation (both team manager and workers), and the assignment of products and machines to each team. The process involves little manipulation possibility by team managers and workers. There are two possible sources of contamination. First, 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 effect of temperature 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.

Second, 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 condition.* One may be concerned that temperature may affect machine condition, which in turn affects worker productivity. In particular, if high temperatures caused more machines to break down, the estimates may in fact reflect machine reliability. To address this concern, we first examine the effect of temperature on the incidence of machine breakdowns. The estimates, reported in column 6, show that there are no significant impacts of temperatures on machine conditions. These results are consistent with the findings of Zhang et al. (2016) that capital inputs in the Chinese manufacturing sector are not affected

by temperature. Second, we include the indicator of machine breakdowns as an additional control in our baseline estimation. As reported in column 7, results similar to our baseline estimates are found. Combined, these two exercises suggest that machine breakdown is not a serious confounder of the temperature-productivity linkage we have established in this paper.

*Typhoon events.* 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 8, the main finding remains robust to this additional control variable, suggesting that typhoons do not contaminate the temperature effect.

*Alternative measurement of air pollution.* The API is also replaced with an alternative measure of air pollution—the visibility index. The estimation results in column 9 confirm the same pattern, suggesting that the results are not sensitive to the pollution indicator used.

*Persistent effects.* To consider the potential persistent effects, we include lagging and leading indicators of temperature in column 10. 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 Economic Magnitude and Policy Implications**

The coefficients in column 3 of Table 3 can be used to gauge the economic magnitude of the temperature effects. Below  $78^{\circ}F$ , an increase of  $10^{\circ}F$  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  $78^{\circ}F$ , an increase of  $10^{\circ}F$  in maximum temperature is associated with a 0.15 percentage point decrease in the over-target percentage of output.

We then calculate the worker’s economic loss. Recall 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  $10^\circ F$  in maximum temperature below  $78^\circ F$  leads to a change of over-target output by a 1.1 percent increase, i.e.,  $\Delta y_{id} = 1.1\%$ . As a result,  $\Delta w_{id} = \bar{Q}_p \alpha_2 \Delta y_{id} = 1.98$ . Similarly, an increase of  $10^\circ F$  in the maximum temperature above  $78^\circ F$  leads to  $\Delta w_{id} = -0.27$ . 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 ( $78^\circ F$ ), the daily losses per worker are calculated in Table 5. 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  $78^\circ F$ .

[Insert Table 5 here]

Using an estimate of the negative effects of temperature on daily productivity to assess losses, a related concern is that temperature perhaps does not change the aggregate amount of orders received by the firm. So, the total quantity produced is presumably constant. Firms and workers might simply substitute effort intertemporally. However, we find no indication of target adjustment to temperature (see section 4.3 in detail). Moreover, the aggregate order could be easily increased, and new orders would be received if the labor productivity is higher, and vice versa.

Following the lead of Chang et al. (2016), 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  $78^\circ F$ , 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).

The current study is based on personnel data from a specific Chinese manufacturing firm. Potential issues of external validity arise regarding the interpretation of the findings and their wider applicability. To address such concerns, first, we show that the estimates of this study compare well with those of previous scholarly work. For example, a meta-analysis by Seppänen, Fisk, and Lei (2006) finds that increasing temperature from  $23^{\circ}C$  ( $\sim 73^{\circ}F$ ) to  $30^{\circ}C$  ( $\sim 86^{\circ}F$ ) decreases labor productivity by around 9 percent. Using the estimates in Figure 6, moving from the  $75^{\circ}F - 79^{\circ}F$  to the  $80^{\circ}F - 84^{\circ}F$  range causes worker productivity to fall by about 6 percent. Second, the interplay between thermal stress and labor (i.e., the biological effects of temperature) highlighted in this paper suggests that the results can be, to a large extent, generalized to other workers and to other firms.

Furthermore, a key feature of this workplace is that manufacturing workers are exposed to non-climate controlled environment, which is common in low and middle income countries. 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. As highlighted in Kahn (2016, p6), “facing rising heat, it will be more difficult to attract workers to jobs that require more exposure to heat than jobs that are located in climate-controlled indoor spaces. Wages will rise for such unpleasant jobs, which will incentivize firms to take steps to protect their workers.” Firms or governments in poor countries can improve job amenities by purchasing cooling devices, for example, air conditioners. 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).

## 4.5 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 6.

[Insert Table 6 here]

In columns 1, we examine the potential differential effects across male and female workers. While the pattern of the single terms of temperature variables remains the same and the coefficients are statistically significant, the interaction terms of the temperature variables with the male indicator are statistically insignificant and small in magnitude. 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).

Furthermore, we study the potential differential effects between young and old workers in column 2. The interactions between the temperature variables and an indicator for old workers (i.e., those aged above the sample's median age) are statistically insignificant, 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).

Lastly, the differential effects of temperature on non-local and local workers are investigated in column 3. The estimation results show that while there are some differences between migrants and local workers, they are statistically insignificant. One possible explanation is that the local and non-local workers live, eat and work together in the factory. In other

words, they have encountered very similar conditions.

Combined, these results suggest that the effects of temperature on worker productivity are fairly homogeneous among the populations, i.e., there are no significant differences across gender, age groups, and home origin of workers.

## 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. This pattern persists across subgroups classified by gender, age and home of origin.

The economic loss due to reduced labor productivity in manufacturing in response to ambient temperature is sizeable. Back-of-the envelope calculations show that if the temperature could be maintained at the optimal level, this would translate into a \$64.6 million increase in city-wide worker earnings in 2013. These findings have important policy implications for climate change adaptation. Governments and firms in poor countries may gain from investing in air-conditioning, fans or other cooling systems in workplaces.

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.

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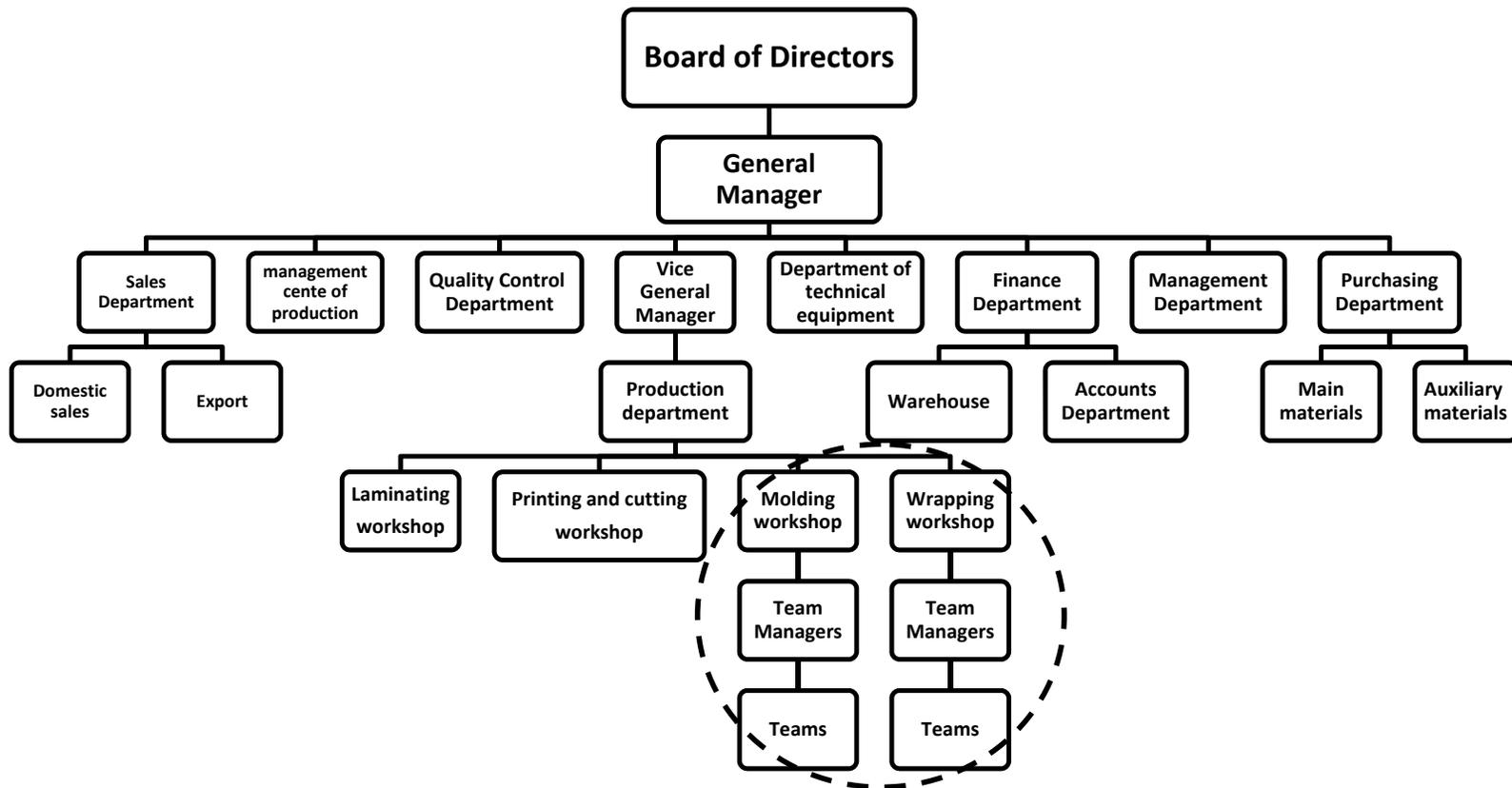


Figure 1. The Corporate Hierarchy

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

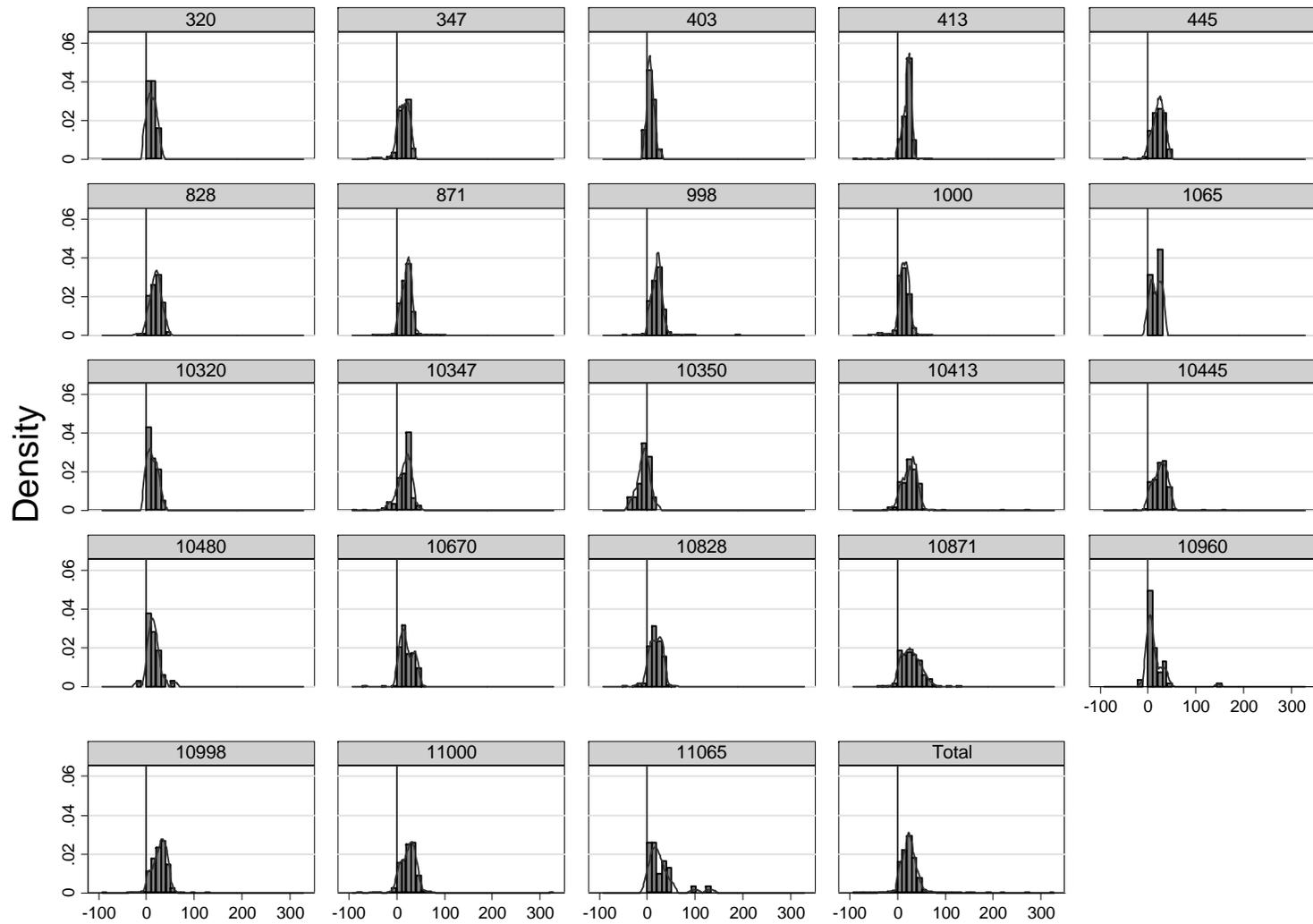


Figure 2: Over-target percentage of output by product and for all products

Notes: 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.

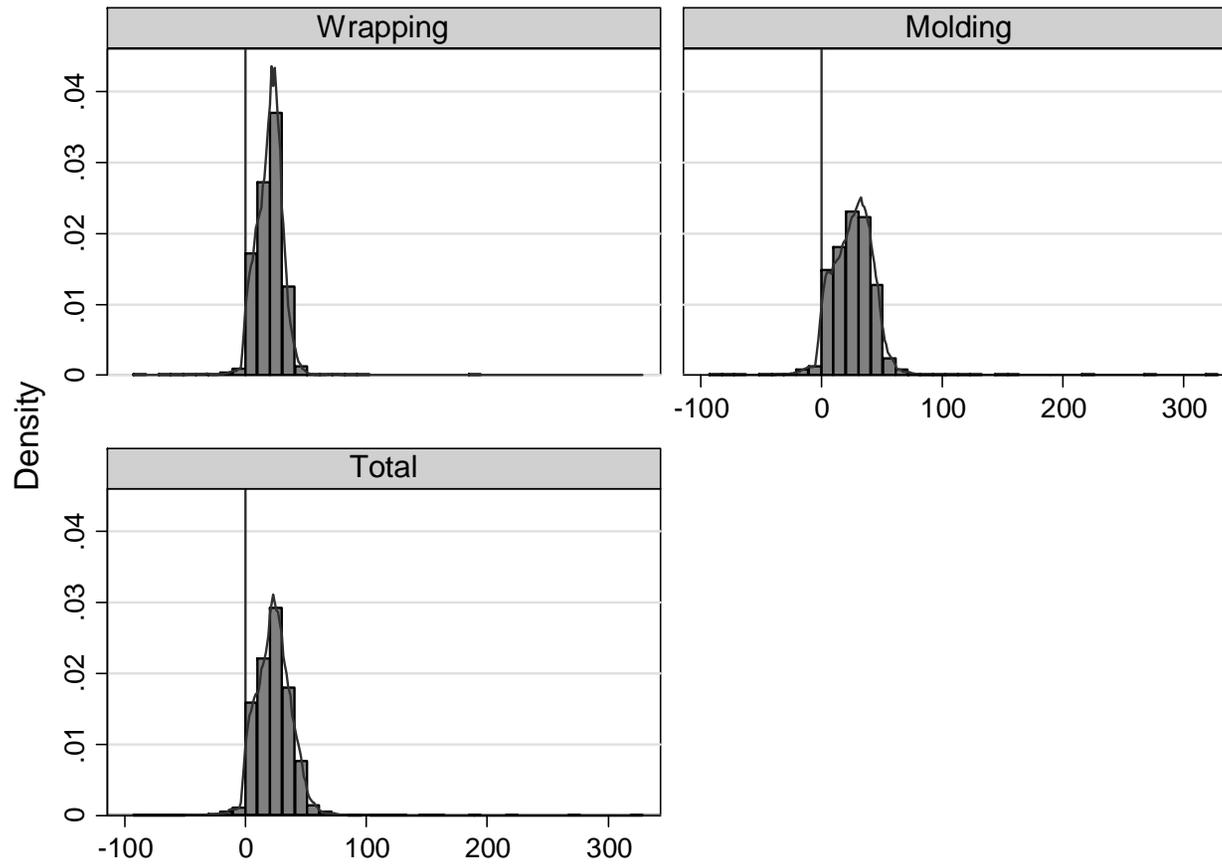


Figure 3: Over-target percentage of output by job task and for all tasks

Notes: 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 tasks.

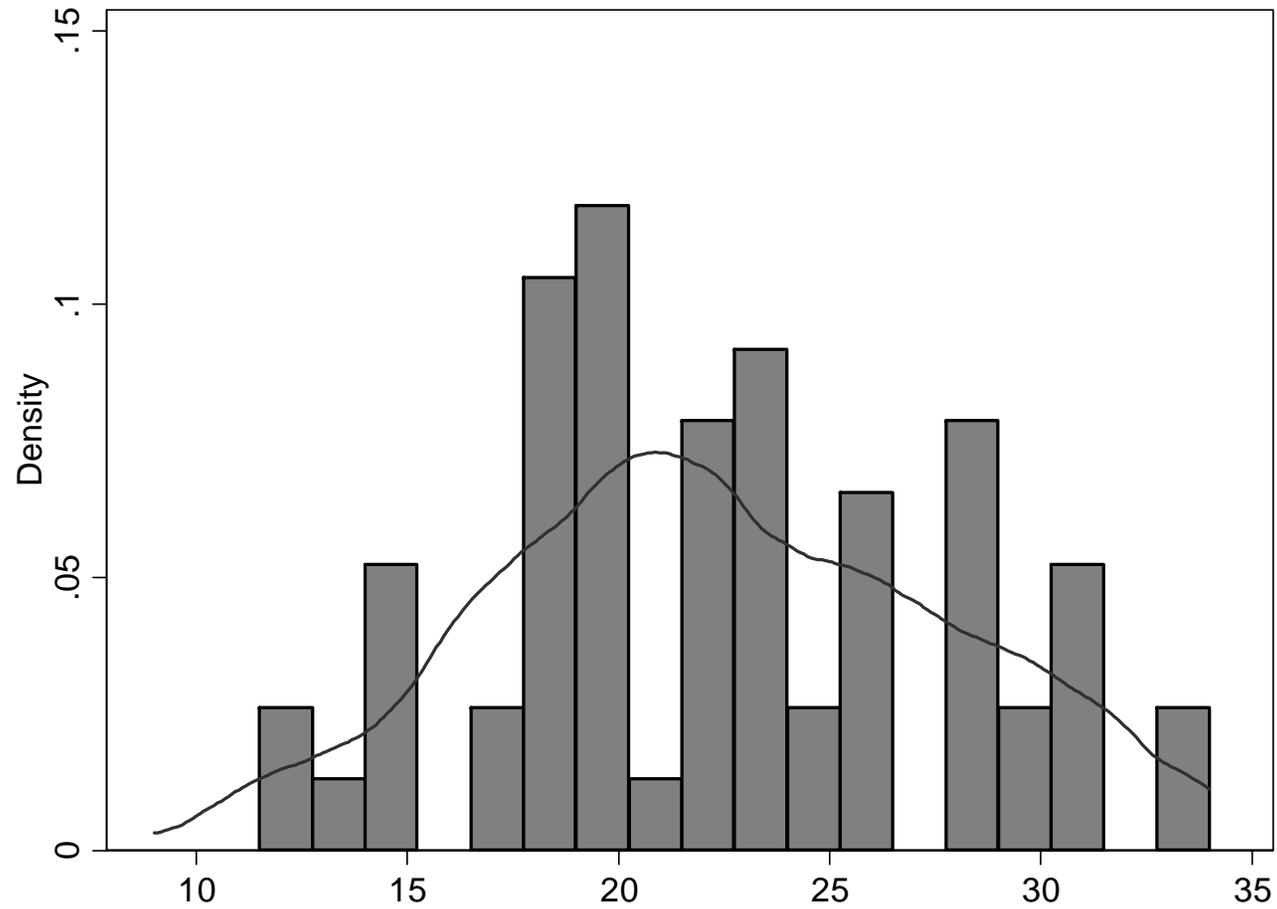


Figure 4. Variation in Productivity by worker, all products

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

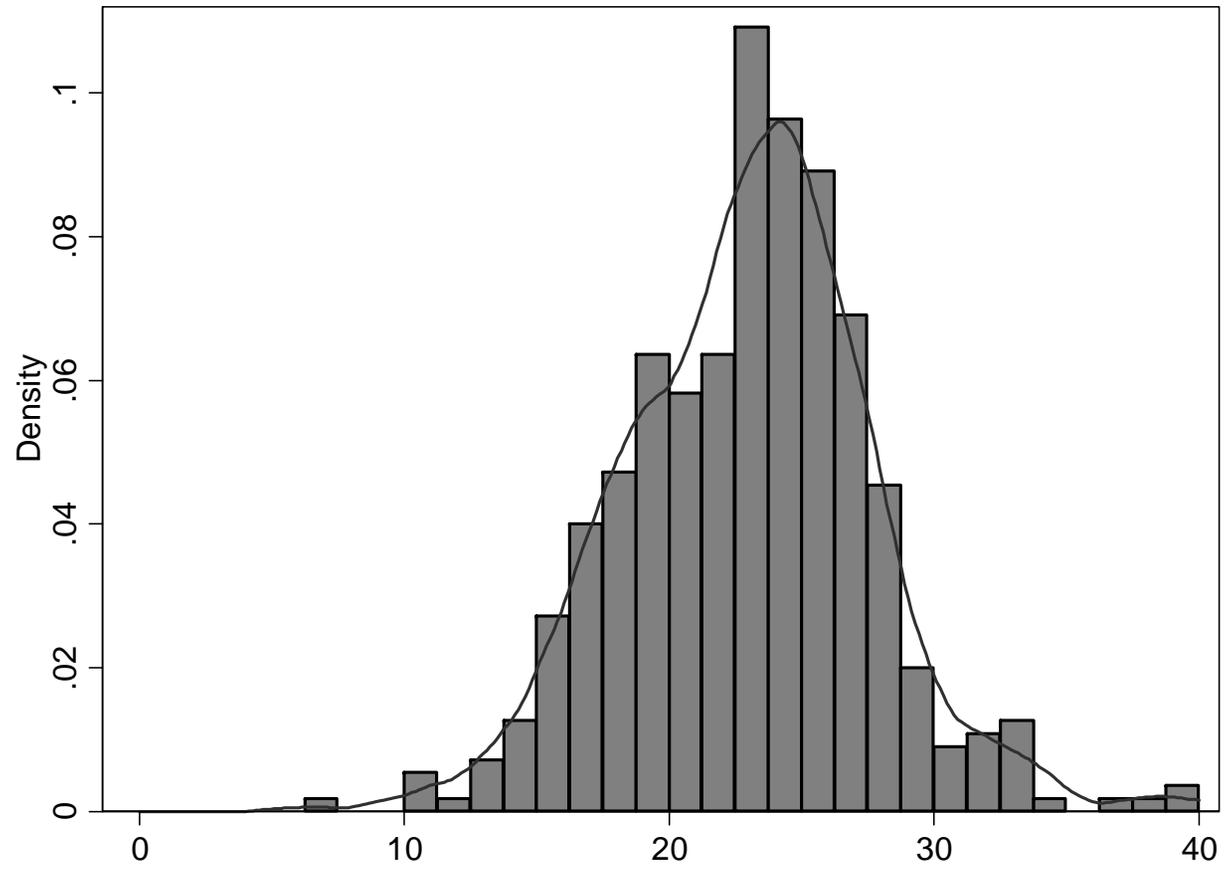


Figure 5. Variation of Productivity by day, all products

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

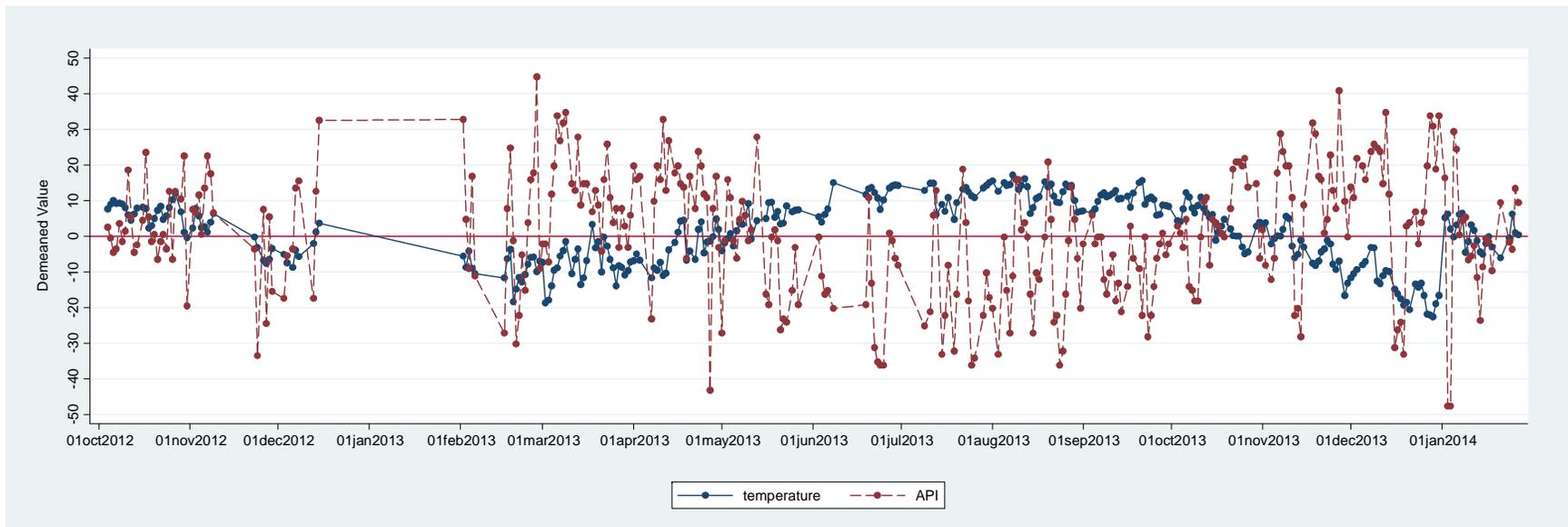


Figure 6. Average Demeaned Daily Temperature and API

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).

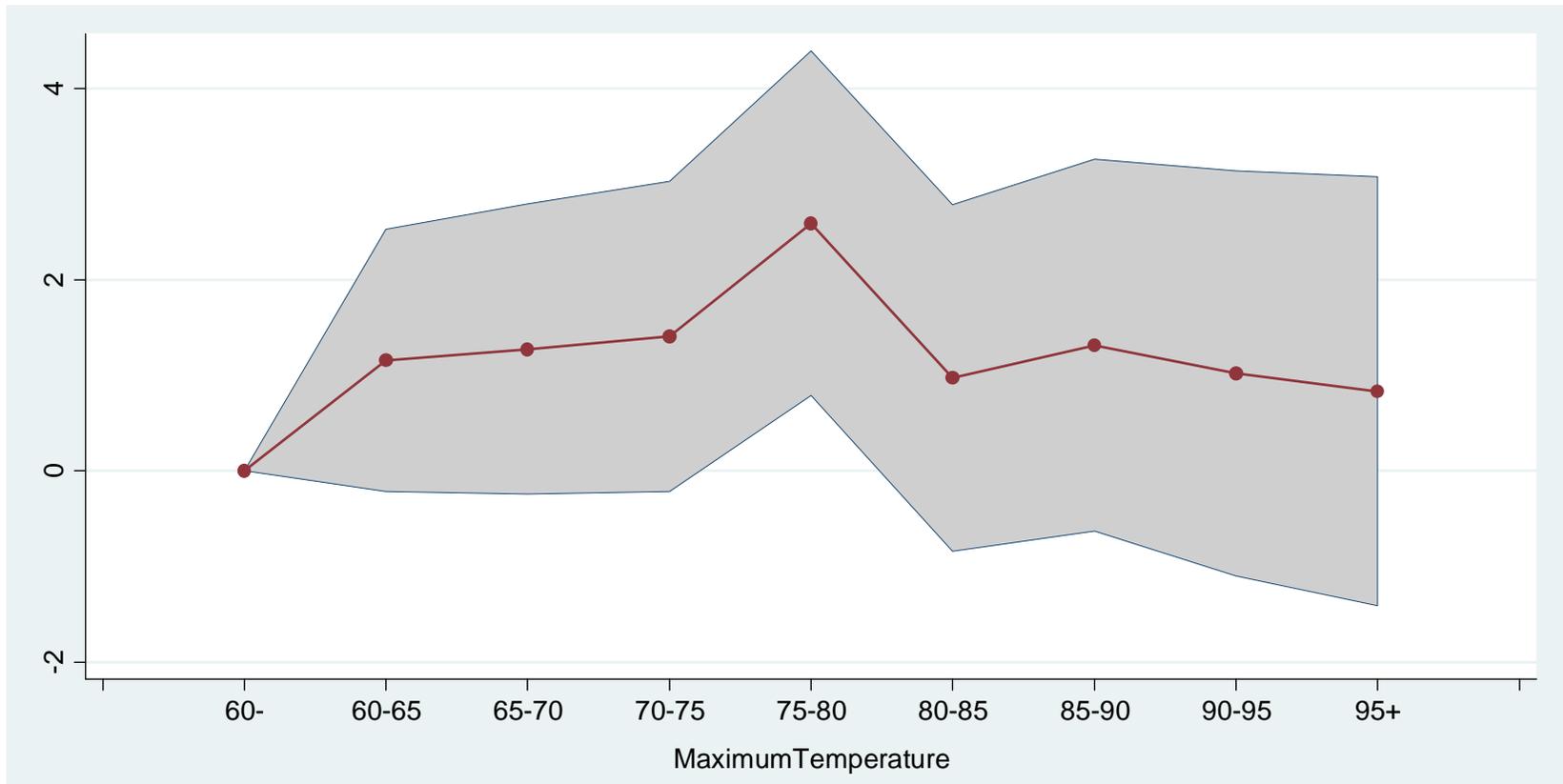


Figure 7. Relationship between maximum temperature and productivity for all individuals.

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  $\times$  year dummies, and a night shift dummy.

Table 1 Summary Statistics

	Observations	Mean	SD		
<i>Panel A. Productivity variables (N=14,128)</i>					
Productivity	14128	23.11	15.40		
Hour worked	14128	11.27	1.95		
Night shift	14128	0.51	0.50		
Worker characteristics					
Male	14128	0.39	0.49		
Local worker	14128	0.37	0.48		
Age	14128	32.08	8.71		
	Mean	SD	Min	Max	
<i>Panel B. Environmental variables (N=473)</i>					
Maximum temperature (F)	78.42	10.80	55.4	98.6	
Minimum temperature (F)	64.44	10.59	39.7	82.8	
Precipitation (.01 inches)	0.16	0.53	0	7.69	
Dew point (F)	61.23	12.57	27.7	78.6	
Wind speed (.1 knots)	6.41	2.35	2	22	
Station pressure (.1 mb)	998.55	6.13	976.5	1011.9	
API	53.84	17.42	10	99	
Visibility (.1 miles)	7.03	2.10	0.8	15.5	
<i>Panel C. Sample</i>					
Number of dates	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 dates. SD denotes standard deviation.

Table 2 The Behavior Effects of Temperature: Labor Supply

Variables	Extensive margin: probability(work)		Intensive margin: hours worked	
	(1)	(2)	(3)	(4)
Max temperature	0.0059 (0.022)	0.0056 (0.022)	-0.0103 (0.052)	-0.0164 (0.052)
Max temperature square	-0.0001 (0.000)	-0.0001 (0.000)	-0.00002 (0.000)	0.00002 (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  $\times$  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 The Biological Effects of Temperature: Worker Productivity

Model	(1) Linear	(2) Tobit	(3) Parametric Spline
Max temperature	0.5741** (0.287)	0.6094** (0.280)	
Max temperature square	-0.0037* (0.002)	-0.0039** (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 78°F, above which it is recorded as a constant 78°F. Max temperature>78 is defined as the maximum temperature minus 78°F 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 Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Max temperature	0.5741** (0.287)	0.5403* (0.291)	0.5879** (0.288)	0.4515* (0.268)	0.4626* (0.268)	-0.0026 (0.011)	0.6160** (0.285)	0.5743** (0.286)	0.4969* (0.281)	0.6115* (0.318)
Max temperature square	-0.0037* (0.002)	-0.0035* (0.002)	-0.0038** (0.002)	-0.0028 (0.002)	-0.0029* (0.002)	0.00004 (0.00008)	-0.0038** (0.002)	-0.0037* (0.002)	-0.0032* (0.002)	-0.0039* (0.002)
Max temperature d+1										0.0586 (0.307)
Max temperature d+1 square										-0.0008 (0.002)
Max temperature d-1										-0.0534 (0.359)
Max temperature d-1 square										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	Machine condition	Include machine breakdown	Include typhoon	Visibility	Include Lag and Lead Temperature
year-month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
day of week FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	14,128	14,453	14,453	14,128	14,128	441	14,128	14,128	14,892	14,040
R-squared	0.045	0.165	0.037	0.074	0.074	0.217	0.133	0.045	0.046	0.047

Notes: Standard errors clustered on date and worker are reported in brackets. The dependent variable in all columns except column (6) is the fraction of over-target output. The dependent variable for column (6) is the daily machine breakdown ratio. All regressions include controls for maximum temperature, maximum temperature square, minimum temperature, minimum temperature square, air pressure, wind speed, dew point, precipitation, API, day of week dummies and month  $\times$  year dummies. All columns except column (6) also include controls for gender, a local worker dummy, age and a night shift dummy. All environmental variables, except for the temperature, are the mean values. \*\*\* denotes significance at 1%, \*\* at 5%, and \* at 10%.

Table 5 Economic Magnitude of Annual Losses Per Worker

Temperature	Frequency	Daily losses	Daily 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  $20000 \times 0.009 \times 0.01149 \times (\text{Temperature} - 78)\%$ . If temperature is above 78°F, daily losses equal  $20000 \times 0.009 \times 0.015 \times (78 - \text{Temperature})\%$ .

Table 6 Impact Heterogeneity by Worker Characteristics

	(1)	(2)	(3)
Max temperature	0.6239*	0.7181*	0.7272**
	(0.328)	(0.424)	(0.358)
Max temperature square	-0.0041*	-0.0046*	-0.0047**
	(0.002)	(0.003)	(0.002)
Max temperature*Male	-0.1349		
	(0.550)		
Max temperature square*Male	0.0010		
	(0.004)		
Max temperature*Above median age		-0.3105	
		(0.475)	
Max temperature square*Above median age		0.0019	
		(0.003)	
Max temperature*Local			-0.4153
			(0.443)
Max temperature square*Local			0.0028
			(0.003)
year-month FE	YES	YES	YES
day of week FE	YES	YES	YES
Observations	14,128	14,128	14,128
R-squared	0.045	0.046	0.045

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 maximum temperature, maximum temperature square, minimum temperature, minimum temperature square, air pressure, wind speed, dew point, precipitation, API, a night shift dummy, gender and a local worker dummy. Column (1) includes the interaction terms of maximum temperature and the male indicator, the interaction terms of maximum temperature square and the male indicator. Column (2) includes the above median age dummy variable, the interaction terms of maximum temperature and the above median age dummy variable, the interaction terms of maximum temperature square and the above median age dummy variable. Column (3) includes the interaction terms of maximum temperature and the local worker indicator, the interaction terms of maximum temperature square and the local worker indicator. Columns (1) and (3) also include age. All environmental variables, except the temperature, are the mean values. \*\*\* denotes significance at 1%, \*\* at 5%, and \* at 10%.