

The Light and the Heat: Productivity Co-benefits of Energy-saving Technology*

Achyuta Adhvaryu[†]

Namrata Kala[‡]

Anant Nyshadham[§]

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Abstract

The impacts of technologies that mitigate climate change are tempered by the willingness of individuals and firms to adopt them. Absent costly, sustained taxes or subsidies, this willingness rests on the technologies' private returns, which are generally assumed to be modest. We document a novel productivity co-benefit to the adoption of energy-saving LED lighting. First, using detailed daily production data from garment factories in Bangalore, India, we show that efficiency (realized output over target output) decreases substantially on hotter days. But the introduction of energy-saving LED lighting, which emits less heat than incandescent or fluorescent lighting, attenuates 75 percent of the negative impact of temperature on productivity. Our results are robust to a variety of measures of temperature, specifications, and the incorporation of relative humidity. Our estimates suggest that the productivity returns to LED adoption are more than 4 times larger than the energy savings.

Keywords: climate change, mitigation, co-benefits, energy-saving technology, LED, firm productivity
JEL Codes: D22, O13, O14, Q54, Q56

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[†]University of Michigan; adhvaryu@umich.edu; achadhvaryu.com

[‡]Yale University; namrata.kala@yale.edu; environment.yale.edu/profile/namrata-kala

[§]University of Southern California; nyshadha@usc.edu; anantnyshadham.com

1 Introduction

The Inter-governmental Panel on Climate Change (IPCC) projects that the mean global temperature will likely rise by more than 1.5 degrees Celsius relative to pre-industrial temperature by 2100 for a range of climate change scenarios (IPCC, 2013). Developing countries, whose adaptive and protective capacities are low and who are on average hotter than developed countries, will bear the lion's share of the negative impacts of climate change (Mendelsohn et al., 2006). Productivity in agriculture and unskilled industrial labor will likely decline drastically, not only due to the increased frequency of extreme weather events¹ but also because excessive heat decreases the body's capacity for exertion (Kjellstrom et al., 2009; Lemke and Kjellstrom, 2012; Sudarshan and Tewari, 2013).

Given these repercussions, there is great academic and policymaking interest in identifying effective climate change mitigation strategies and convincing individuals and firms to adopt them. This process is not easy: though the public benefits of mitigation may be high, the immediate private returns are generally assumed to be low or even negative (Knittel and Sandler, 2011). If this were true, then achieving widespread adoption might require costly sustained subsidies or taxation.

In this study, we ask: do mitigation strategies have hidden private returns? In particular, we estimate the productivity consequences of the adoption of energy-saving technology. Using detailed production data from garment factories in Bangalore, India, we show that the introduction of light-emitting diode (LED) technology on factory floors substantially attenuates the negative relationship between temperature and worker efficiency. LED lighting is 7 times more energy-efficient than standard fluorescent lighting in our setting, and emits about 1/7th the heat. We study the impacts of a staggered roll-out of LEDs over four years on the stitching floors of 25 factories operated by a large garment export firm in India.²

We begin by estimating the effect of changes in temperature on worker efficiency (realized output over target output) at the production line by day level. We find that efficiency decreases substantially on hotter days: a 1 degree Celsius increase in mean daily heat index lowers production efficiency by .161 points (average efficiency is 53.4 percent). Contemporaneous effects of temperature on attendance are small and tightly bounded around 0, suggesting that the temperature-efficiency gradient derives from the direct physiological effect of temperature on workers' productive capacity, rather than an indirect mechanism via worker attendance.³ We do, however, find evidence that lagged temperature (the average over the past 7 days) significantly affects absenteeism.

We then estimate the extent to which the introduction of LED lighting, through the reduced intensification of temperature on factory floors, flattens the temperature-efficiency gradient. Our

¹See, e.g., Deschênes and Greenstone (2007); Guiteras (2009); Hsiang (2010); Kala et al. (2012); Kurukulasuriya et al. (2006); Lobell et al. (2011).

²Our data sample includes 29 factories, four of which did not receive LED lighting.

³It bears mentioning that absenteeism is a significant problem in these factories, so there is substantial day-to-day variation in attendance.

estimated magnitudes are startling: on average, the introduction of LED lighting eliminates nearly 75 percent of the negative impact of temperature on efficiency. These results are quite robust to changes in empirical specification and to a variety of temperature measures. Interestingly, though we find that LED introduction generates significant attenuation of the temperature-productivity gradient across the temperature distribution, this differential effect is nearly twice as large below median temperature as compared to above.

Our study contributes to the understanding of the effects of environmental factors on economic productivity. Recent work has documented significant labor supply and productivity impacts of air pollution (Graff Zivin and Neidell, 2012; Hanna and Oliva, 2011) and temperature (Graff Zivin and Neidell, 2010; Hsiang, 2010; Sudarshan and Tewari, 2013). Our detailed productivity measures, relatively long time span, and high-frequency temperature data allow us to quantify impacts with precision. Our findings are quite consistent with the previous studies: deviations in temperature strongly impact labor productivity. These studies make important inroads, but they stop short of evaluating policies that actually lessen the negative impact of heat on productivity. We provide the first evidence to our knowledge of the impact of technology that flattens the temperature-productivity gradient, while also having important environmental benefits via climate change mitigation.

Second, we add to the body of work on the negative impacts of high temperatures in developing country contexts. Recent studies have demonstrated the impacts of either long-term mean temperature or temperature anomalies on agricultural output (Deschênes and Greenstone, 2007; Guiteras, 2009; Kala et al., 2012; Kurukulasuriya et al., 2006; Lobell et al., 2011); industrial production (Hsiang, 2010; Sudarshan and Tewari, 2013); health and survival (Burgess et al., 2013; Danet et al., 1999; Deschênes and Greenstone, 2011; Kudamatsu et al., 2012); and conflict (Burke et al., 2009; Hsiang et al., 2013). We contribute to this literature new evidence of temperature's effects on industrial productivity, which represents a rising fraction of GDP in the developing world.

Finally, we contribute to the literature on the returns to climate change mitigation.⁴ The few recent studies that examine "co-benefits," or additional gains, of mitigation focus largely on the indirect public returns (Bollen et al., 2009; Knittel and Sandler, 2011). For example, a carbon tax aimed primarily at reducing CO_2 emissions may also reduce emissions of accompanying pollutants such as nitrous oxides or carbon monoxide, thus reducing substantially the tax's welfare costs. Our study examines a novel, *private* co-benefit of climate change mitigation. This distinction is important because the success of most mitigation strategies relies on individuals' and firms' willingness to adopt them, and this willingness is largely driven by private returns. If energy-saving technologies like LEDs do have substantial private co-benefits, this should meaningfully alter firms' benefit-cost calculations. Indeed, by our estimation, the benefits of LEDs in terms of productivity are substantially larger than energy savings (in fact, roughly 4 times as large), indicating that ignoring the former source of benefit would seriously underestimate the private returns

⁴A related literature has established patterns of adaptation to climate change and the returns to this adaptation (e.g. Barreca et al. (2013)).

to adoption.

The remainder of the paper is organized as follows. Section 2 describes contextual details regarding garment production in India and LED technology. Section 3 provides details on the temperature and production data. Section 4 describes our empirical strategy. Section 5 describes the results, and section 6 has a concluding discussion.

2 Context

In this section, we 1) discuss the garment sector in India and key elements of the garment production process; 2) review the physiology of the relationship between temperature and worker productivity; 3) provide an overview of energy usage and heat emissions in LED v. fluorescent lighting; and 4) describe the roll-out of LED lighting across the garment factories in our data.

2.1 The Indian Garment Sector

Global apparel is one of the largest export sectors in the world, and vitally important for economic growth in developing countries (Staritz, 2010). India is the world's second largest producer of textile and garments, with the export value totaling \$10.7 billion in 2009-2010. Women comprise the majority of the workforce (Staritz, 2010). Total employment in India's formal apparel and textile industry was about 2 million in 2008, of which 675,000 was in the formal apparel sector, making this a crucial component of India's industrial sector.

2.2 The Garment Production Process

There are three broad stages of garment production: cutting, sewing, and finishing. In the factories that comprise our production data, garments are sewn in production lines. Each line will produce a single style of garment at a time (i.e. color and size will vary but the design of the style will be the same for every garment produced by that line until the order for that garment is met). Lines consist of 20-100 sewing machine operators (depending on the complexity of the style) arranged in sequence and grouped in terms of segments of the garment (e.g. sleeve, collar, placket).⁵ Completed sections of garments pass between these groups, are attached to each other in additional operations along the way, and emerge at the end of the line as a completed garment. These completed garments are then transferred to the finishing floor.

Before reaching the sewing floor, pieces of fabric needed for each segment of the garment are cut using patterns from a single sheet so as to match color and quality perfectly. These pieces are divided according to groups of sewing operations (e.g. sleeve construction, collar attachment) and pieces for 10-20 garments are grouped and tied into bundles. These bundles are then transported

⁵In general, we describe here the process for woven garments; however, the steps are quite similar for knits and even pants, with varying number and complexity of operations. Even within wovens, the production process can vary a bit by style or factory.

to the sewing floors where they are distributed across the line at various “feeding points” for each group of sewing operations.

In finishing, garments are checked, ironed, and packed. A great degree of quality checking is done “in-line” on the sewing floor, but final checking occurs in the finishing stage. Any garments with quality issues are sent back to the sewing floor for rework or, if irreparably ruined, are discarded before packing. Orders are then packed and sent to port.

2.3 Physiology of the Temperature-Productivity Gradient

The physical impact of temperature on human beings is a very well-studied area (Enander, 1989; Parsons, 2010), and has traditionally been important in order to establish occupational safety standards for workers exposed to very high or low temperatures for continued periods of time (Vanhoorne et al., 2006). Higher temperatures and consequent thermal stress can impact human beings not only physically, but also through lower cognition and psychomotor ability (Hancock et al., 2007). For instance, Ramsey et al. (1983) find increases in unsafe behavior by workers at temperatures greater than 35 degrees Celsius WBGT (Wet Bulb Globe Temperature). The individual impact on a person varies based on factors such as the type of task and its complexity, duration of exposure, as well as the worker-level skill and acclimatization level (Pilcher et al., 2002), which contributes to the issues in setting a particular limit in working environments (Hancock et al., 2007).

2.4 LED v. Fluorescent Lighting

LED light bulbs are approximately 7 times as energy-efficient as fluorescent bulbs (requiring about 3 as opposed to 21 KWh/year in electricity in our setting), and thus operate at about 1/7 the cost of fluorescent lighting. In addition, they generate a tenth of the CO_2 emissions (5.01 pounds of CO_2 per year per bulb, as compared to 35.11 pounds for fluorescent lighting).⁶ Heat emissions for LEDs are substantially lower than fluorescent bulbs: the average LED bulb emits 3.4 Btus, as against 23.8 Btus for fluorescent lighting in the setting we study.

2.5 LED Roll-out: Summary and Timeline

The factories began installing LED lighting in October 2009 and completed the installations by February 2013. There was no formal documentation of the reasons for LED adoption in each factory, but according to senior management at the firm, the reasons were twofold. First, over the last decade, buyers have become more stringent in their regulation of their suppliers’ production standards and environmental policies. This generated a staggered roll-out of LEDs across factories within the firm because some factories were more heavily involved in the production of orders

⁶Note that while both fluorescent and LED lighting are much more efficient than incandescent bulbs, the factories in our sample did not have any incandescent lighting on the production floor. For details on emissions calculations, please refer to section 6.

from particular buyers than others. So, for example, if buyer A's environmental regulations or production guidelines become more stringent, then the supplier might choose to convert to LED lighting in factories processing many orders from buyer A. When buyer B's regulation change, the firm will prioritize factories servicing buyer B, and so on. Second, over the study period, the firm itself began a variety of "green" initiatives firm-wide, and thus scaled up LED introduction across its factories. These two factors combine to generate wide variation in the timing of LED take-up across the factories we study. To test whether this timing was exogenous to line-daily efficiency, we perform some checks, which are described in detail in section 5.

The replacement took the form of replacing all fluorescent lights targeted at individual operations with an equivalent number of small LED lights mounted on individual workers' machines. The replacements were designed to maintain the original level of illumination. On average, each unit replaced about 1,000 fluorescent lights of 7W each with 1,000 LED lights of 1W each.⁷ Based on the factories' operating time cost calculation, this meant an energy saving of 18KWh per light per year. In the conclusion, we discuss the magnitude of the environmental benefits from the installation.

A particular factory received the installation within a single month. 8% of the LED rollout (2 units) was completed in 2009, 48% (12 units) in 2010, 16% (4 units) in 2011, about 24% (6 units) in 2012 and rest (1 unit) in 2013. Of the 29 units from which we have productivity data, LED replacements occurred in 25 units. Since our productivity data ranges from April 2010 to June 2013, some units have LED since the beginning of our productivity data, and all but four units have LED for the last four months of our productivity data range. This is why our results report the impact of temperature not only for the whole sample, but also separately for the units that did not have LED at a particular time.

3 Data

Here we provide an overview of data sources, describe our data via summary statistics, and provide preliminary graphical evidence on the temperature-productivity gradient and the effects of LED introduction.

3.1 Data Sources

3.1.1 Temperature Data

Our temperature data is from the National Climatic Data Center (NCDC) at the National Oceanic and Atmospheric Administration (NOAA). The Center compiles global station-level weather data at the hourly level, although most stations outside the US report data only at 3-hour intervals. We have temperature data from three stations in Bangalore over the period spanned by our productiv-

⁷The number of lights installed unit by unit is a function of the number of machines in the unit, and varies from about 100 to 2,550 with a mean of 1,000.

ity data (April 2010 to June 2013). Over 80% of the observations are at the 3 hourly level (midnight IST onwards), and the rest are across somewhat arbitrary time measurements. We consider all observations across the three available stations between 9am and 6pm for each day as our daily temperature measure, which constitutes the working hours at the factories we consider.⁸ This is dry bulb temperature, and at the daily level ranges between 18.8 and 34.4 degrees Celsius, with an average of about 27.6 degrees Celsius.

We have relative humidity data at the monthly level for three stations in Bangalore from January 2010 to November 2013, from the NOAA's National Data Center (NNDC). We were unable to find relative humidity data at a daily level for Bangalore, and are consequently unable to include daily relative humidity. At the monthly level, relative humidity ranges between about 44% and 85.7%.⁹

With the daily temperature and monthly relative humidity data, we construct two measures that incorporate both temperature and humidity. The first is the Heat Index (HI) that is calculated based on the formula:

$$\begin{aligned}
HI = & -42.379 + 2.04901523 * T_d + 10.14333127 * rh - .22475541 * T_d * rh \\
& - .00683783 * T_d^2 - .05481717 * rh^2 + .00122874 * T_d^2 rh \\
& + .00085282 * T_d * rh^2 - .00000199 * T_d^2 * rh^2.
\end{aligned} \tag{1}$$

where T_d = dry bulb temperature in Fahrenheit and rh = relative humidity (%). The formula for the calculation is derived from the Rothfus regression that replicates the HI values from Steadman (1979).

For about 0.6% of our data, the relative humidity is greater than 85% and daily temperature ranges between 80 and 87 degrees Fahrenheit, and the following adjustment is applied:

$$HI = HI + [(rh - 85)/10] * [(87 - T_d)/5] \tag{2}$$

The second measure is a particular method for calculation Wet Bulb Globe Temperature that is suitable for indoor exposure. The formula is from Lemke and Kjellstrom (2012), and is given by:

$$WBGT = 0.567T_d + 0.216 \left(\frac{rh}{100} * 6.105 \exp \left(\frac{17.27T_d}{237.7 + T_d} \right) \right) + 3.38. \tag{3}$$

All the three measures of temperature – dry bulb temperature, Heat Index (HI), and Wet Bulb Globe Temperature (WBGT) – are converted into Celsius to ensure interpretative ease across re-

⁸Note that since not all observations are available for each of the three stations, assigning factories to the nearest station is not feasible. About 60% of our observations come from the first station, and about 20% each from the second and third. The correlation between the observations from the first and second station as well as the first and third station is between 0.92 and 0.93, which is very high (the second and third stations do not overlap in terms of data availability).

⁹Analogous to the temperature calculations, we average over the station observations - the correlation between station-level observations ranges from 0.92 to 0.99

gression specifications. While there are numerous formulae for the calculation of varied heat indices, we chose these two since they were relatively easy to calculate and interpret. For all our results, we report the main effect of dry bulb temperature as well as the main effect of dry bulb temperature controlling for relative humidity in addition to the impact of the Heat Index and the Wet Bulb Globe Temperature.

3.1.2 Factory Data

We use data on line-level daily production from 29 garment factories in and around Bangalore, India. Identifiers include factory unit number and line number within the factory. For each line and day within each factory unit, production measures include actual quantity produced, actual efficiency, and budgeted efficiency.

Actual efficiency is actual quantity produced divided by target quantity. The target quantity is derived from an industrial engineering (IE) measure for the complexity of the garment called “Standard Allowable Minute” (SAM). This measure amounts to the estimated number of minutes required to produce a single garment of a particular style. This estimate comes from a central database of styles, but is then amended by the factory’s IE department during “sampling.” Sampling is the process by which a style that is ordered by a buyer is costed in terms of labor and production time. The highest skill grade tailor, called a sampling tailor, will make a garment of a particular style entirely and recommend a SAM for that style to the IE department.

This SAM is then used to calculate the target quantity for the line for each hour of production. Each line runs for 8 hours during a standard work day. Accordingly, a line producing a style with a SAM of .5 will have a target of 120 garments per hour, 960 garments per day. If 900 garments are actually produced on that day, the actual efficiency will be $900/960=93.75\%$.

Each line will only produce a single style at any time. However, depending on the order size (or “scheduled quantity”) for a style, multiple lines might be producing the same style at one time and each line could produce a style for many days.¹⁰ Of course, a line which has been producing the same style for many days will likely be more efficient at producing that style than will a line which has been producing a style (of even the same complexity or SAM) for less days. These types of variations in efficiency, in addition to dimensions such as the number of operations the SAM must be divided into for producing a style, are reflected in the budgeted efficiency. Consequently, actual efficiency of a given style will vary systematically across lines and within line over time. We will accordingly control for budgeted efficiency and include line fixed effects in the regression analysis below.

Most importantly, we use actual efficiency rather than produced quantity as our outcome of choice. Produced quantity would not account for systematic variation due to complexity of style or number of operations. Without normalizing production observations to target quantity, one could potentially misrepresent an association between temperature and style complexity or order size as an impact on productivity. Accordingly, we argue that actual efficiency, controlling for

¹⁰Indeed, in our data, lines produce styles for between 1 and 199 days.

budgeted efficiency, is the most appropriate outcome for the empirical exercise proposed in this study.

3.2 Summary Statistics

We present means and standard deviations of variables used in the analysis below. Our sample consists of 446 lines across 29 factory units. The range of dates over which we have production data spans 941 days in total. However, we do not observe all factory units, nor all lines within a unit, for all dates. We restrict our attention to lines for which we observe production data for at least 40% of dates. Altogether, our data includes nearly 215,000 line-day observations. Roughly, one-third of the observations correspond to days in factory units prior to the introduction of LED lighting and the rest are post-LED observations.

The summary statistics indicate a great deal of variation in the measures of temperature. The means of these measures appear quite similar before and after the introduction of LED. This is to be expected given that the timing of LED introduction varied at the factory level across nearly the entire date range. That is, 6 units already have LED lighting at the beginning of the date range and 4 units still have not received LED lighting by the end of the date range. On the other hand, both actual and budgeted efficiency appear to differ on average between the before and after LED samples. Average efficiency appears higher after LED introduction, while budgeted efficiency appears lower.

3.3 Preliminary Graphical Evidence

We begin by motivating the central exercise of this study with descriptive plots of production and temperature data.

3.3.1 Temperature-Productivity Gradient

Underlying the analysis conducted below is the assertion that productivity and temperature are negatively correlated. In order to check this assertion in our empirical context, we plot both the daily time series of actual production efficiency and the heat index. These plots, presented in Figure 1, depict a distinct negative correlation and, perhaps, a slight lag in the impact of temperature on efficiency.

We next collapse the time element of the data and plot actual efficiency as a function of the heat index. Figure 2 shows that indeed efficiency appears to be a downward-sloping function of temperature.

3.3.2 Impacts of LED Introduction

Having provided preliminary evidence of a negative temperature-productivity gradient for the garment factories in our data, we next check for evidence that this gradient is affected by the

FIGURE 1: EFFICIENCY AND TEMPERATURE TIME SERIES

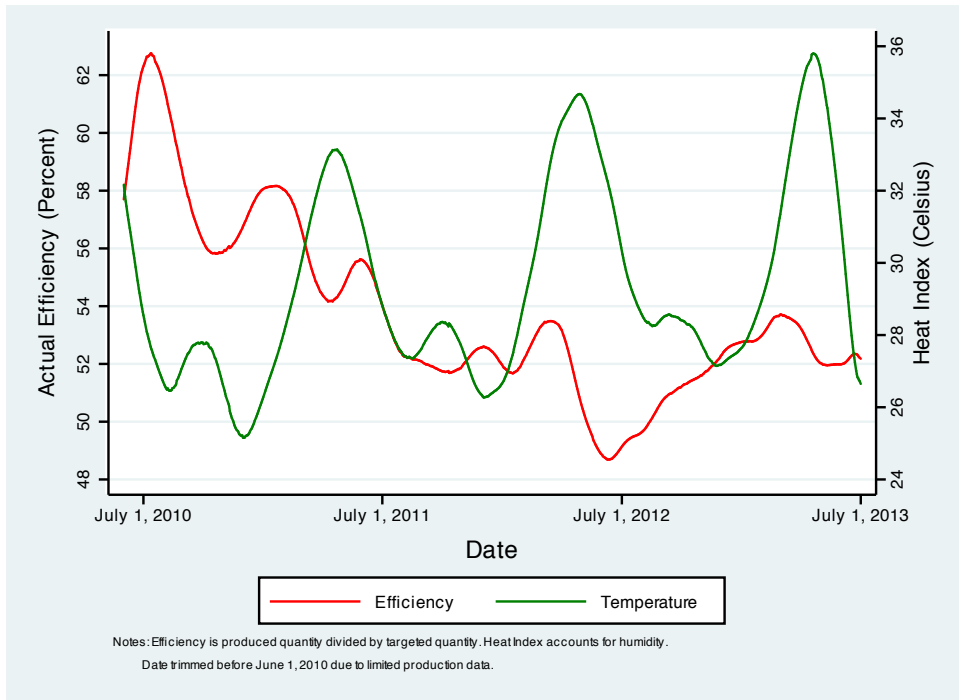


FIGURE 2: EFFICIENCY AGAINST TEMPERATURE

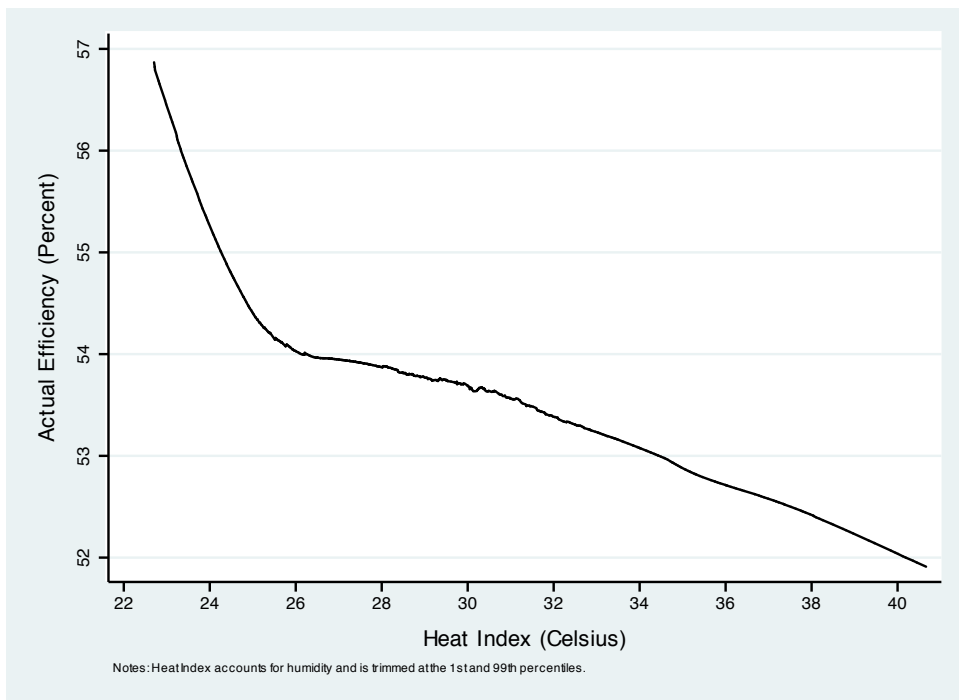
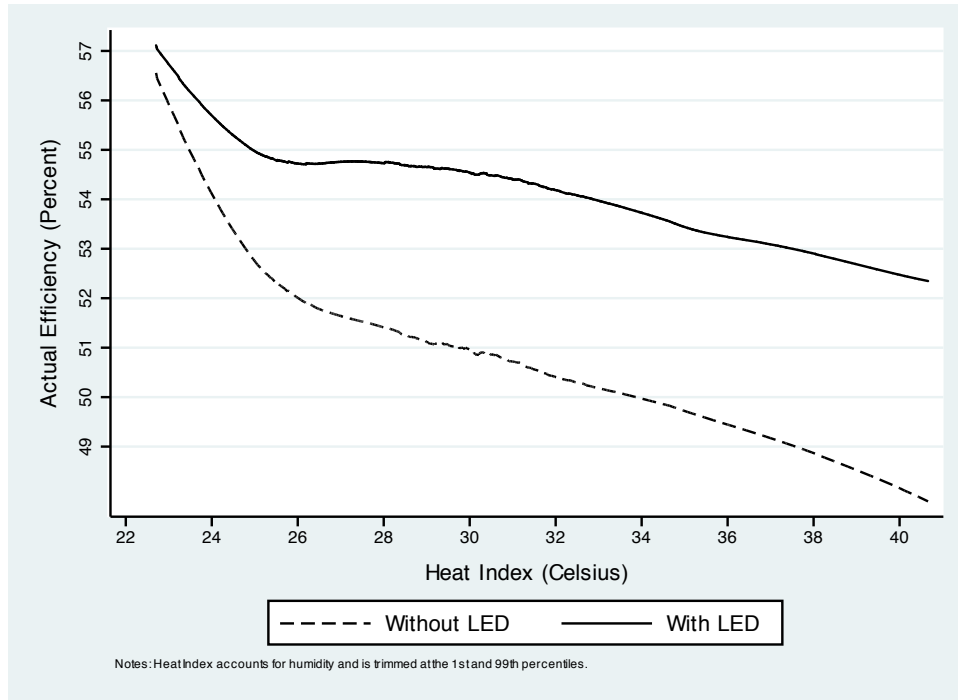


FIGURE 3: EFFICIENCY AGAINST TEMPERATURE BY LED

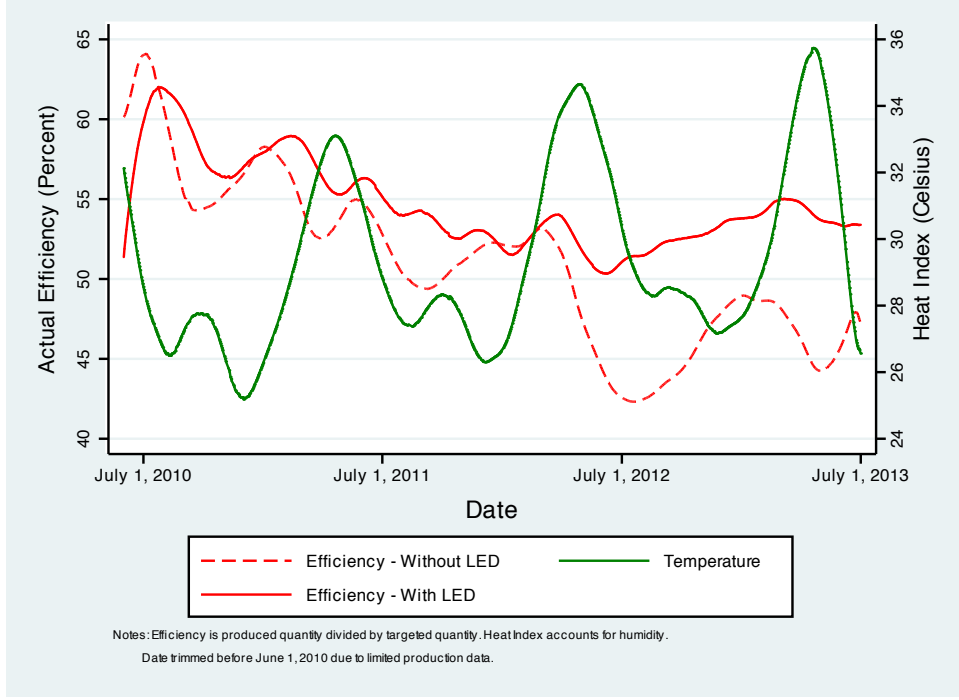


replacement of the ambient fluorescent lighting in factories with focused, machine-mounted LED lighting. We repeat the exercise from Figure 2 for subsets of the data from before and after the LED roll-out in each factory. These plots are presented in Figure 3. The evidence suggests that factories are more efficient at all temperatures after the LED introduction.

Lastly, we return to the exercise conducted in Figure 1, but plot the efficiency series separately for factory-day observations with and without LED lighting. Once again, we include the temperature time series for comparison and present the plots in Figure 4. The evidence in Figure 4 also suggests that LED lighting improves efficiency on all days, but particularly smooths the fluctuations in efficiency due to temperature.

Motivated by this preliminary evidence we set forth a more rigorous regression analysis below to causally identify both the effect of temperature on production efficiency and the attenuation of this impact driven by the replacement of traditional fluorescent lighting with LED technology. In particular, we address concerns regarding unit-level trends in efficiency, line-level unobservables, seasonality in efficiency, and the exogeneity of the LED introduction.

FIGURE 4: EFFICIENCY AND TEMPERATURE TIME SERIES BY LED



4 Empirical Strategy

First, we estimate the following empirical specification of the relationship between worker efficiency and temperature:

$$E_{ludmy} = \beta T_{dmy} + \alpha_l + \gamma_{uy} + \eta_m + \delta_d + \varepsilon_{ludmy}. \quad (4)$$

Here, E is efficiency in line l of unit u on day d in month m and year y ; T is daily temperature in degrees Celsius; α_l are line fixed effects; γ_{uy} are unit \times year fixed effects; η_m are month fixed effects; and δ_d are day-of-week fixed effects. β is the coefficient of interest, giving the impact of a 1-degree Celsius increase in temperature on line-level efficiency.

In addition to the average effect of temperature on efficiency, we are also interested in testing whether this effect, and its corresponding attenuation by LED lighting, is heterogenous across the distribution of temperature. To implement this, we estimate equation 4 allowing for varying slopes of temperature above and below the median of the temperature distribution. We use the following empirical specification:

$$E_{ludmy} = \zeta_1 (Q_1 \times T_{dmy}) + \zeta_2 (Q_2 \times T_{dmy}) + \zeta_5 Q_1 + \zeta_6 Q_2 + \alpha_l + \gamma_{uy} + \eta_m + \delta_d + \varepsilon_{ludmy}. \quad (5)$$

where Q_1 is a dummy variable that is 1 if temperature is above median temperature and zero

otherwise, and Q_2 is a dummy variable that is 1 if temperature is below median temperature and zero otherwise.

We then estimate the extent to which the introduction of LED lighting attenuates the temperature-productivity relationship via the following specification:

$$E_{ludmy} = \beta_1 (T_{dmy} \times LED_{umy}) + \beta_2 LED_{dmy} + \beta_3 T_{dmy} + \alpha_l + \gamma_{uy} + \eta_m + \delta_d + \varepsilon_{ludmy}. \quad (6)$$

Here LED_{umy} is a dummy for presence of LED lighting in unit u in month m and year y . It changes from 0 to 1 in the month following LED introduction in a particular factory unit. The coefficients of interest in the above specification are β_1 and β_3 . β_3 indicates the effect of temperature on productivity *before* LED introduction. β_1 is the extent of attenuation of the temperature-productivity gradient once LED lighting is introduced. The sum of these two, $\beta_1 + \beta_3$, gives the net effect of temperature on productivity following LED introduction. Finally, we test if the attenuation impact of LED is heterogenous for temperatures above and below the median temperature by estimating the following specification:

$$E_{ludmy} = \beta_1 Q_1 \times T_{dmy} \times LED_{umy} + \beta_2 Q_2 \times T_{dmy} \times LED_{umy} + \psi_1 Q_1 \times T_{dmy} + \psi_2 Q_2 \times T_{dmy} + \zeta_1 Q_1 \times LED_{umy} + \zeta_2 Q_2 \times LED_{umy} + \theta Q_1 + \alpha_l + \gamma_{uy} + \eta_m + \delta_d + \varepsilon_{ludmy}. \quad (7)$$

Following Graff Zivin and Neidell (2012), we use two-way clustering of standard errors in all regressions (Cameron et al., 2011). Standard errors are clustered 1) at the production line level, because our cross-sectional variation is the line level, and we would expect inter-temporal correlation in productivity within lines; and 2) at the date level, since this is the level at which temperature varies.

5 Results

In this section, we present and discuss the results of the estimation strategy proposed in section 4 above.

5.0.3 Average Impact of Temperature

We begin by verifying the apparent negative temperature-productivity gradient depicted in Figure 2. In Table 2, we present results from the regression of actual efficiency on various measures of temperature. Unless otherwise noted, all specifications, as discussed in section 4, include budgeted efficiency as a control as well as month, day-of-week, line, and unit by year fixed effects.

Column 1 in Panel A shows that a one degree Celsius increase in the heat index leads to a .1 percentage point reduction in efficiency (as compared to a mean efficiency of roughly 53.4 per-

cent). This estimate is significant at the 1 percent level and is robust across various temperature measures. Column 2 presents the impact of a one degree rise in wet bulb globe temperature; while columns 3 and 4 present the impact of a one degree rise in dry bulb temperature with and without relative humidity as a control, respectively. Across all measures estimates are negative, statistically significant and of nearly identical magnitude. Estimates range from .135 to .17 percentage points across the other measures of temperature.

Panel B of Table 2 shows estimates from regressions identical to those reported in Panel A, but restricting attention to observations prior to the introduction of LED lighting. To the extent that LED lighting affects the temperature-productivity gradient, the true estimate of the gradient will be most precisely estimated in the absence of LED lighting. Indeed, point estimates from Panel B are consistently larger than those from Panel A ranging from .16 to .26 percentage points. All estimates in Panel B, as in Panel A, are significant at the 1 to 5 percent level.

5.1 Lagged Impact of Temperature

Having shown the significant impact of contemporaneous temperature on efficiency, we next explore the degree to which this impact persists and/or compounds over time. We test for persistent, cumulative effects of temperature by re-estimating the regression from Table 2 including the mean temperature over the prior week as an additional regressor. The results of these regressions are reported in Table 3. The point estimates on lagged temperature measures in panel A, using the pooled sample, are imprecisely estimated (likely due to serial correlation in temperature). Nevertheless, the sign and magnitude of the estimates suggest that mean temperature in the past week does have an incremental negative impact on current efficiency above current temperature.

Indeed, in panel B, we repeat the exercise for the sample of observations corresponding to factory days before LED lighting. For this subsample, the point estimate on the one week lag is precisely estimated, negative, and large in magnitude across all measures of temperature. Point estimates are more than 50 percent larger than the contemporaneous effect of temperature, presented in panel B of Table 2. These results suggest that the effect of temperature on efficiency does in fact persist or even compound.¹¹

Next, we explore the impact of temperature on worker attendance. Considering that when the work attendance decision is made in the morning the temperature is still quite mild, we do not expect that contemporaneous temperature will have much of an effect on attendance. Rather, we suspect that lagged temperature will impact future attendance, perhaps by way of exhaustion. We estimate regressions identical those reported in Table 3, but with a binary for whether the worker attended a full day of work. We present results from these regressions in Table 4.

Notice these data are available at the worker level, rather than the production line level. Accordingly, the sample of observations is much larger. The results indicate that the probability that

¹¹The fact that the estimates include observations after the introduction of LED lighting presented in Panel A are attenuated and insignificant might indicate that the introduction of LED lighting offsets the persistent impacts of temperature on efficiency as well. However, there is insufficient residual variation in the interaction of the 1 week lagged temperature with LED after controlling for the interaction of LED with contemporaneous temperature.

a worker comes to work today is indeed reduced by the mean temperature over the prior week. A one degree celsius increase in mean temperature over the prior week leads to between a .2 and .5 percentage point reduction in the probability of attending. Estimates are quite similar from both the whole sample (reported in panel A) and the sample of observations prior to LED introduction (reported in Panel B).

5.2 LED and the Temperature-Efficiency Gradient

Having established the impacts of temperature on production outcomes, we next investigate the degree to which LED attenuates these impacts. We regress actual efficiency on the interactions of our four measures of temperature with a dummy for the presence of LED lighting in the factory along with the main effects of temperature and LED introduction. The remainder of the specification is identical to that presented in Table 2. The results of these regressions are presented in Table 5. Estimates of the coefficients on the interaction of LED introduction with all measures of temperature are positive, statistically significant, and large in magnitude relative to the main effects of temperature. The estimates overall provide strong evidence that the partial replacement of incandescent bulbs with LED bulbs significantly offset the negative impact temperature on production efficiency.

The results in column 1 indicate that the introduction of LED lighting offsets .15 percentage points in efficiency loss for each degree of the heat index. This amounts to roughly a 75% reduction in the impact of temperature on efficiency. The final row of Table 4 shows that the impact of temperature on efficiency net of attenuation from LED introduction is only weakly negative and insignificant. Estimates in columns 2 through 4 using alternate measures of temperature are very similar: LED introduction reduces the negative effects of temperature by 75-93% leading to a insignificant, weakly negative net impact of temperature on efficiency.

While we may not necessarily expect that LED has as strong a mitigative effect on the impacts of lagged temperature, we are not able to explicitly test for this effect. In the data, there is insufficient independent variation in the interaction of LED with the 1 week lagged mean of temperature once we control for the interaction of the contemporaneous temperature with LED. Given the lack of evidence for effects of contemporaneous temperature on attendance, we do not report results from regressions of attendance on the interaction of lagged temperature with LED introduction.¹²

5.2.1 Distributional Impacts of Temperature

In Table 6, we investigate the degree to which the temperature-efficiency gradient has different slopes above and below the median of the temperature distribution, and accordingly, the degree to which the mitigative impact of LED is more strongly realized at above or below median temperatures. The regressions reported in Table 6 are identical to those in the first columns of Tables 2 and 5, with added triple interactions of heat index, LED, and dummies for temperatures below

¹²The results show no evidence of a role for LED and are available upon request.

and above the median. The main effect of the below median dummy is omitted to preserve the constant.

The results suggest that indeed the slope of the temperature-efficiency gradient is steeper below the median. As might be expected, the mitigative impact of LED appears to be strongest for below median temperatures as well. These results could perhaps indicate that at sufficiently high temperatures the reduction in indoor temperature due to LED lighting replacement is less noticeable.

5.3 Exogeneity of LED Introduction

In Table 7, we report results from checks of the exogeneity of the timing of the roll-out of LED bulb replacement across factory units. To the degree that temperature deviations from monthly means are plausibly exogenous, we do not necessarily need LED roll-out to also be exogenous in order to interpret the coefficient on the interaction of LED introduction and temperature in the main results as causal. That is, any correlation of LED introduction timing with unobservable determinants of efficiency across factories or over time ought to be addressed by the inclusion of the main effect of LED introduction, so long as these unobservables are orthogonal to temperature deviations within month. Furthermore, as mentioned in section 2, senior managers at the garment factories indicated that LED introduction was driven mostly by efforts to comply with changing environmental policies of the companies of specific buyers.

Nevertheless, for the sake of interpretation and external validity, we investigate determinants of the timing of LED introduction. Specifically, we investigate the degree to which budgeted efficiency and scheduled quantity predict LED introduction. That is, to the extent that LED replacement is, for example, more likely during lean production times or less likely during the production of large orders from important buyers, these will be reflected in the scheduled quantity and budgeted efficiency for the days leading up to LED introduction.

We first plot budgeted efficiency against the date relative to LED introduction using data from the quarters before and after LED introduction for each factory unit. This plot is presented in Figure 5 and shows no clear evidence of abnormal trends in budgeted efficiency leading up to LED introduction. Next, we perform the regression analog to Figure 5 by regressing budgeted efficiency on the date relative to LED introduction, again including the usual fixed effects. The results of this regression are reported in column 1 of Table 7 and provide no evidence of any correlation.

We then repeat both exercises for scheduled quantity. The plot of scheduled quantity against the date relative to LED introduction is presented in Figure 6. The results from the analogous regression are reported in columns 2 of Table 6. Both further support the exogeneity of the introduction of LED lighting.

FIGURE 5: EFFICIENCY BY DATE RELATIVE TO LED INTRODUCTION

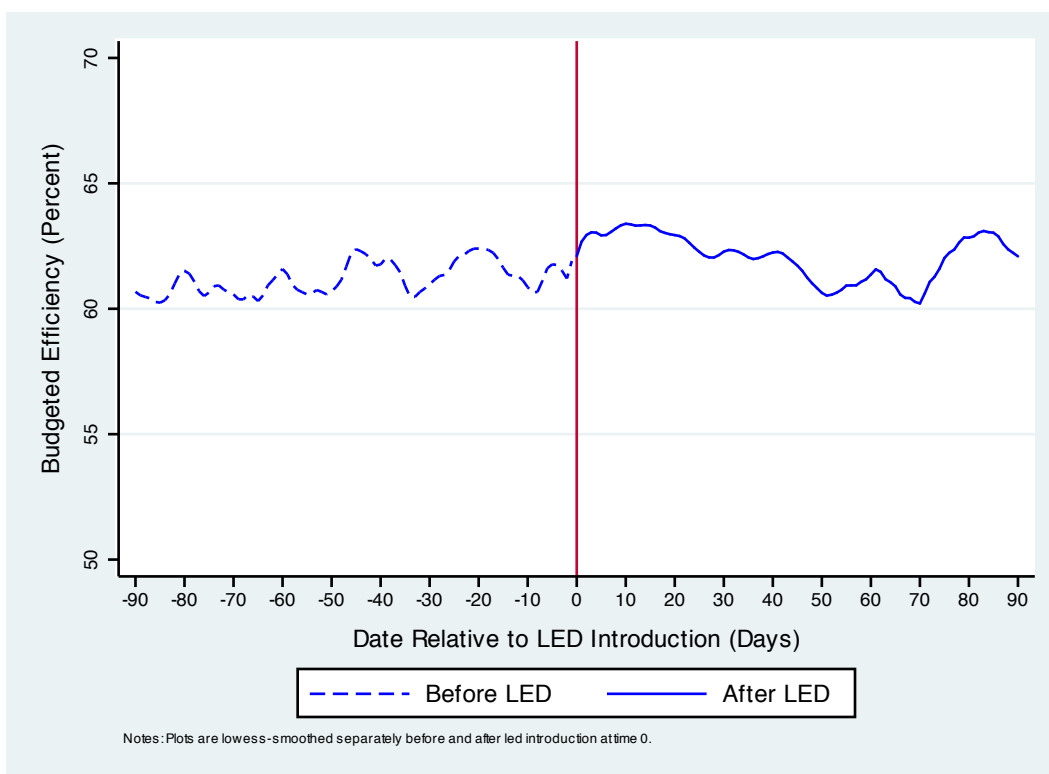
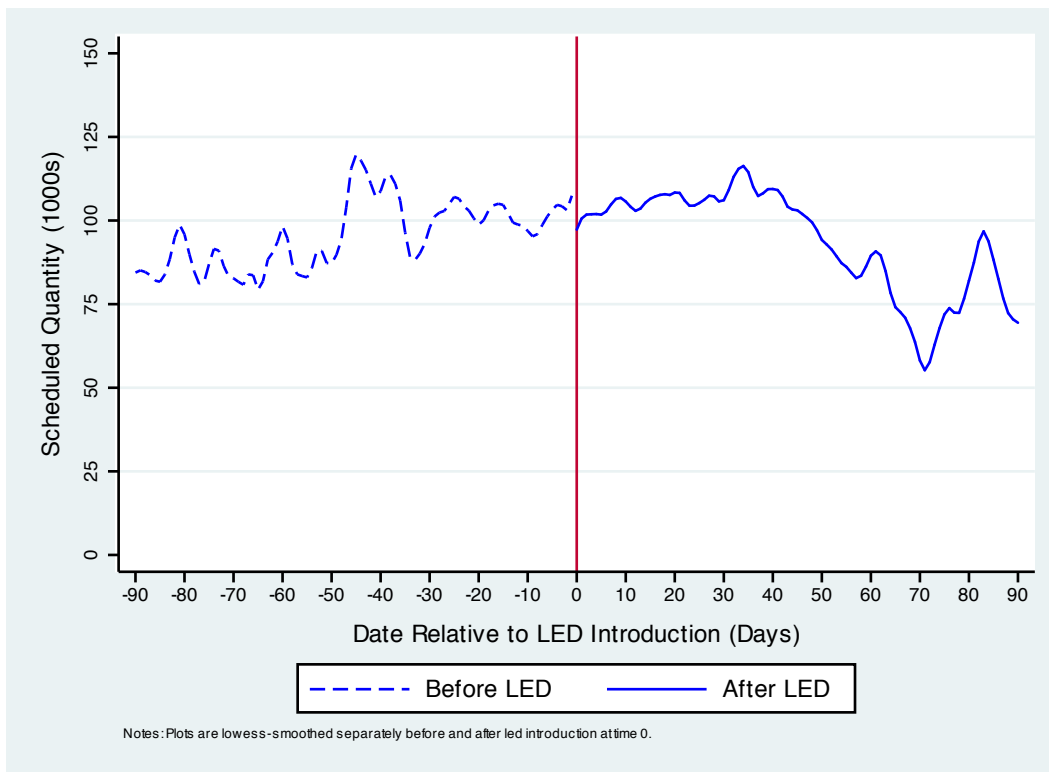


FIGURE 6: SCHEDULED QUANTITY BY DATE RELATIVE TO LED INTRODUCTION



6 Discussion

The promise of climate change mitigation is tempered by the willingness of individuals and firms to adopt these beneficial technologies on a large scale. This willingness, in turn, is a function of the private returns to adoption, which, for most mitigation strategies, are cited as low or negative even when the public benefits are large. In this study, we show that the introduction of energy-saving LED lighting in Indian garment factories has substantial productivity co-benefits. In particular, the introduction of LEDs eliminates 75% percent of the negative impact of temperature on worker efficiency.

What are the benefit-cost implications for the firm of this productivity impact? From the coefficient estimates in Table 4, we find that, at the average daily heat index of 29.669, LED introduction is associated with an increase in efficiency of $-3.87 + (.15 \times 29.669) = .58$ percentage points. What does this mean to the firm? Senior management at the firm we worked with estimated that the profit gains for each percentage point gain in efficiency were 0.2 percentage points (a fifth of every point gained in efficiency is translated to profit). Thus, at 1,067.58 dollars (USD), the approximate value of profit per factory unit per operating day, LED introduction results in a profit increase of about 41.4 USD per factory unit per operating day, or 12,922.46 USD per factory per year. This is equivalent to about 3.9 percent of daily profit per unit. Put another way, installing LEDs results in each factory unit “gaining” 12 additional days in profit per year.

How does this estimate change the benefit-cost calculations of LED adoption for the firm? To begin with, we obtained energy cost-savings calculations the firm used when making its LED adoption choices. Management estimated that the total energy and operating cost savings per year per factory unit of LEDs (as compared with CFL bulbs, which were being used before LED introduction) were approximately 1,83,000 rupees (INR), or about 3,000 USD. The productivity savings we compute are more than 4 times this amount. The cost of replacing a single factory’s bulbs to LEDs is 3,84,000 INR, or about 6,300 USD. Thus, if only energy savings were taken into account, it would take more than 2 years to break even. But when the productivity benefits are included, the firm breaks even within 5 months of LED introduction.

In addition to the private benefits of increased productivity and energy cost savings, the replacement of LED lighting has public benefits of avoided damages due to reduced carbon emissions. On average, the LED replacement saves 18,000 KWh of electricity per factory unit per year, which in this case reduces electricity emissions by about 3.73 tC emissions per unit per year.¹³ Valuing this reduction of carbon emissions at the Nordhaus (2008) estimate of \$27/tC (a 2005 carbon price) gives us avoided damages of \$101.23 per unit per year, and valuing this at the mean value of the review by Tol (2005) of \$93/tC yields avoided damages of \$345.68 per unit per year. Interestingly, at the current estimates of carbon prices, these benefits are relatively small in com-

¹³The conversion from electricity consumption to carbon emissions is done as follows: According to the CO2 Baseline Database for the Indian Power Sector (version 8) by the Central Electricity Authority of India, a MWh of electricity generated on the Southern grid causes 0.76 tCO₂ of emissions. Thus, 18,000 KWh causes about 13.68 tCO₂, or about 3.73 tC.

parison to the annual private benefits.¹⁴

We believe our work is an important first step in quantifying private co-benefits of climate change mitigation strategies, but that much more needs to be done quantify the full returns to the variety of mitigation strategies. For example, as Knittel and Sandler (2011) suggest, carbon taxes likely have health benefits due to decreases in local air pollution. If consumers internalize these benefits, the effective costs of the tax will be substantially lower. Whether similar co-benefits exist for other types of mitigation – e.g., renewable energy investments, public transport systems, energy-efficient built environments, etc. – is an open and vital question.

¹⁴Adding the corresponding reduction in local air pollutants would increase the valuation of public benefits, but given the sparsity of accurate data regarding marginal damages of local pollutants in Bangalore, we are unable to include this valuation in this study.

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A Additional Tables

We test the robustness of our main results—that is, the main effect of temperature on efficiency, as well as the interaction of LED introduction and temperature—to the subtraction of a variety of fixed effects, including month, day-of-week, production line, and unit \times year. We find that the results are very robust to these alternate fixed effects specifications, and that the coefficients on temperature and the interaction of temperature and LED introduction are quite stable.

B Data Appendix

We have daily line-level data from 29 factories in Bangalore. To ensure accurate estimation, we remove extreme outlier values as well as unrepresentative days (such as Sundays) from the dataset. The following factors are taken into consideration when deciding our final sample.

- We create a measure of the difference between the maximum and minimum date for which each line is observed divided by the total number of days for which it is observed. This measure essentially captures the proportion of time for which a line is observed relative to its time in the data. We remove observations for which this proportion is strictly greater than 1 (10 lines) and less than 0.38, which is the 5th percentile of the observations. This is done to ensure that the sample includes lines that are consistently producing, not ad hoc lines that are sometimes set up to fulfil rush orders or orders behind schedule.
- We remove lines observed greater than twice a day, about 0.6% of our observations, since these are likely coding errors. While it is possible that a line finished a set of orders and moved onto producing a different style of garment midway through the day, it is not possible that a line finished several sets of garment orders in a single day, since orders are usually for hundreds or thousands of garments per order. For lines that are observed more than twice a day, we consider mean actual efficiency and mean budgeted efficiency across the two styles produced that day.
- We remove extreme outliers from the efficiency and quantity produced. We consider all observations between the 5th and 95th percentile of the efficiency measurements, which ranges from about 3% to about 111%. After removing these values, we also trim physical quantity produced at the 1st and 99th percentile. These decisions were taken following meetings with the Industrial Engineering experts at the factory regarding what constitutes feasible values of output and efficiency.
- Finally, we remove Sundays as well as days which have very few lines, since these are likely regional holidays or days of unrepresentatively low productivity. We consider only days for which 117 or more lines are present in the data (the 1st percentile of observations).

Table 1
Summary Statistics: Weather, Production, and LED Introduction

	(1)		(2)		(5)	
	<i>Whole Sample</i>		<i>Without LED</i>		<i>With LED</i>	
Number of line-day observations	214,968		71,969		142,999	
Number of lines	446					
Number of days	941					
Number of units	29					
	Mean	SD	Mean	SD	Mean	SD
<i>Weather</i>						
Temperature (degree Celsius)	27.599	2.786	27.441	2.730	27.679	2.811
Relative Humidity (%)	67.418	11.159	68.423	11.380	66.913	11.012
Wet Bulb Globe Temperature (degree Celsius)	24.348	1.921	24.289	1.903	24.377	1.929
Heat Index (degree Celsius)	29.669	4.026	29.502	4.039	29.752	4.016
<i>Production</i>						
Actual Efficiency	53.411	21.452	52.054	21.411	54.095	21.440
Budgeted Efficiency	61.929	11.364	63.325	10.490	61.226	11.717

Table 2
Impact of Temperature on Production Efficiency

Panel A: Whole Sample	(1)	(2)	(3)	(4)
	Actual Efficiency (Actual Production / Targeted Production)			
Heat Index	-0.102*** (0.0388)			
Wet Bulb Globe Temperature		-0.170** (0.0680)		
Temperature			-0.152*** (0.0591)	-0.135** (0.0590)
Relative Humidity				0.0622 (0.0513)
Fixed Effects	Month, Day of Week, Factory x Year, Production Line			
Observations	214,968	214,968	214,968	214,968
R-squared	0.209	0.209	0.209	0.209

Panel B: Without LED	(1)	(2)	(3)	(4)
	Actual Efficiency (Actual Production / Targeted Production)			
Heat Index	-0.161*** (0.0587)			
Wet Bulb Globe Temperature		-0.263** (0.109)		
Temperature			-0.232** (0.0963)	-0.211** (0.0970)
Relative Humidity				0.0980 (0.0887)
Fixed Effects	Month, Day of Week, Factory x Year, Production Line			
Observations	71,969	71,969	71,969	71,969
R-squared	0.228	0.229	0.228	0.229

Notes: Cameron, Gelbach, Miller (2011) two-way clustered standard errors in parentheses (** p<0.01, * p<0.05, * p<0.1). Clustering is done at the production line and day level. All measures of temperature are in degree Celsius. All regressions include daily budgeted efficiency as a control variable.

Table 3
Impact of Lagged Temperature on Production Efficiency

Panel A: Whole Sample	(1)	(2)	(3)	(4)
Actual Efficiency (Actual Production / Targeted Production)				
Heat Index	-0.0744*			
	(0.0392)			
Heat Index (1 Week Lag)	-0.115*			
	(0.0587)			
Wet Bulb Globe Temperature		-0.133*		
		(0.0718)		
Wet Bulb Globe Temperature (1 Week Lag)		-0.183		
		(0.116)		
Temperature			-0.114*	-0.108*
			(0.0632)	(0.0623)
Temperature (1 Week Lag)			-0.154	-0.129
			(0.0950)	(0.0982)
Relative Humidity				0.0477
				(0.0528)
Fixed Effects		Month, Day of Week, Factory x Year, Production Line		
Observations	214,968	214,969	214,968	214,968
R-squared	0.209	0.210	0.209	0.209

Panel B: Without LED	(1)	(2)	(3)	(4)
Actual Efficiency (Actual Production / Targeted Production)				
Heat Index	-0.103*			
	(0.0593)			
Heat Index (1 Week Lag)	-0.260***			
	(0.0883)			
Wet Bulb Globe Temperature		-0.177		
		(0.111)		
Wet Bulb Globe Temperature (1 Week Lag)		-0.462***		
		(0.178)		
Temperature			-0.155	-0.147
			(0.0984)	(0.0994)
Temperature (1 Week Lag)			-0.340**	-0.312**
			(0.149)	(0.154)
Relative Humidity				0.0980
				(0.0887)
Fixed Effects		Month, Day of Week, Factory x Year, Production Line		
Observations	71,969	71,970	71,969	71,970
R-squared	0.229	0.230	0.229	0.230

Notes: Cameron, Gelbach, Miller (2011) two-way clustered standard errors in parentheses (***) p<0.01, ** p<0.05, * p<0.1). Clustering is done at the production line and day level. All measures of temperature are in degree Celsius. All regressions include daily budgeted efficiency as a control variable.

Table 4
Impact of Lagged Temperature on Attendance

Panel A: Whole Sample	(1)	(2)	(3)	(4)
Attendance 1(Present for Full Work Day)				
Heat Index	-1.03e-05 (0.000776)			
Heat Index (1 Week Lag)	-0.00194* (0.00114)			
Wet Bulb Globe Temperature		-0.000361 (0.00152)		
Wet Bulb Globe Temperature (1 Week Lag)		-0.00555** (0.00228)		
Temperature			-0.000202 (0.00130)	-0.000328 (0.00133)
Temperature (1 Week Lag)			-0.00520*** (0.00200)	-0.00560*** (0.00189)
Relative Humidity				-0.000828 (0.000917)
Fixed Effects		Month, Day of Week, Factory x Year		
Observations	25,894,156	25,894,156	25,980,894	25,980,894
R-squared	0.004	0.004	0.004	0.004
Panel B: Without LED	(1)	(2)	(3)	(4)
Attendance 1(Present for Full Work Day)				
Heat Index	0.000896 (0.000631)			
Heat Index (1 Week Lag)	-0.00194* (0.00105)			
Wet Bulb Globe Temperature		0.00124 (0.00128)		
Wet Bulb Globe Temperature (1 Week Lag)		-0.00560** (0.00221)		
Temperature			0.00130 (0.00112)	0.00112 (0.00114)
Temperature (1 Week Lag)			-0.00556*** (0.00203)	-0.00599*** (0.00196)
Relative Humidity				-0.00195** (0.000877)
Fixed Effects		Month, Day of Week, Factory x Year		
Observations	7,630,496	7,630,496	7,630,496	7,630,496
R-squared	0.005	0.005	0.005	0.005
Notes: Cameron, Gelbach, Miller (2011) two-way clustered standard errors in parentheses (** p<0.01, * p<0.05, * p<0.1). Clustering is done at the individual and day level. All measures of temperature are in degree Celsius.				

Table 5
LED Lighting and the Temperature-Productivity Gradient

	(1)	(2)	(3)	(4)
	Actual Efficiency (Actual Production / Targeted Production)			
Heat Index X LED	0.150** (0.0608)			
Wet Bulb Globe Temperature x LED		0.415*** (0.123)		
Temperature x LED			0.237** (0.102)	0.244** (0.102)
Heat Index	-0.199*** (0.0535)			
Wet Bulb Globe Temperature		-0.446*** (0.104)		
Temperature			-0.314*** (0.0899)	-0.300*** (0.0903)
LED	-3.870** (1.918)	-9.493*** (3.047)	-5.917** (2.900)	-6.117** (2.891)
Relative Humidity				0.0712 (0.0513)
Fixed Effects	Month, Day of Week, Factory x Year, Production Line			
Observations	214,968	214,968	214,968	214,968
R-squared	0.209	0.209	0.209	0.209
Temperature Impacts Net of LED	-0.049 (.045)	-0.031 (0.082)	-0.078 (0.069)	-0.056 (0.068)

Notes: Cameron, Gelbach, Miller (2011) two-way clustered standard errors in parentheses (** p<0.01, ** p<0.05, * p<0.1). Clustering is done at the production line and day level. All measures of temperature are in degree Celsius. All regressions include daily budgeted efficiency as a control variable.

Table 6
Impacts on Production Efficiency and LED Attenuation (Above and Below Median Temperature)

	(1)	(2)	(3)
	Actual Efficiency (Actual Production / Targeted Production)		
	Whole Sample	Without LED	Whole Sample
Heat Index x 1(Above Median)	-0.121*** (0.0460)	-0.261*** (0.0728)	-0.288*** (0.0706)
Heat Index x 1(Below Median)	-0.130** (0.0521)	-0.303*** (0.0871)	-0.187 (0.134)
Heat Index x 1(Above Median) x LED			0.170** (0.0803)
Heat Index x 1(Below Median) x LED			0.299* (0.161)
Fixed Effects	Month, Day of Week, Factory x Year, Production Line		
Observations	214,968	71,969	214,968
R-squared	0.209	0.228	0.209

Notes: Cameron, Gelbach, Miller (2011) two-way clustered standard errors in parentheses (***) p<0.01, ** p<0.05, * p<0.1). Clustering is done at the production line and day level. Heat Index is measured in degree Celsius. All regressions include daily budgeted efficiency as a control variable. Column 3 also includes additional regressors: 1(Above Median) x LED, 1(Below Median) x LED and 1(Above Median) .

Table 7
Checks for Exogeneity of LED Roll-Out

	(1)	(2)
	Budgeted Efficiency	Scheduled Quantity
Date Relative to LED Introduction	-0.00563 (0.00566)	32.97 (110.9)
Fixed Effects	Month, Day of Week, Factory x Year, Production Line	
Observations	214,968	185,383
R-squared	0.288	0.352

Notes: Cameron, Gelbach, Miller (2011) two-way clustered standard errors in parentheses (***) p<0.01, ** p<0.05, * p<0.1). Clustering is done at the production line and date level.

Table 8
Cost-Benefit Calculations for LED Adoption

<i>Cost of Implementation (one-time)</i>	
Investment per bulb (bulb, wiring, etc.)	\$8.53
Number of bulbs replaced per factory unit	1000
Total Cost of Implementation	\$8,533.33
<i>Energy and Maintenance Savings (per year)</i>	
Power consumption savings per bulb	\$2.40
Reduced replacement cost of incandescent bulb	
Number of bulbs replaced	1000.000
Total Energy and Maintenance Savings	\$2,400.00
<i>Efficiency Savings (per year)</i>	
Average profit gain in USD from LED-caused temperature reductions per factory unit per year	\$3,340.00
Total Net Savings from LED Adoption in the first year	-\$2,793.33
Total Net Savings from LED Adoption in the second year	\$2,673.34
Carbon (Public) Benefits from LED adoption (at \$27/tC)	\$101.23
Carbon (Public) Benefits from LED adoption (at \$93/tC)	\$345.68
Notes: For details on the calculation of carbon benefits, please refer to the Conclusion section.	

Table A
Alternative Regression Specifications

Panel A: Main Impact of Temperature	(1)	(2)	(3)
	Actual Efficiency (Actual Production / Targeted Production)		
Heat Index	-0.0763** (0.0324)	-0.0957*** (0.0324)	-0.0969*** (0.0367)
Fixed Effects	None	Year, Month, Day of Week	Year, Month, Day of Week, Line No
Observations	214,968	214,968	214,968
R-squared	0.099	0.108	0.186
	Actual Efficiency (Actual Production / Targeted Production)		
Panel B: Impact of LED	(1)	(2)	(3)
	Actual Efficiency (Actual Production / Targeted Production)		
Heat Index X LED	0.166** (0.0684)	0.184*** (0.0664)	0.113* (0.0666)
Heat Index	-0.197*** (0.0614)	-0.211*** (0.0542)	-0.171*** (0.0558)
LED	-1.585 (2.111)	-0.865 (2.062)	-3.396* (2.004)
Fixed Effects	None	Year, Month, Day of Week	Year, Month, Day of Week, Line No
Observations	214,968	214,968	214,968
R-squared	0.105	0.117	0.186
Notes: Cameron, Gelbach, Miller (2011) two-way clustered standard errors in parentheses (** p<0.01, * p<0.05, * p<0.1). Clustering is done at the production line and month level. All measures of temperature are in degree Celsius. All regressions include daily budgeted efficiency as a control variable.			