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Human Capital Costs of Climate Change: Evidence from Test Scores in India*

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Abstract

We present estimates of the effect of temperature on cognitive performance, and find that an additional 10 days in a year above 29C reduces math and reading test scores by 0.03 and 0.02 standard deviations respectively. However, in contrast to prior work, we find evidence for an income mechanism - hot days during the growing season reduce agricultural yields and test score performance with comparatively modest effects of hot days in the non-growing season. The roll-out of a conditional cash transfer program, by providing a safety net for the poor, weakens the link between temperature and test scores. Our results suggest that climate change will have disproportionate and large negative impacts on human capital accumulation of poor populations in agrarian economies, likely increasing the persistence of poverty.

JEL Codes: H41, I0, Q5, Q54

Keywords: climate change, human capital, workfare, agriculture

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1 Introduction

The threat of climate change presents a challenge for policy makers and individuals across the world (Burke, Hsiang and Miguel, 2015). The problem is most acute in poor countries which will experience disproportionately higher temperatures (Harrington et al., 2016), where predominantly agrarian livelihoods are climate-exposed and where individuals are financially constrained in coping with climate stress. Given the central role of human capital accumulation as a driver of economic growth (Nelson and Phelps, 1966; Romer, 1986) and as a pathway out of poverty (Barro, 2000), we investigate the impacts of extreme temperatures on *contemporaneous* human capital accumulation in India, where the number of extremely hot days is expected to double by the end of the 21st century (figure 1).

In this paper, we use performance on low-stakes cognitive tests as an output measure of human capital accumulation to examine how extreme temperatures affect test performance, identify the mechanism of impact through reduced agricultural productivity and estimate impacts of policy interventions designed to offset fluctuations in agricultural income. In the U.S. and developed countries, temperature affects performance primarily through exposure to higher temperatures on the day of the test (Graff-Zivin, Hsiang and Neidell, 2015; Park, 2016), effects that can likely be offset by climate-controlled classrooms and test centers. However, in poor countries, human capital accumulation is also affected by agricultural productivity (Maccini and Yang, 2009) and to the extent that agricultural productivity is temperature sensitive (Schlenker and Roberts, 2009; Schlenker and Lobell, 2010), higher temperatures can affect performance through such an income mechanism¹.

We first validate our results with the literature on the effect of short-run temperature – measured as the average temperature on the day of the test – on cognitive performance (Hocking et al., 2001; Graff-Zivin, Hsiang and Neidell, 2015; Park, 2016). Similar to prior

¹While not the focus of our paper, hot weather can also affect human capital through harmful effects of early childhood exposure to extreme temperature on health. A growing literature has documented that exposure to extreme temperatures has harmful contemporaneous effects on human health (IPCC, 2014; Basu and Samet, 2002; Barreca et al., 2013; Deschenes and Moretti, 2009; Deschênes and Greenstone, 2011). Such effects in turn have adverse implications for human morbidity and mortality. Further, evidence suggests that the very young and very old are most sensitive to temperature exposure (Deschênes and Greenstone, 2011; Deschenes and Moretti, 2009). The excess sensitivity of infants to heat may stem from the fact that their thermoregulatory systems are not yet fully functional (Knobel and Holditch-Davis, 2007). The fact that fetal and infant health may be especially sensitive to temperature is important in light of recent evidence pointing to the persistent impacts of early-life environmental conditions on long-run outcomes (Isen, Rossin-Slater and Walker, 2015; Black et al., 2013; Almond, Edlund and Palme, 2009; Sanders, 2012; Almond and Currie, 2011). For instance, Isen, Rossin-Slater and Walker (2015), find that early childhood exposure to extreme heat causes a decrease in later-life earnings.

research in developed countries, we find that test day average temperature above 27C relative to test day average temperature below 23C reduces math score performance by 0.3 standard deviations but has no effect on reading scores. However, this physiological effect of heat exposure on performance is temporary; an extra hot day in the week prior to the test has no effect on performance - consistent with the earlier work documenting the human body’s internal self-regulation of higher ambient temperatures ([Taylor, 2006](#)).

Second, using data from over 4 million cognitive tests in India from 2006-2014 we show that over a longer-run horizon – measured as the number of hot days in the calendar year² prior to the test – extreme temperatures affect both math and reading scores; 10 extra days in a year with average *daily* temperature above 29C relative to 15-17C reduces math and reading test performance by 0.03 and 0.02 standard deviations respectively, equivalent to erasing one-fourth of the gains from smaller class sizes³. We find strong evidence that the likely underlying mechanism is driven through insults of higher temperatures to agricultural yields. In particular we find that (a) extreme temperature days during the agricultural growing season have large effects on test score performance whereas those in the non-growing season have minimal effects, (b) the effects of hot days are concentrated in areas that don’t grow heat resistant crops, and (c) extreme temperatures have large negative effects on agricultural yields. Furthermore, we find that the likely channel through which income plays a role in our context is nutrition; an extra 10 hot days reduce age-specific BMI z-scores by 0.04 and grain expenditures by 11.1%.

Third, we examine the effect of a national policy, designed to offset fluctuations in agricultural income, in modulating the effect of temperature on test scores. We consider the world’s largest workfare program, the National Rural Employment Guarantee Scheme (NREGA) that guarantees every rural household in India 100 days of paid work each year. We find that NREGA attenuates the marginal effect of extra hot days on both math and reading scores by 38%. Additionally, we show that hotter days in the growing season in the previous year increase participation in NREGA. Importantly, our NREGA results not only reinforce the underlying agricultural income mechanism linking hotter days to lower test scores, but

²We don’t have information on the exact date of these tests and so we use the previous calendar year. We validate our results against a smaller sample of cognitive tests from an individual panel data set where we have the exact date and time of the test. We elaborate on this in the data and results section.

³See [McEwan \(2015\)](#) for a review of educational interventions in developing countries

also demonstrate the critical role of pro-social programs in helping the poor cope with climate stressors.

We make contributions to several areas of economics. First, we build on the literature on the impacts of contemporaneous weather and longer-run climate on human-capital accumulation. Prior work has focussed entirely in the US ([Graff-Zivin, Hsiang and Neidell, 2015](#); [Park, 2016](#)) and on a single channel of exposure - the direct physiological effect of heat stress. We document that while such an effect exists, it is temporary and that a longer-run mechanism exists through a completely independent channel driven by the weather dependence of livelihoods in our context⁴. To the best of our knowledge, we are the first to document multiple pathways through which weather and climate can affect a single outcome of interest, over different time frames. This is particularly important because the existing literature on climate change has used the difference between short-run weather and long-run climate as an estimate of the magnitude of adaptation, with short-run estimates giving impacts without adaptation, and long-run estimates measuring impacts inclusive of adaptation ([Burke and Emerick, 2016](#)). Our evidence of different pathways over the short-run and longer-run demonstrates that such an approach may not be appropriate in all contexts.

Second, we are the first to provide evidence on the role of pro-social programs in helping households in poor countries to cope contemporaneously with extreme temperatures in the face of climate change. Despite consideration of technological mechanisms such as air conditioners playing a role in attenuating the impacts of extreme temperatures on households (particularly in developed countries; see [Barreca et al. \(2013\)](#); [Rogot and Backlund \(1992\)](#) for more details), they are unlikely to be part of the adaptation strategy amongst a large share of households in developing countries given cost considerations⁵. By contrast, pro-social programs are more likely to allow households to cope with extreme temperatures.

⁴Higher wages increase human capital investments ([Jacoby, 1997](#); [Jensen, 2000](#); [Maccini and Yang, 2009](#)), and increased investment in human capital has been shown to increase test scores ([Das et al., 2013](#)). Therefore, if extreme weather affects household income, such income effects could be another potential channel through which extreme temperatures affect human capital formation in the long-run. Relatedly, recent research in India has documented a causal link between rainfall and agricultural incomes, as well as hot weather and agricultural incomes ([Burgess and Greenstone, 2014](#)). Moreover, [Shah and Steinberg \(2016\)](#), have translated these effects into long-term impacts on human capital. Our detailed temperature and test score data that includes information on the day of the test, allows us to separately estimate the direct neurological short-run effect as distinct from long-run effects that may differ due to other channels and endogenous adaptation.

⁵In October 2016, over 170 countries, including India agreed to ban Hydrofluorocarbons (HFCs) that are essential for low-cost air-conditioners. The ban is likely to make air-conditioners inaccessible to a large number of Indians who can't afford more expensive alternatives to HFCs.

Our results can substantially inform climate policy in developing countries that are likely to see considerable increases in hot days. First, we find that temperature affects not just short-run cognitive performance through a physiological channel, but also longer-run performance through the income channel. Extreme temperatures reduce agricultural yields and consequently nutritional investments resulting in lower longer-run human capital accumulation. In contrast to prior work emphasizing the need for climate-proof classrooms (Graff-Zivin, Hsiang and Neidell, 2015; Park, 2016), our results indicate that while such interventions can reduce the injuries from short-run temperature, they are unlikely to ameliorate the effects of longer-term temperature on human capital accumulation that arise from the climate dependence of livelihoods. On the other hand, pro-social programs can play an important role in reducing vulnerability to weather in climate-exposed occupations.

The rest of the paper is organized as follows. Section 2 describes the data. In section 3 we outline the empirical strategy and our main results for the short-run effects of temperature on test scores. In section 4 we describe our results on the longer-run effects of temperature on test scores. In section 5 we demonstrate the role of pro-poor programs in attenuating the marginal effect of temperature. Finally, in section 6 we provide concluding remarks.

2 Data

In this section, we provide details on the various datasets we employ to uncover the relationship between temperature and test scores. We use multiple data sets on test performance as well as detailed gridded data on daily weather variables including temperature, rainfall and humidity. We obtain agricultural data from the International Crops Research Institute for Semi-Arid Tropics (ICRISAT).

2.1 Test Scores

We obtain data on cognitive performance from two sources of secondary data - the Annual Status of Education Report (ASER) and the Young Lives Survey (YLS). The ASER provides a repeated cross-section that allows us to generate a pseudo-panel at the district level for all of India, whereas the YLS is an individual panel that provides coverage for the single state

of Andhra Pradesh.

2.1.1 Annual Status of Education Report (ASER)

The Annual Status of Education Report (ASER) is a survey on educational achievement in primary school children in India and has been conducted by Pratham, an educational non-profit, every year starting in 2005⁶. The sample is a representative repeated cross section at the district level. The ASER surveyors ask each child four potential questions in math and reading (in their native language). In each subject, they begin with the hardest of four questions. If a child is unable to answer that question, they move on to the next easiest question and so on and so forth.

The ASER is a valuable dataset for our analysis for multiple reasons. First, ASER provides national coverage and a large sample size; in our study period of 2006-2014, ASER conducted over 4 million tests across every rural district in India⁷. Given the considerable spatial variation in weather in India, the national coverage of ASER allows us to study the impacts of temperatures on test scores over a large support. Importantly, it is administered each year on 2-3 weekends from the end of September to the end of November limiting considerations of spatially systematic seasonality in data collection. Second, unlike schools-based data, ASER is not administered in schools and therefore covers children both in and out of school. To ensure that children are at home, the test is administered on weekends. This allows us to measure effects on test performance without confounding selection around school attendance, access to schools etc. ASER tests children ages 5-16, who are currently enrolled, dropped out, or have never enrolled in school.

2.1.2 Young Lives Survey (YLS)

While the ASER has the advantage of national coverage and large number of tests, its repeated cross-sectional nature (as opposed to an individual level panel) doesn't allow us to account for the role of prior human capital accumulation. Therefore, we also employ the Young Lives Survey, which is an international study of childhood poverty coordinated by a

⁶We are incredibly grateful to Prof. Willima Wadhwa who continues to make this data generously available to researchers.

⁷While the ASER originated in 2005, that wave is not in public domain and the organizing body is no longer making the 2005 data available.

team based at the University of Oxford. In this study we use data from between 2002 and 2011 in the state of Andhra Pradesh (unlike ASER, YLS is conducted in a single state in India)⁸. The study has collected data on two cohorts of children: 1008 children born between January 1994 and June 1995, and 2011 children born between January 2001 and June 2002. We limit our sample to the younger cohort since we have at least three survey rounds for those children. Data was collected from children and their families using household visits in 2002, 2007 and 2009/10. Extensive test data were collected from children in the sample in all rounds of the survey. The tests differed in their focus on which dimension of cognitive achievement they attempted to capture and how closely they related to the formal school curriculum in Andhra Pradesh; often, different tests were administered to children across rounds in order to ensure that they were appropriate for the age and the stage of education that the children were in. In contrast to the ASER tests, the YLS tests are much longer and comprehensive with the math questionnaire containing 30 questions and the reading test covering close to 100 questions. Further, YLS has particularly rich information about the socio-economic background of the children’s households, child-specific data on time-use, nutritional intake data, health data and data on medical expenditures.

2.2 Weather Data

In an ideal research setting, we would employ observational data from ground stations in each location where the ASER and YLS data were collected. However, the spatial and temporal coverage of ground stations in India is several lacking, particularly in recent years. In the absence of consistent coverage from ground weather stations, we use temperature, precipitation and relative humidity reanalysis data from the ERA-Interim archive, which is constructed by researchers at the European Centre for Medium-Term Weather Forecasting (ECMWF). Such reanalysis data has been supported in the literature as generating a consistent best-estimate of weather in a grid-cell and has been used extensively in economics (Schlenker and Roberts, 2009; Schlenker and Lobell, 2010; Auffhammer et al., 2013) We use the ERA-Interim daily temperature and precipitation data on a 1 x 1 degree latitude-

⁸Andhra Pradesh is the fourth-largest state in India by area and had a population of over 84 million in 2011. Administratively the state is divided into districts, which are further sub-divided into sub-districts which are the primary sampling units within our sample.

longitude grid, from 1979 to present day.⁹ To construct weather variables for each district or village, we construct an inverse-distance weighted average of all the weather grid points within a 100km range of the village or district centroid. For each district, we construct the daily average temperature, daily total rainfall and daily mean relative humidity. Figure 2 shows the spatial distribution of temperature in India during the study period and figure 3 shows the distribution of daily temperatures for India and the state of Andhra Pradesh. Figure 4 shows the long-run variation in temperature in Andhra Pradesh (panel A) and all India (panel B, C).

2.3 Other Data Sources

We use multiple data sets to uncover the mechanisms underlying the relationship between temperature and test scores. In particular, we use data on agricultural yields (ICRISAT), health and medical expenditures data (IHDS), time-use data (YLS), consumption data (IHDS, YLS) and data on NREGA. In this subsection we describe these data and the respective sources.

Agricultural Data

We use agricultural data from the Village Dynamics in South Asia Meso data set (henceforth VDSA), which is compiled by researchers at the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT 2015). The data set provides district-level information on annual agricultural production, prices, acreage and yields, by crop. We generate aggregate price-weighted district level measures of total yield in each district for the six major crops (rice, wheat, sugarcane, groundnut, sorghum and maize) as well as the five major monsoon crops (no wheat).

India Human Development Survey (IHDS)

The India Human Development Survey (IHDS) is a nationally representative, multi-topic survey conducted across urban and rural areas. There are currently two waves of IHDS (2004-

⁹Dee et al. (2011) provide more details about the methodology and construction of the ERA-Interim dataset.

05 and 2011-12), both of which we obtain from the survey’s public portal. We primarily use IHDS to corroborate our results from other surveys, and in particular focus on information on health, nutritional intake and health-related expenditures. The survey covers children and adults.

National Rural Employment Guarantee Scheme (NREGA)

The National Rural Employment Guarantee Scheme (NREGA) was rolled-out non-randomly starting in 2006 according to a poverty and backwardness index. The scheme was rolled-out by non-randomly in three phases with the first phase beginning with 200 districts in February 2006. By April 2008 the scheme was operational in all rural districts in India. We obtain data on NREGA participation for 2011-2015 from the Management Information Systems (MIS). In particular, we focus on the number of rural households enrolled in NREGA in a particular district in a given month. We aggregate monthly enrollment data at the annual level as well as by growing season and non-growing season months.

3 Temperature and Test Scores in the Short-Run

Ambient temperature affects brain temperature. The brain’s chemistry, electrical properties, and function are all temperature sensitive (Bowler and Tirri, 1974; Schiff and Somjen, 1985; Hocking et al., 2001; Deboer, 1998; Yablonskiy, Ackerman and Raichle, 2000), and both warm environmental temperatures and cognitive demands can elevate brain temperature¹⁰. We begin our analysis by validating the effect on test scores of the day-of-test temperature that has been documented in the U.S. (Graff-Zivin, Hsiang and Neidell, 2015; Park, 2016).

We perform our short-run analysis on data from the Young Lives Survey which provides the date of the cognitive test¹¹. Since the YLS is an individual panel, we exploit within-

¹⁰There exists a vast body of empirical evidence linking cognitive impairment to high temperatures as a result of heat stress. For instance, military research has shown that soldiers executing complex tasks in hot environments make more errors than soldiers in cooler conditions (Fine and Kobrick, 1978; Froom et al., 1993). Further, LED lighting, which emits less heat than conventional bulbs, decreases indoor temperature, and has been shown to raise productivity of workers in garment factories in India, particularly on hot days (Adhvaryu and Nyshadham, 2015). Exposure to heat has also been shown to diminish attention, memory, information retention and processing, and the performance of psycho-perceptual tasks (e.g. Vasmatazidis, Schlegel and Hancock (2002) and Hyde et al. (1997)).

¹¹We were unable to obtain information on the date of test for cognitive tests conducted as part of ASER and therefore unable to identify the date-of-test effects for the ASER data.

child variation in exposure to temperature on the day of test on different waves of the survey. Given that the date of the test is generally pre-arranged and invariant to short-run fluctuations in weather, we can identify the causal effect of short-run temperature on test score performance. To estimate the effect on test scores of day-of-test temperatures, we employ two specifications. First, we construct a binary indicator for average day-of-test temperature being above 23C to estimate the following equation.

$$Y_{ijdmt} = \alpha + \beta(> 23C)_{jdmt} + rain_{jdmt} + \eta_i + \mu_{1d} + \mu_{2m} + \mu_{3t} + \epsilon_{ijdmt} \quad (1)$$

Y_{ijdmt} is the math or reading test score of child i in district j on day-of-week d in month-of-year m in survey round t , standardized by year-age. Our parameter of interest is β , which is the marginal effect of the average day-of-test temperature being above 23C relative to a day with average temperature below 23C. We control for rainfall on the day-of-test and include fixed effects for child (η_i), day-of-week (μ_{1d}), month-of-year (μ_{2m}) and year of survey (μ_{3t}). We cluster standard errors at the district-week level to allow for arbitrary correlation in test scores across villages in a week and for conservative inference when multiple children are assigned the same temperature observation.

The specification in equation (1) imposes the key assumption that the marginal effect of day-of-test temperature on performance is constant above and below 23C. To ease this assumption, we employ a second, more flexible specification that relaxes the constant marginal effect assumption over smaller temperature bins.

$$Y_{ijdmt} = \alpha + \beta_2(23 - 25C)_{jdmt} + \beta_3(25 - 27C)_{jdmt} + \beta_4(> 27C)_{jdmt} + rain_{jdmt} + \eta_i + \mu_{1d} + \mu_{2m} + \mu_{3t} + \epsilon_{ijdmt} \quad (2)$$

The omitted bin is $(> 23C)$. Therefore, for example, β_4 is the effect on performance of the day-of-test temperature being above 27C relative to below 23C.

3.1 Results

We report the effects of temperature on test scores in the short-run in table 1 and illustrate the results graphically in figure 5. Column (1) and (2) report the effect of temperature on math scores for equations (1) and (2) respectively. Consistent with the neuroscience literature and recent work in economics on the impacts of temperature on cognitive performance we find strong evidence for the presence of physiological channel connecting temperatures to test scores in the short-run (Bowler and Tirri, 1974; Schiff and Somjen, 1985; Hocking et al., 2001); we find that average day-of-test temperature being above 27C reduces within-cohort math test performance by 0.3 standard deviations relative to day with average temperature below 23C.¹² The marginal effects of temperature are non-linear and as a result, we employ our preferred specification is equation (2) as illustrated in figure 12(a). To the extent that channels such as income effects and cumulative learning manifest over a duration longer than a single day, the day-of-test effects represent a short-run physiological effect of temperature on math test scores. We rule-out same day behavioral channels (e.g., heat-driven distraction during the test, time spent on other activities, surveyors changing time of day when test is conducted) using two additional pieces of evidence: (1) we show that the effect of temperature on performance is subject-specific, and (2) there are negligible effects of temperature on the timing of test and time taken to complete the test.

Math v. Reading Performance

Different portions of the brain perform different cognitive functions. For instance, the pre-frontal cortex, which is responsible for providing “working memory” needed for performing mathematical problems, is more temperature sensitive than portions of the brain responsible for reading functions (Hocking et al., 2001). Consequently, while we observe substantial effects of higher temperatures on math score performance, we don’t find any discernible or meaningful relationship between higher temperatures and reading comprehension (columns (3 - 4), table 1; figure 12(b)). The subject-specific effect of day-of-test temperature on performance suggests that the underlying mechanism is likely physiological rather than behavioral.

¹²Our magnitudes are comparable to those in Graff-Zivin, Hsiang and Neidell (2015) and Park (2016).

Timing of the Test

Since these tests are conducted at home, one concern is that temperature may directly affect the time of the day when the test takes place. If heat affects the time of day when the test takes place, enumerators may choose the hottest times of the day when kids are at home (and not playing outside, for example) or may choose to go in the evenings to reduce their own heat exposure resulting in biased estimates of the immediate effect of temperature on test scores. To overcome this potential source of endogeneity, we directly test the effect of day-of-test temperature on the time-of-day when the test takes place and show that temperature does not alter the time-of-day when the test takes place (table [A.2](#)).

Furthermore, the YLS records not only cognitive performance in math and reading tests, but also the duration of time taken to complete both tests as well as the time of day when the test is held. We find that on days above 27C, students spend marginally more time on tests (2 minutes on math and 1 minute on reading tests respectively) than on days below 23C. Since these are low-stakes examinations that are of no consequence to the children, the nominally extra time spent on tests is inconsistent with a model where heat driven changes in test takers' effort or behavior are driving the relationship between short-run temperature and performance.

3.2 Do the Short-Run Physiological Effects Persist in the Longer-Run?

The link between short-run physiological effects of temperature on performance and longer-run human capital accumulation rests on the persistence of short-run effects. There are three ways in which short-run effects can persist. First, temperature on day-of-test can affect performance on high-stakes exams and translate into lower human capital accumulation due to the structure of the education system, typically in the form of arbitrary cutoffs for passing or placing into high-achievement programs ([Park, 2016](#)). In our study, however, we evaluate the effects of temperature on low-stakes cognitive tests. As a result we can rule out this pathway in our context.

Second, temperature can have persistent impacts; a hot day today could continue to

affect performance in the future if the human body is unable to internally self-regulate to higher ambient temperatures. We directly examine this possibility by testing for leads and lags on the short-run effects of temperature. We find no evidence for the persistence of the short-run effects of temperature on test scores; over the week prior to the test, extra hot days have no effect on test performance (figure 6). This pattern largely holds for at least up to 4 weeks of leads and lags. The large day-of-test effect and the null week-of-test effect are consistent with a model of internal self-regulation where the human body self-regulates higher temperatures making the direct effects of temperature on human capital accumulation temporary (Taylor, 2006).

Finally, temperature could indirectly affect learning which cumulatively over time may result in lower human capital accumulation. Temperature may affect learning either through either cumulative heat exposure where the damage curve is convex in the number of hot days or through insults to agricultural income resulting in lower human capital investments. In the next section, we demonstrate that longer-run temperature affects human capital accumulation through insults to agricultural income.

4 Temperature and Test Scores in the Longer-Run

Hot days can affect agricultural productivity and agricultural incomes. Reduced household agricultural product and incomes may consequently result in lower human capital investments such as nutrition, lower educational expenditures etc. In this section, we show that longer-run temperature affects human capital accumulation through insults to agricultural income and rule out alternative channels.

4.1 Research Design

To examine the effect of temperature on test scores in the longer-run, we employ the ASER and YLS data sets. The ASER data set has the advantage of national coverage with greater spatial variation in temperature exposure with a repeated cross-section whereas the YLS data set provides an individual level panel but with coverage limited to a single state. First,

using ASER data we estimate the following equation:

$$\begin{aligned}
Y_{ijq,t+1} = & \alpha + \gamma_1(< 13C)_{ijqt} + \gamma_2(13 - 15C)_{jqt} + \gamma_4(17 - 19C)_{jqt} + \\
& \gamma_5(19 - 21C)_{jqt} + \gamma_6(21 - 23C)_{jqt} + \gamma_7(23 - 25C)_{jqt} + \\
& \gamma_8(25 - 27C)_{jqt} + \gamma_9(27 - 29C)_{jqt} + \gamma_{10}(> 29C)_{jqt} + f(rain_{jqt}) + \\
& g(humidity_{jqt}) + \eta_j + \mu_t + \epsilon_{ijqt}
\end{aligned} \tag{3}$$

Y_{ijqt} is Math or Reading test scores for child i , in district j , in state q , in year $t + 1$, standardized by year-age. The temperature bins capture the number of days in the previous year with an average daily temperature in the denoted range. For example, $(27 - 29C)_{jqt}$ is the number of days with an average daily temperature between 27C and 29C in district j , in state q , in year t with $(15 - 17C)_{jqt}$ being the omitted bin. Therefore, we interpret γ_{10} as the marginal effect on test scores of an extra day with average temperature greater than 29C relative to a day with average temperature between 15C and 17C. We control for rainfall (in annual cumulative terciles relative to district-specific historical averages)¹³, relative humidity, district fixed effects (η_j) and year fixed effects (μ_t). We cluster standard errors at the district level. The consistent identification of each γ_i rests on the assumption that the number of hot days in a particular temperature bin is exogenous to test score performance in ASER surveys. The assumption is plausible given the inability of rural households in India to accurately predict daily temperature. In estimating this flexible approach we follow prior work in climate economics and avoid imposing restrictive assumptions on the functional relationship between temperature and test scores. As such, we approximate a non-parametric approach where temperatures are allowed to flexibly affect test scores.

The national coverage of the ASER data allows us to capture a wider temperature distribution when examining the effects of temperature on test scores but does not allow us to take into account past human capital accumulation since it is a district level pseudo panel rather than an individual panel. To account for the role of prior human capital accumulation, we

¹³Our results are robust to alternative specifications of rainfall including linear and quadratic annual rainfalls

use the individual level panel data in the YLS survey to estimate the following equation:

$$Y_{ijdmt} = \alpha + \gamma_2(23 - 25C)_{jdmt} + \gamma_3(25 - 27C)_{jdmt} + \gamma_4(> 27C)_{jdmt} \\ + f(rain_{jdmt}) + \eta_i + \mu_{1d} + \mu_{2m} + \mu_{3t} + \epsilon_{ijdmt} \quad (4)$$

Y_{ijdmt} is the math or reading test score of child i in district j on day-of-week d in month-of-year m in survey round t , standardized by year-age. The temperature bins follow a similar interpretation as above but since YLS covers a single state, the temperature distribution is narrower and the reference bin is $(< 23C)_{jdmt}$. In addition, to account for prior human-capital accumulation, the temperature bins record the number of days with average temperature in that bin since the last YLS test (instead of the calendar year, since in the YLS data we know the actual date of the test). We flexibly control for rainfall and relative humidity and include fixed effects for child (η_i), day-of-week (μ_{1d}), month-of-year (μ_{2m}) and year of survey (μ_{3t}). We cluster standard errors at the district-week level to allow for arbitrary correlation in test scores across villages in a week and for conservative inference when multiple children are assigned the same temperature observation.

4.2 Results

We estimate equation (3) and find that an extra 10 days in a year with average daily temperature above 29C relative to a day with average daily temperature between 15C and 17C reduce math performance 0.03 standard deviations and reading performance by 0.02 standard deviations (table 2) which would effectively erase one-fourth of the effects of reduced class sizes. In fact, using our binned approach, we find that test performance decreases linearly in temperatures above 17C (figures 7). As a falsification test, we find no effect of hotter days in the current year or next year on performance in the current year (figure 3). For our main specification, we include all students, but also find that our results hold in the limited sample of “on-track” students who are in the correct school grade-for-age (appendix A.4). Accounting for prior human capital, we estimate equation (4) using individual panel data from the YLS survey and find similar results. Considering the effects of temperature on human capital accumulation between successive tests conditional on prior test performance,

we find that an extra 10 days between successive tests above 27C relative to below 23C, reduces test math and reading scores by 0.07 standard deviations each (table 4). Noticeably, the temperature range over which we find effects is smaller in YLS than in ASER given that the YLS was fielded in a single state in India limiting spatial variation in temperature. As in the case of ASER, the deleterious effects of temperature on test score performance are increasing with higher temperatures above 21C (figures 8). Interestingly, and in contrast to the short-run results, extremely cold days in the longer-run also reduce cognitive performance in both math and reading; an extra 10 days with average temperature below 13C relative to a day between 15C and 17C reduce math scores by 0.04 standard deviations and reading scores by 0.03 standard deviations. We detect longer-run temperature effects on performance even when controlling for day of test temperature (appendix table A.3) and reject alternative linear specifications using degree days (appendix A.5).

Next, we provide evidence that the likely mediator of these longer-run effects of temperature on test scores is agricultural income. Unlike the short-run effects that are driven entirely by physiology (the brain’s exposure to higher temperatures), the longer-run effects can largely be explained by insults to the livelihoods of agrarian households.

4.3 Temperature and Agricultural Income

India is primarily an agricultural country where most households in rural areas rely on agricultural incomes. Given that our data is focussed on rural areas (with ASER being collected exclusively in rural areas), we find strong evidence to support an income mechanism underscoring the effect of temperature on test scores. Specifically, we present two pieces of evidence. First, the effect of temperature on test scores is primarily driven through higher temperatures in the previous years’ agricultural growing seasons; an extra hot day above 29C in the growing season has an order of magnitude larger effect on test scores than a corresponding extra hot day above 29C in the non-growing season days.¹⁴ Specifically, an

¹⁴We broadly follow Burgess and Greenstone (2014) in partitioning every year’s weather data for each district into the growing and non-growing season. However, while Burgess and Greenstone (2014) define the non-growing season as all dates that are within the three-month window prior to each district’s ‘typical’ monsoon arrival date, and the growing season as every date after the district- specific date of monsoon arrival till the 31st of December, we define the non-growing season from March-May and the growing season from June-December. The southwest monsoon begins to arrive (from the south) on the Indian subcontinent around the start of June of every year, and covers all of north India by the start of July.

extra 10 days above 29C in the growing season reduces math scores by 0.102 standard deviations and reading scores by 0.062 standard deviations compared to negligible effects in the non-growing season (table 5). The differences between the effects of temperature on test scores across growing v. non-growing seasons increase with higher temperatures for both math and reading scores¹⁵ (figures 9).

Additionally, we test the impact of temperature on agricultural yields in the 6 major crops as well as the 5 major monsoon crops¹⁶. Using district level yields data, we find that an extra day above 29C in the growing season reduces yields by three times more than the same day in the non-growing season. In absolute terms, the magnitude is large; an extra day above 29C in the growing relative to a day between 15C and 17C reduces yields by 1% (table A.7). The large impact of temperature on yields is consistent with a model where temperature affects test scores through declines in agricultural income. Consistent with our finding that extremely cold days also reducing cognitive performance, cold days also reduce agricultural yields though to a lesser extent than hot days do.

Second, we find that the effects of temperature on test scores are pronounced in districts where the dominant crops are not heat-resistant with no economically meaningful effects of temperature on test scores in districts that grow heat resistant crops¹⁷. In fact, growing heat resistant crops erases most of the effect of temperature on test scores in the long-run. An extra 10 hot days above 21C in districts that don't grow heat-resistant crops lowers math scores by 0.022 standard deviations compared with a near-null effect in districts that grow heat-resistant crops (table 6). While the choice to grow heat-resistant crops is endogenous, the differential effects across districts growing such crops and not is consistent with a model where temperature affects test scores through insults to agricultural income.

¹⁵In theory, it is possible that this effect is not driven by agricultural incomes but rather by increased exposure to higher temperatures from working on the field. While we explore time-use in greater detail in subsequent sections, we do find that extra hot days in the year don't affect work time of children (appendix table A.11.)

¹⁶The six major crops are rice, wheat, sugarcane, groundnut, sorghum and maize. Wheat is excluded in the list of major monsoon crops.

¹⁷Following Hu and Li (2016), we separate crops into C4 crops and C3 crops. C4 crops extract carbon from carbon dioxide differently than C3 crops, and are more resistant to high temperatures. For our data, the C4 crops are maize, sorghum, pearl millet, sugar cane, finger millet and fodder. All the remaining crops are C3 crops. For each district-year, we calculate the fraction of cultivated area that is planted with C4 crops, and then we calculate a long-run average of this value. Then, we label a district to be a heat-resistant district if it's long-run average of the proportion of C4 crops is above the median value (which is 23%).

4.4 Alternative Explanations

In this section, we rule out alternative channels that could potentially explain the relationship between longer-run temperature and test scores. Specifically, we consider two alternative explanations: (1) higher temperatures increase cost of attendance for teachers, resulting in teacher absenteeism and lower test performance by students and (2) higher temperatures have a cumulative direct effect physiological effect on health.

Teacher Attendance

Quality of instruction is a central component of virtually all proposals to raise school quality (Hanushek and Rivkin, 2012). Teaching quality has been linked to student test scores, as well as later-life outcomes (Chetty, Friedman and Rockoff, 2014a,b). Hot temperatures can increase the cost of effort required to attend school, and lead to teacher absenteeism. Using unannounced visits to measure attendance, a nationally representative survey found that 24 percent of teachers in India were absent during school hours (Chaudhury et al., 2006). Duflo, Hanna and Ryan (2012) use a randomized control trial in India that incentivized teachers' attendance and find that teacher absenteeism fell and test scores of children in the treatment group increased. Thus, if hot climate encourages teacher absenteeism, it could have an impact of human capital accumulation. We rule out this mechanism by directly testing the effect of hot days on teacher attendance using the teacher attendance module of the ASER data. We find that hot days in the previous and current year have no negative impact on teacher attendance appendix table A.9). This is consistent across different formulations of teacher attendance (binary, continuous) and across different specifications (linear, tobit). Therefore, at least in our data set, we observe no effect of temperature on teacher attendance and can rule out teacher attendance as the mechanism linking hotter days to reduced test score performance.

Direct effects on health

An alternative explanation to the temperature test score relationship in the longer-run could be through the direct physiological effects of temperature - either through cumulatively in-

creasing effects (convex damage function) or through increased disease prevalence (Patz et al., 2005). To the extent that health affects performance, temperature could affect performance through direct effects on health. Importantly, we consider these mechanisms distinct from the agricultural income channel where reduced household income affects health through insults to nutrition, which we tackle in this next section. Here we rule out the direct health effects of temperature as the mechanism linking temperature to test scores with three tests. First, and as mentioned earlier, we find that hotter days during the growing season in the previous year drive the temperature-performance relationship with no effect of the non-growing season. If temperature affected health through direct exposure, we should expect similar effects on performance of temperature in either season. Moreover, younger kids who don't work on fields are the ones who see the largest effects of temperature on performance (figure 10). Second, given the lifecycle of disease pathogens¹⁸, we would expect that more recent higher temperatures to have a larger effect on health and therefore performance than previous years. In table 3, we show that temperature in the current year has no effect on test score performance.

4.5 Why does income matter?

Given that temperature, in the longer-run, affects test scores through negative impacts on agricultural incomes, we further investigate the channels through which such an effect transpires. In theory, there are three possible channels. First, temperature affects yields and consequently nutritional intake amongst households¹⁹. Lower nutritional intake can reduce learning through incidence of illness particularly in resource-constrained households. Second, the effects of temperature on agricultural yields can change time-use in households; lower yields may end up requiring parents to spend more time on income-generating activities resulting in kids spending more time with household chores and less time in school. Third, insults to income can result in the inability of households to procure defensive investments such as air-conditioners and fans, and thereby being unable to protect themselves against

¹⁸For instance, hotter days in the current year have been associated with higher prevalence of malaria (Patz et al., 2005).

¹⁹There is a vast literature documenting the role of adequate nutritional intake in human capital accumulation. A non-exhaustive list of papers includes Victora et al. (2008); Strauss and Thomas (1998); Thomas and Strauss (1997); Strauss (1986).

the effects of temperature. We find strong evidence to suggest that the dominant mechanism through which income mediates the longer-run temperature-performance relationship amongst our largely agrarian and poor households, is nutrition.

Health and Nutrition

Nutritional intake is an important component of human capital development and poor nutritional intake can affect test performance. We examine the effects of hot days in the previous year on nutritional consumption and health outcomes. We exploit the panel nature of the Young Lives Survey (YLS) and find that temperature extremes affect own-grown nutritional intake, lead to increased sickness and consequently absence from schools. We report three important findings. First, a hot day above 27C in the year of test reduce consumption (measured in value, not quantity) of own-grown crops and own animal products by 1.6% and 0.5% respectively (table 8, columns 4-6). Consequently each additional hot day reduces value of household overall (home and market) consumption of grains by 0.6% (table 8, column 1) although the coefficient is not statistically significant.

Second, we show that hot days in the previous year lower children’s BMI. An extra 10 hot days above 27C in the previous year reduces BMI by 0.04 age-specific standard deviations which is comparable to the effect of temperature on test scores for both math and reading.

Third, we do find hot days increase school absence modestly, and much of this is driven by increased sickness (table A.10). However, these effects are not a result of the direct physiological exposure to heat. We find that, consistent with the agricultural income channel, only temperature during the growing season of the previous year affects student absence in the current year (A.8).

We further corroborate this evidence from an additional survey with coverage for all of India - the India Human Development Survey (IHDS). We find that under extreme temperatures, overall grain consumption decreases (table A.13), sickness increases (table A.14) and medical expenditures increase (table A.15).

Time-Use

We find modest evidence to support the time-use hypothesis. We find that during extreme temperatures, households adjust their time use (table A.11,A.12). We find that an extra hot day above 23C increases time spent by children in caring for infants by 5% (table A.11, column 2) and a 7% increase in household chores (table A.11, column 3). Simultaneously, we observe a corresponding drop in self-study time by 4% (table A.12, column 2). Importantly however, we don't see any reduction in time spent in school (table A.12, column 1). We verify this using drop-out data from ASER and show that there is no change in drop-out rates as a result of higher temperatures (table A.16).

Adaptation

We divide districts into hot and not-hot districts based on historical temperatures. We classify hot districts as those where the average historical temperature (1979-2014) is above the 75th percentile of temperature distribution. We find that the effects of temperature on test scores are most pronounced in districts that are not historically the hot districts. By contrast, in the historically hot districts, an extra hot day has no measurable impact on test performance (figure 11). This source of heterogeneity is also consistent with a model where households engage in self-protection against high temperatures when they have had a historically compelling reason to do so.

5 Role of Pro-social Programs

Given the critical role of agricultural income in mediating the relationship between hot days in the previous year and test scores, we should expect that pro-social programs designed to offset fluctuations in agricultural income can ameliorate the effects of hot days on test scores. We consider the largest workfare program in the history of the world – the National Rural Employment Guarantee Act of 2005 (NREGA) – which guarantees every person in rural India 100 days of paid employment. The majority of such work is manual labor on infrastructure projects, making NREGA in effect, a self-targeting conditional cash transfer

program that has an income-stabilizing effect in the event of shocks to agricultural yields. We provide more details on the nature of the program in appendix section [B.1](#).

Our hypothesis is that insults to agricultural income adversely affect nutritional in-take of children and thereby reducing cognitive performance. If NREGA modulates this relationship, it must be the case that NREGA in the previous agrarian year attenuates the temperature test-score relationship and hotter days must increase NREGA take-up to be able to compensate for any losses in income in that year and maintain baseline levels of nutritional intake. We find evidence to support both.

First, NREGA attenuates the effect of temperature on test scores. Ideally we would exploit information on the NREGA status of households whose children were tested under ASER. Absent such data, we perform a district level analysis where we provide the effect of NREGA on the average child’s test score sensitivity to temperature. We exploit the staggered district-level roll-out of NREGA across India’s 650 districts to perform an event study ²⁰. We set the omitted category to be the concurrent year of the introduction of NREGA in a district. We find that the introduction of NREGA attenuates the impact of an extra hot day above 29C on math and reading scores by 38%. Specifically, prior to NREGA roll-out in a district, an extra 10 days above 29C (relative to between 15C and 17C) reduces math and reading scores by 0.03 and 0.04 standard deviations respectively (table 9). Figure 12 pictorially depicts the event study and shows that the introduction of NREGA attenuates the effect of those extra 10 hot days above 29C on test scores by 0.013 and 0.015 standard deviations on math and reading respectively ²¹.

Second, we find strong evidence to suggest that NREGA take-up responds to temperature. We obtain monthly NREGA take-up data from 2012-2015 and show that hotter days in the current year drive NREGA take up in both the growing and the non-growing seasons

²⁰In appendix [B.3](#) we show that our approach is robust to a triple differences specification. The counterfactual analysis involves comparing the marginal effect of an extra hot day before after NREGA was introduced in a district against the differential marginal effect of a hot day in a district that didn’t receive NREGA. To the extent that NREGA roll-out was non-random and determined on a backwardness and poverty index, the attenuation effect is understated - prior to NREGA, we’d expect the marginal effect of temperature to be higher in poorer districts.

²¹In our preferred specification, we employ district and *state-by-year* fixed effects. Our results remain robust to the use of district and *year* fixed effects as shown in appendix section [B.4](#) though we are underpowered. We retain power using the hot days approach where we don’t trace the non-linearity of the effect of temperature on test scores. Our preferred specification, by eliminating much of the roll-out variation in NREGA, doesn’t find any level effect of NREGA as documented in [Shah and Steinberg \(2016\)](#). However, in our district and year fixed effects specification in the appendix we are able to recover the opportunity cost level effects of NREGA found in [Shah and Steinberg \(2016\)](#).

(appendix table [B.1](#)). Specifically, an extra hot day with average temperature above 21C in a district, increases NREGA take up by nearly 4%. Previous year hot days also drive NREGA participation, but primarily in the current year’s non-growing season. These results suggest that households use NREGA to stabilize insults to agricultural income driven by hotter days.

That NREGA attenuates the relationship between temperature and test scores is of considerable importance. First, the result reinforces the underlying income mechanism linking higher temperatures to lower test score performance. Not only do higher temperatures lower test performance by adversely affecting household agricultural income, but also income stabilizing pro-social programs can build resilience and attenuate the negative effects of higher temperatures. In poor countries, where adaptation strategies such as air conditioners are unaffordable for large portions of the population, pro-social programs can be an important tool in combating the harmful effects of increasing temperatures.

Second, while there is considerable work on the benefits of conditional cash transfers and similar pro-social programs ²², we know relatively little about the role of such programs in combating vulnerability. If the susceptibility of cognitive performance to temperature can be characterized as vulnerability, pro-social program can not only have direct benefits (as documented in the literature), but also indirect benefits in reducing vulnerability.

6 Conclusion

As weather, in the age of climate change, becomes more pronounced, it is likely to disproportionately impact the poor by limiting pathways out of poverty that are dependent on human capital accumulation. We find that short-run temperature affects human capital through a temporary physiological effect. However, longer-run temperature affects human capital through a separate agricultural income mechanism. The separation of the pathways through which temperature affects human capital in the short- and longer-run has important implications for climate policy. Short-run effects are driven by physiology that can likely be corrected through defensive investments such as air-conditioners, or changing the test day or calendar. However, the longer-run effects are driven by insults to livelihoods that,

²²A non-exhaustive list of excellent papers in this area include [Baird, McIntosh and Özler \(2011\)](#); [Gertler \(2004\)](#).

in agrarian poor settings, are increasingly climate-exposed. Importantly, these longer-run effects of temperature that affect human capital accumulation by reducing nutritional intake may require social programs that can protect the livelihoods of the poor from weather and climate. At the same time, governments and policy makers should expect the dependence on their social programs to increase in the face of climate change. Given the central role of human capital accumulation as a pathway out of poverty in poor countries ([Barrett, Garg and McBride, 2016](#)), climate change will not only disproportionately affect the rural poor but absent social programs also likely perpetuate persistent poverty.

References

- Adhvaryu, A., Kala N., and A. Nyshadham. 2015. “The light and the heat: Productivity co-benefits of energy-saving technology.” *Working Paper*.
- Almond, D., and J. Currie. 2011. “Human Capital Development before Age Five.” *Handbook of Labor Economics*, ed. by O. Asheneter, and D. Card, 4: 1315–1486.
- Almond, D., L. Edlund, and M. Palme. 2009. “Chernobyl’s Subclinical Legacy: Prenatal Expo-sure to Radioactive Fallout and School Outcomes in Sweden.” *The Quarterly Journal of Economics*, 124(4): 1729–1772.
- Auffhammer, Maximilian, Solomon M Hsiang, Wolfram Schlenker, and Adam Sobel. 2013. “Using weather data and climate model output in economic analyses of climate change.” *Review of Environmental Economics and Policy*, ret016.
- Baird, Sarah, Craig McIntosh, and Berk Özler. 2011. “Cash or condition? Evidence from a cash transfer experiment.” *The Quarterly Journal of Economics*, qjr032.
- Barreca, Alan, Karen Clay, Olivier Deschenes, Michael Greenstone, and Joseph S. Shapiro. 2013. “Adapting to climate change: The remarkable decline in the US temperature-mortality relationship over the 20th century.” *NBER Working Paper 18692*.
- Barrett, Christopher B, Teevrat Garg, and Linden McBride. 2016. “Well-Being Dynamics and Poverty Traps.” *Annual Review of Resource Economics*, 8(1).
- Barro, Robert. 2000. “Inequality and Growth in a Panel of Countries. Journal of Economic Growth.” *Annual Review of Resource Economics*, 5(1): 5–32.
- Basu, R., and J. M. Samet. 2002. “Relation Between Elevated Ambient Temperature and Mortality: A Review of the Epidemiologic Evidence.” *Epidemiologic Review*, 24(12): 190–202.
- Black, S. E., A. Butikofer, P. J. Devereux, and K. G. Salvanes. 2013. “This Is Only a Test? Long-Run Impacts of Prenatal Exposure to Radioactive Downfall.” *NBER Working Paper 18987*.
- Bowler, K., and R. Tirri. 1974. “The temperature characteristics of synaptic membrane ATPases from immature and adult rat brain.” *Journal of Neurochemistry*, 23(3): 611–613.
- Burgess, R., Deschenes O. Donaldson D., and M Greenstone. 2014. “The unequal effects of weather and climate change: Evidence from mortality in India.” *Working Paper*.
- Burke, Marshall, and Kyle Emerick. 2016. “Adaptation to Climate Change: Evidence from US Agriculture.” *American Economic Journal: Economic Policy*.
- Burke, Marshall, Solomon M Hsiang, and Edward Miguel. 2015. “Global non-linear effect of temperature on economic production.” *Nature*, 527(7577): 235–239.

- Chaudhury, Nazmul, Jeffrey Hammer, Michael Kremer, Karthik Muralidharan, and F. Halsey Rogers.** 2006. “Missing in Action: Teacher and Health Worker Absence in Developing Countries.” *Journal of Economic Perspectives*, 20(1): 91–116.
- Chetty, Raj, John N. Friedman, and Jonah E. Rockoff.** 2014*a*. “Measuring the Impacts of Teachers I: Evaluating Bias in Teacher Value-Added Estimates.” *American Economic Review*, 104(9): 2593–2632.
- Chetty, Raj, John N. Friedman, and Jonah E. Rockoff.** 2014*b*. “Measuring the Impacts of Teachers II: Teacher Value-Added and Student Outcomes in Adulthood.” *American Economic Review*, 104(9): 2633–79.
- Das, Jishnu, Stefan Dercon, James Habyarimana, Pramila Krishnan, Karthik Muralidharan, and Venkatesh Sundararaman.** 2013. “School Inputs, Household Substitution, and Test Scores.” *American Economic Journal: Applied Economics*, 5(2): 29–57.
- Deboer, Tom.** 1998. “Brain temperature dependent changes in the electroencephalogram power spectrum of humans and animals.” *Journal of Sleep Research*, 7(4): 254–262.
- Dee, D. P., S. M. Uppala, A. J. Simmons, P. Berrisford, P. Poli, S. Kobayashi, U. Andrae, M. A. Balmaseda, G. Balsamo, P. Bauer, P. Bechtold, A. C. M. Beljaars, L. van de Berg, J. Bidlot, N. Bormann, C. Delsol, R. Dragani, M. Fuentes, A. J. Geer, L. Haimberger, S. B. Healy, H. Hersbach, E. V. Hólm, L. Isaksen, P. Kållberg, M. Köhler, M. Matricardi, A. P. McNally, B. M. Monge-Sanz, J.-J. Morcrette, B.-K. Park, C. Peubey, P. de Rosnay, C. Tavalato, J.-N. Thépaut, and F. Vitart.** 2011. “The ERA-Interim reanalysis: configuration and performance of the data assimilation system.” *Quarterly Journal of the Royal Meteorological Society*, 137(656).
- Deschenes, O., and E. Moretti.** 2009. “Extreme Weather Events, Mortality and Migration.” *Review of Economics and Statistics*, 91(4): 659–681.
- Deschênes, Olivier, and Michael Greenstone.** 2011. “Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US.” *American Economic Journal: Applied Economics*, 3(4): 152–85.
- Duflo, Esther, Rema Hanna, and Stephen P. Ryan.** 2012. “Incentives Work: Getting Teachers to Come to School.” *American Economic Review*, 102(4): 1241–78.
- Fine, Bernard J., and John L. Kobrick.** 1978. “Effects of altitude and heat on complex cognitive tasks.” *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 20(1): 115–122.
- Froom, Paul, Yeheskial Caine, Igal Shochat, and Joseph Ribak.** 1993. “Heat stress and helicopter pilot errors.” *Journal of Occupational and Environmental Medicine*, 35(7): 720–732.

- Gertler, Paul.** 2004. “Do conditional cash transfers improve child health? Evidence from PROGRESA’s control randomized experiment.” *The American Economic Review*, 94(2): 336–341.
- Graff-Zivin, Joshua S, Solomon M Hsiang, and Matthew J Neidell.** 2015. “Temperature and human capital in the short-and long-run.”
- Hanushek, Eric, and Steven G. Rivkin.** 2012. “The Distribution of Teacher Quality and Implications for Policy.” *Annual Review of Economics*, 4: 131–57.
- Harrington, Luke J, David J Frame, Erich M Fischer, Ed Hawkins, Manoj Joshi, and Chris D Jones.** 2016. “Poorest countries experience earlier anthropogenic emergence of daily temperature extremes.” *Environmental Research Letters*, 11(5): 055007.
- Hocking, Chris, Richard B. Silberstein, Wai Man Lau, Con Stough, and Warren Roberts.** 2001. “Evaluation of cognitive performance in the heat by functional brain imaging and psychometric testing.” *Comparative Biochemistry and Physiology Part A: Molecular and Integrative Physiology*, 128(4): 719–734.
- Hu, Zihan, and Teng Li.** 2016. “Too hot to hold: the effects of high temperatures during pregnancy on birth weight and adult welfare outcomes.”
- Hyde, Dale, John R. Thomas, John Schrot, and W. F. Taylor.** 1997. “Quantification of special operations mission-related performance: Operational evaluation of physical measures.” *Naval Medical Research Institute, Bethesda MD*.
- IPCC.** 2014. “Climate Change 2014: Synthesis Report.”
- Isen, Adam, Maya Rossin-Slater, and W. Reed Walker.** 2015. “Heat and Long-Run Human Capital Formation.” *Working Paper*.
- Jacoby, H., Skoufias E.** 1997. “Risk, Financial Markets, and Human Capital in a Developing Country.” *The Review of Economic Studies*, 64(3): 311–335.
- Jensen, Robert.** 2000. “Agricultural volatility and investments in children.” *American Economic Review*, 90(2): 399–404.
- Knobel, Robin, and Diane Holditch-Davis.** 2007. “Thermoregulation and Heat Loss Prevention After Birth and During Neonatal Intensive-Care Unit Stabilization of Extremely Low-Birthweight Infants.” *American Economic Journal: Applied Economics*, 36: 280–287.
- Maccini, Sharon, and Dean Yang.** 2009. “Under the Weather: Health, Schooling, and Economic Consequences of Early-Life Rainfall.” *American Economic Review*, 99(3): 1006–26.
- McEwan, Patrick J.** 2015. “Improving Learning in Primary Schools of Developing Countries A Meta-Analysis of Randomized Experiments.” *Review of Educational Research*, 85(3): 353–394.

- Nelson, Richard R, and Edmund S Phelps.** 1966. "Investment in humans, technological diffusion, and economic growth." *The American economic review*, 56(1/2): 69–75.
- Park, Jisung.** 2016. "Temperature, Test Scores, and Educational Attainment."
- Patz, Jonathan A, Diarmid Campbell-Lendrum, Tracey Holloway, and Jonathan A Foley.** 2005. "Impact of regional climate change on human health." *Nature*, 438(7066): 310–317.
- Rogot, Sorlie PD, and E. Backlund.** 1992. "Air-conditioning and mortality in hot weather." *Am J Epidemiol*, 136(1): 106–16.
- Romer, Paul M.** 1986. "Increasing returns and long-run growth." *The journal of political economy*, 1002–1037.
- Sanders, N.** 2012. "What Doesn't Kill You Makes You Weaker Prenatal Pollution Exposure and Educational Outcomes." *Journal of Human Resources*, 47(3): 826–850.
- Schiff, Steven J., and George G. Somjen.** 1985. "The effects of temperature on synaptic transmission in hippocampal tissue slices." *Brain Research*, 345(2): 279–284.
- Schlenker, Wolfram, and David B Lobell.** 2010. "Robust negative impacts of climate change on African agriculture." *Environmental Research Letters*, 5(1): 014010.
- Schlenker, Wolfram, and Michael J Roberts.** 2009. "Nonlinear temperature effects indicate severe damages to US crop yields under climate change." *Proceedings of the National Academy of sciences*, 106(37): 15594–15598.
- Shah, Manisha, and Bryce M. Steinberg.** 2016. "Drought of Opportunities: Contemporaneous and Long-Term Impacts of Rainfall Shocks on Human Capital." *Journal of Political Economy*, Forthcoming.
- Strauss, John.** 1986. "Does better nutrition raise farm productivity?" *Journal of political economy*, 94(2): 297–320.
- Strauss, John, and Duncan Thomas.** 1998. "Health, nutrition, and economic development." *Journal of economic literature*, 36(2): 766–817.
- Taylor, Nigel AS.** 2006. "Challenges to temperature regulation when working in hot environments." *Industrial health*, 44(3): 331–344.
- Thomas, Duncan, and John Strauss.** 1997. "Health and wages: Evidence on men and women in urban Brazil." *Journal of Econometrics*, 77(1): 159–185.
- Vasmatazidis, Ioannis, Robert E. Schlegel, and Peter A. Hancock.** 2002. "An investigation of heat stress effects on time-sharing performance." *Ergonomics*, 45(3): 218–239.
- Victora, Cesar G, Linda Adair, Caroline Fall, Pedro C Hallal, Reynaldo Martorell, Linda Richter, Harshpal Singh Sachdev, Maternal, and Child Undernutrition Study Group.** 2008. "Maternal and child undernutrition: consequences for adult health and human capital." *The lancet*, 371(9609): 340–357.

Yablonskiy, Dmitriy A., Joseph JH Ackerman, and Marcus E. Raichle. 2000. “Coupling between changes in human brain temperature and oxidative metabolism during prolonged visual stimulation.” *Proceedings of the National Academy of Sciences*, 97(13): 7603–7608.

Figures

Figure 1: Historical and Projected Distribution of Daily Average Temperatures in India

Figure 2: Average Daily Temperature by District

Figure 3: Distribution of Daily Temperatures for India and Andhra Pradesh

(a) Andhra Pradesh

(b) All India

(c) All India (continued)

Figure 4: Long Run Temperature Variation

(a) Math Scores

(b) Reading Scores

Figure 5: Short Run Temperature and Test Scores (YLS)

Figure 6: Leads and Lags in Weeks: Short Run Temperature and Math Scores

Notes: The figure present the impact of short-run temperature from 4 weeks before test day to 4 weeks after the test. Temperature is captured as the number of days when the temperature is $>23^{\circ}\text{C}$ during a week for 'No. Week', and if temperature is > 23 on the day of the test for 'Test Day'. Includes individual, day of week, month and survey round fixed effects. We control for precipitation in all periods. The sample includes only those children who were tested thrice in both Math and PPVT. Standard errors are in parentheses, clustered by district-week.

(a) Math Scores

(b) Reading Scores

Figure 7: Long Run Temperature and Test Scores (ASER)

(a) Math Scores

(b) Reading Scores

Figure 8: Long Run Temperature and Test Scores (YLS)

(a) Math Scores

(b) Reading Scores

Figure 9: Growing vs. Non-Growing Season: Long Run Temperature and Test Scores

(a) Math Scores

(b) Reading Scores

Figure 10: Effect of Long Run Temperature on Test Scores by age (ASER)

(a) Math Scores

(b) Reading Scores

Figure 11: Hot vs. Not-so Hot Districts: Long Run Temperature and Test Scores

(a) Math Scores

(b) Reading Scores

Figure 12: Event Study: Long Run Temperature, NREGA and Test Scores

Tables

Table 1: Short Run Temperature and Test Scores

	(1) Math Score (in SD) β / SE	(2) Math Score (in SD) β / SE	(3) PPVT Score (in SD) β / SE	(4) PPVT Score (in SD) β / SE
Day >23C	-0.168*** (0.046)		-0.012 (0.058)	
Day 23-25C		-0.154*** (0.046)		-0.030 (0.059)
Day 25-27C		-0.259*** (0.057)		0.060 (0.076)
Day >27C		-0.303*** (0.077)		0.147 (0.094)
Observations	2604	2604	2541	2541
R^2	0.023	0.027	0.009	0.012

Notes: Includes individual, day of week, month and survey round fixed effects. We control for precipitation in all specifications. The sample includes only those children who were tested thrice in both Math and PPVT. Standard errors are in parentheses, clustered by district-week.

*Significant at 10%.

**Significant at 5%.

***Significant at 1%.

Table 2: Long Run Temperature and Test Scores (ASER)

	(1) Math Score (in SD) β / SE	(2) Math Score (in SD) β / SE	(3) Read Score (in SD) β / SE	(4) Read Score (in SD) β / SE
Days <15C	-0.0024*** (0.0006)		-0.0019*** (0.0006)	
Days >21C	-0.0016*** (0.0005)		-0.0007* (0.0004)	
PY Days <13C		-0.0034*** (0.0009)		-0.0025*** (0.0008)
PY Days 13-15C		-0.0031*** (0.0009)		-0.0021*** (0.0008)
PY Days 17-19C		-0.0021** (0.0009)		-0.0012 (0.0008)
PY Days 19-21C		-0.0008 (0.0007)		0.0000 (0.0006)
PY Days 21-23C		-0.0027*** (0.0008)		-0.0009 (0.0007)
PY Days 23-25C		-0.0030*** (0.0008)		-0.0014** (0.0007)
PY Days 25-27C		-0.0023*** (0.0008)		-0.0011 (0.0007)
PY Days 27-29C		-0.0024*** (0.0009)		-0.0010 (0.0008)
PY Days >29C		-0.0030*** (0.0009)		-0.0018** (0.0008)
Observations	4581616	4581616	4581616	4581616
R^2	0.084	0.084	0.068	0.068

Notes: This table presents the impact of temperature in the previous year (captured via temperature bins) on test scores in the current year for children between the ages of 5-16 for 2006-2014. All specifications include district, year, and age fixed effects. We control for precipitation and humidity in all specifications. The sample only includes on-track children between the age 5-16. Standard errors are in parentheses, clustered by district.

*Significant at 10%.

**Significant at 5%.

***Significant at 1%.

Table 3: Falsification Test: Temperature Test Scores

	(1) Math Score (in SD) β / SE	(2) Read Score (in SD) β / SE
PY Days <15C	-0.0030*** (0.0007)	-0.0027*** (0.0006)
PY Days >21C	-0.0020*** (0.0005)	-0.0008* (0.0005)
CY Days <15C	-0.0004 (0.0007)	-0.0008 (0.0006)
CY Days >21C	0.0012* (0.0006)	0.0002 (0.0005)
NY Days <15C	-0.0006 (0.0007)	-0.0017*** (0.0006)
NY Days >21C	0.0007 (0.0006)	0.0001 (0.0005)
Observations	4182681	4182681
R^2	0.088	0.071

Notes: This table presents the impact of temperature in the previous year and current year (captured via temperature bins) on test scores in the current year for children between the ages of 5-16 for 2006-2014. All specifications include district and age fixed effects. We control for precipitation and humidity in all specifications. The sample includes children between the age 5-16. Standard errors are in parentheses, clustered by district.

*Significant at 10%.

**Significant at 5%.

***Significant at 1%.

Table 4: Long Run Temperature and Test Scores (YLS)

	(1) Math Score (in SD) β / SE	(2) Math Score (in SD) β / SE	(3) PPVT Score (in SD) β / SE	(4) PPVT Score (in SD) β / SE
Days >23C	-0.004*** (0.001)		-0.005*** (0.001)	
Days 23-25C		-0.007*** (0.001)		0.002 (0.002)
Days 25-27C		-0.002** (0.001)		-0.007*** (0.001)
Days >27C		-0.007*** (0.001)		-0.010*** (0.002)
Observations	2604	2604	2541	2541
R^2	0.048	0.058	0.057	0.077

Notes: Includes individual, day of week, month and survey round fixed effects. We control for precipitation and humidity in all specifications. The sample includes only those children who were tested thrice in both Math and PPVT. Standard errors are in parentheses, clustered by district-week.

*Significant at 10%.

**Significant at 5%.

***Significant at 1%.

Table 5: Growing vs. Non-Growing Season: Long Run Temperature and Test Scores

	(1) Math Score (in SD) β / SE	(2) Read Score (in SD) β / SE
GS Days <13C	-0.0009 (0.0012)	-0.0011 (0.0011)
GS Days 13-15C	-0.0032*** (0.0011)	-0.0021** (0.0010)
GS Days 17-19C	-0.0040*** (0.0010)	-0.0026*** (0.0009)
GS Days 19-21C	-0.0039*** (0.0009)	-0.0023*** (0.0008)
GS Days 21-23C	-0.0058*** (0.0011)	-0.0033*** (0.0009)
GS Days 23-25C	-0.0073*** (0.0011)	-0.0044*** (0.0009)
GS Days 25-27C	-0.0068*** (0.0011)	-0.0042*** (0.0010)
GS Days 27-29C	-0.0083*** (0.0013)	-0.0050*** (0.0012)
GS Days >29C	-0.0097*** (0.0015)	-0.0064*** (0.0013)
NGS Days <13C	-0.0055* (0.0031)	-0.0019 (0.0032)
NGS Days 13-15C	-0.0030 (0.0030)	-0.0008 (0.0028)
NGS Days 17-19C	-0.0002 (0.0022)	-0.0003 (0.0020)
NGS Days 19-21C	0.0026 (0.0018)	0.0008 (0.0018)
NGS Days 21-23C	-0.0014 (0.0020)	-0.0013 (0.0019)
NGS Days 23-25C	0.0019 (0.0021)	0.0014 (0.0019)
NGS Days 25-27C	-0.0008 (0.0021)	-0.0009 (0.0019)
NGS Days 27-29C	0.0017 (0.0022)	0.0006 (0.0020)
NGS Days >29C	0.0023 (0.0023)	0.0009 (0.0021)
Observations	4581616	4581616
R^2	0.085	0.069

Notes: This table presents the impact of temperature in the previous year (captured via temperature bins) on test scores in the current year for children between the ages of 5-16 for 2006-2014. All specifications include district, year, and age fixed effects. We control for precipitation and humidity in all specifications. The sample only includes on-track children between the age 5-16. Standard errors are in parentheses, clustered by district.

*Significant at 10%.

**Significant at 5%.

***Significant at 1%.

Table 6: Heat Resistant Crops: Long Run Temperature and Test Scores

	(1) Math Score (in SD) β / SE	(2) Read Score (in SD) β / SE
Days <15C	-0.0026*** (0.0007)	-0.0020*** (0.0006)
Days >21C	-0.0030*** (0.0006)	-0.0015*** (0.0005)
Days >21C * HRC	0.0021*** (0.0007)	0.0009 (0.0006)
Observations	4403838	4403838
R^2	0.083	0.069

Notes: This table presents the impact of temperature in the previous year (captured via temperature bins) on test scores in the current year for children between the ages of 5-16 for 2006-2014. All specifications include district, year, and age fixed effects. We control for precipitation and humidity in all specifications. The sample only includes on-track children between the age 5-16. Standard errors are in parentheses, clustered by district.

*Significant at 10%.

**Significant at 5%.

***Significant at 1%.

Table 7: PY Temperature and BMI

	(1) BMI β / SE	(2) BMI-for-Age Z-Score β / SE
PY Days 23-25C	-0.006** (0.003)	-0.003 (0.002)
PY Days 25-27C	-0.008*** (0.003)	-0.005*** (0.002)
PY Days >27C	-0.006 (0.003)	-0.004* (0.003)
Observations	3460	3460
R^2	0.332	0.066

Notes: Includes individual, month and survey round fixed effects. We control for precipitation in all specifications. The sample includes only those children who were tested thrice in both Math and PPVT. Standard errors are in parentheses, clustered by district-week.

*Significant at 10%.

**Significant at 5%.

***Significant at 1%.

Table 8: Temperature and Log Value of Food Consumption

	(1) Crops β / SE	(2) Animals β / SE	(3) Veg-Fruits β / SE	(4) Own Crops β / SE	(5) Own Animals β / SE	(6) Own Veg-Fruits β / SE
PY Days 23-25C	-0.002 (0.003)	0.005*** (0.002)	-0.002 (0.001)	-0.002 (0.004)	-0.001 (0.002)	0.002 (0.002)
PY Days 25-27C	-0.009* (0.005)	0.014*** (0.004)	0.006** (0.002)	0.010 (0.008)	-0.001 (0.005)	0.004 (0.004)
PY Days >27C	-0.006 (0.006)	0.013*** (0.004)	0.005** (0.003)	-0.016** (0.007)	-0.005 (0.005)	-0.000 (0.004)
Observations	2604	2604	2604	2604	2604	2604
R^2	0.028	0.153	0.370	0.036	0.019	0.045

Notes: Includes individual, month and survey round fixed effects. We control for precipitation in all specifications. The sample includes only those children who were tested thrice in both Math and PPVT. Standard errors are in parentheses, clustered by district-week.

*Significant at 10%.

**Significant at 5%.

***Significant at 1%.

Table 9: Event Study: Long Run Temperature, NREGA and Test Scores

	(1) Math Score (in SD) β / SE	(2) Read Score (in SD) β / SE
Time = -3	-0.1562 (0.1081)	-0.1484 (0.1033)
Time = -2	-0.1189* (0.0616)	-0.1278** (0.0589)
Time = 0	0.0082 (0.0584)	0.0189 (0.0550)
Time = 1	0.0517 (0.1044)	0.0667 (0.0997)
Time = 2	0.1773 (0.1450)	0.1724 (0.1392)
Days <13C	-0.0018 (0.0022)	-0.0002 (0.0021)
Days 13-15C	-0.0008 (0.0018)	-0.0002 (0.0018)
Days 17-19C	0.0013 (0.0018)	0.0004 (0.0017)
Days 19-21C	-0.0006 (0.0018)	-0.0014 (0.0017)
Days 21-23C	-0.0038** (0.0018)	-0.0041** (0.0018)
Days 23-25C	-0.0036* (0.0019)	-0.0037** (0.0018)
Days 25-27C	-0.0031 (0.0021)	-0.0035* (0.0020)
Days 27-29C	-0.0027 (0.0022)	-0.0033 (0.0021)
Days >29C	-0.0034 (0.0023)	-0.0040* (0.0022)
Time = -3 * Days >29C	-0.0004 (0.0006)	-0.0005 (0.0006)
Time = -2 * Days >29C	0.0005 (0.0005)	0.0007* (0.0004)
Time = 0 * Days >29C	0.0004 (0.0004)	0.0003 (0.0004)
Time = 1 * Days >29C	0.0011** (0.0005)	0.0011** (0.0005)
Time = 2 * Days >29C	0.0013 (0.0011)	0.0015 (0.0011)
Observations	1866623	1866623
R^2	0.104	0.085

Notes: This table tests if the impact of last year's temperature were attenuated by NREGA roll-out in that year. To capture these effects, we have interacted the number of days in the previous year when the temperature was over 29C (bin 10) with the event time of NREGA roll-out. t=0 indicates if NREGA was implemented last year in that district. Because we are testing the effects of last year's temperature on current year's test scores, we interact previous year's NREGA roll-out with previous year's temperature, to capture attenuation. The reference temperature bin is 15-17C, and the omitted event time dummy is -1 (one year before NREGA was rolled-out in the previous year). The sample includes test scores in the current year for children between the ages of 5-16 for 2006-2009. All specifications include district, state-by-year and age fixed effects. We control for precipitation terciles and relative humidity in all specifications. The sample includes children between the age 5-16. Standard errors are in parentheses, clustered by district.

*Significant at 10%.

**Significant at 5%.

***Significant at 1%.

A Appendix: Additional Results

A.1 No Persistence in Short Run Physiological Effects

Figure A.4: Leads and Lags in Weeks: Short Run Temperature and PPVT Scores

Notes: The figure present the impact of short-run temperature from 4 weeks before test day to 4 weeks after the test. Temperature is captured as the number of days when the temperature is $>23^{\circ}\text{C}$ during a week for 'No. Week', and if temperature is > 23 on the day of the test for 'Test Day'. Includes individual, day of week, month and survey round fixed effects. We control for precipitation in all periods. The sample includes only those children who were tested thrice in both Math and PPVT. Standard errors are in parentheses, clustered by district-week.

Figure A.4: Leads and Lags in Days: Short Run Temperature and Math Scores

Notes: The figure present the impact of short-run temperature from 4 weeks before test day to 4 weeks after the test. Temperature is captured as 1 if temperature is > 23 on the day of the test for 'Test Day', 0 otherwise. Includes individual, day of week, month and survey round fixed effects. We control for precipitation in all periods. The sample includes only those children who were tested thrice in both Math and PPVT. Standard errors are in parentheses, clustered by district-week.

Figure A.4: Leads and Lags in Days: Short Run Temperature and PPVT Scores

Notes: The figure present the impact of short-run temperature from 4 weeks before test day to 4 weeks after the test. Temperature is captured as 1 if temperature is > 23 on the day of the test for 'Test Day', 0 otherwise. Includes individual, day of week, month and survey round fixed effects. We control for precipitation in all periods. The sample includes only those children who were tested thrice in both Math and PPVT. Standard errors are in parentheses, clustered by district-week.

A.2 Test Times and Timing of Test

Table A.1: Short Run Temperature and Test Duration

	(1) Duration Math Test β / SE	(2) Duration PPVT Test β / SE
Day 23-25C	0.927 (0.626)	-2.331*** (0.710)
Day 25-27C	0.657 (0.781)	-1.420 (0.868)
Day >27C	2.068** (1.040)	0.930 (1.123)
Observations	2590	2528
R^2	0.783	0.245

Notes: Includes individual, day of week, month and survey round fixed effects. We control for precipitation in all specifications. The sample includes only those children who were tested thrice in both Math and PPVT. Standard errors are in parentheses, clustered by district-week.

*Significant at 10%.

**Significant at 5%.

***Significant at 1%.

Table A.2: Short Run Temperature and Test Timing

	(1) Math Start Time β / SE	(2) PPVT Start Time β / SE
Day 23-25C	0.187 (0.372)	-0.029 (0.202)
Day 25-27C	0.211 (0.381)	-0.488 (0.316)
Day >27C	0.449 (0.588)	-0.558 (0.349)
Observations	2604	1694
R^2	0.595	0.034

Notes: Includes individual, day of week, month and survey round fixed effects. We control for precipitation in all specifications. The sample includes only those children who were tested thrice in both Math and PPVT. Standard errors are in parentheses, clustered by district-week.

*Significant at 10%.

**Significant at 5%.

***Significant at 1%.

A.3 Short- and Longer-Run Temperature and Test Scores

Table A.3: Short- and Longer-Run Temperature and Test Scores

	(1) Math Score (in SD) β / SE	(2) Math Score (in SD) β / SE	(3) PPVT Score (in SD) β / SE	(4) PPVT Score (in SD) β / SE
Day >23C	-0.112*** (0.042)		0.030 (0.058)	
Days >23C	-0.004*** (0.001)		-0.005*** (0.001)	
Day 23-25C		-0.100** (0.045)		-0.005 (0.056)
Day 25-27C		-0.178*** (0.056)		0.139* (0.075)
Day >27C		-0.169** (0.073)		0.253*** (0.097)
Days 23-25C		-0.007*** (0.001)		0.001 (0.002)
Days 25-27C		-0.002** (0.001)		-0.007*** (0.001)
Days >27C		-0.007*** (0.001)		-0.009*** (0.001)
Observations	2604	2604	2541	2541
R^2	0.054	0.065	0.060	0.084

Notes: Includes individual, day of week, month and survey round fixed effects. We control for precipitation in all specifications. The sample includes only those children who were tested thrice in both Math and PPVT. Standard errors are in parentheses, clustered by district-week.

*Significant at 10%.

**Significant at 5%.

***Significant at 1%.

A.4 ASER Results: On-track students only

Table A.4: On-track Children: Long Run Temperature and Test Scores

	(1) Math Score (in SD) β / SE	(2) Math Score (in SD) β / SE	(3) Read Score (in SD) β / SE	(4) Read Score (in SD) β / SE
Days <15C	-0.0027*** (0.0006)		-0.0021*** (0.0005)	
Days >21C	-0.0016*** (0.0005)		-0.0007* (0.0004)	
PY Days <13C		-0.0041*** (0.0009)		-0.0031*** (0.0007)
PY Days 13-15C		-0.0029*** (0.0008)		-0.0018** (0.0007)
PY Days 17-19C		-0.0017** (0.0009)		-0.0009 (0.0007)
PY Days 19-21C		-0.0010 (0.0007)		-0.0003 (0.0006)
PY Days 21-23C		-0.0027*** (0.0008)		-0.0009 (0.0007)
PY Days 23-25C		-0.0030*** (0.0008)		-0.0014** (0.0006)
PY Days 25-27C		-0.0022*** (0.0008)		-0.0011* (0.0006)
PY Days 27-29C		-0.0025*** (0.0008)		-0.0013* (0.0007)
PY Days >29C		-0.0028*** (0.0009)		-0.0018** (0.0007)
Observations	3501428	3501428	3501428	3501428
R^2	0.088	0.088	0.065	0.065

Notes: This table presents the impact of temperature in the previous year (captured via temperature bins) on test scores in the current year for children between the ages of 5-16 for 2006-2014. All specifications include district, year, and age fixed effects. We control for precipitation and humidity in all specifications. The sample only includes on-track children between the age 5-16. Standard errors are in parentheses, clustered by district.

*Significant at 10%.

**Significant at 5%.

***Significant at 1%.

A.5 ASER Results - Degree Days

Table A.5: Long Run Temperature and Test Scores: Complete Sample

	(1) Math Score (in SD) β / SE	(2) Read Score (in SD) β / SE
DD <21C	0.0140* (0.0080)	0.0126* (0.0073)
DD >21C	-0.0082 (0.0057)	-0.0116** (0.0048)
Observations	4581616	4581616
R^2	0.084	0.068

Notes: This table presents the impact of temperature in the previous year (captured via degree days) on test scores in the current year for children between the ages of 5-16 for 2006-2014. All specifications include district, year, and age fixed effects. We control for precipitation and humidity in all specifications. The sample includes children between the age 5-16. Standard errors are in parentheses, clustered by district.

*Significant at 10%.

**Significant at 5%.

***Significant at 1%.

Table A.6: Long Run Temperature and Test Scores: On Track Only

	(1) Math Score (in SD) β / SE	(2) Read Score (in SD) β / SE
DD <21C	0.0107 (0.0074)	0.0094 (0.0063)
DD >21C	-0.0077 (0.0057)	-0.0110** (0.0045)
Observations	3446230	3446230
R^2	0.087	0.065

Notes: This table presents the impact of temperature in the previous year (captured via degree days) on test scores in the current year for children between the ages of 5-16 for 2006-2014. All specifications include district, year, and age fixed effects. We control for precipitation and humidity in all specifications. The sample only includes on-track children between the age 5-16. Standard errors are in parentheses, clustered by district.

*Significant at 10%.

**Significant at 5%.

***Significant at 1%.

A.6 Temperatures and Agricultural Yields

Table A.7: Current Year Growing Season Temperature and Agriculture Yields

	(1) Log Yield: Top 6 Crops β / SE	(2) Log Yield: Top 5 Monsoon Crops β / SE
GS Days <13C	-0.0018** (0.0008)	-0.0023** (0.0011)
GS Days 13-15C	0.0004 (0.0007)	0.0029*** (0.0010)
GS Days 17-19C	-0.0013** (0.0006)	-0.0026** (0.0011)
GS Days 19-21C	-0.0032*** (0.0007)	-0.0033*** (0.0009)
GS Days 21-23C	-0.0027*** (0.0007)	-0.0033*** (0.0010)
GS Days 23-25C	-0.0033*** (0.0008)	-0.0040*** (0.0010)
GS Days 25-27C	-0.0042*** (0.0008)	-0.0038*** (0.0010)
GS Days 27-29C	-0.0055*** (0.0010)	-0.0042*** (0.0013)
GS Days >29C	-0.0096*** (0.0012)	-0.0116*** (0.0015)
NGS Days <13C	0.0021 (0.0017)	0.0004 (0.0017)
NGS Days 13-15C	-0.0023 (0.0021)	0.0003 (0.0023)
NGS Days 17-19C	-0.0035* (0.0019)	-0.0042** (0.0019)
NGS Days 19-21C	-0.0029** (0.0012)	-0.0028** (0.0014)
NGS Days 21-23C	-0.0021* (0.0012)	-0.0016 (0.0013)
NGS Days 23-25C	-0.0009 (0.0013)	-0.0012 (0.0014)
NGS Days 25-27C	-0.0015 (0.0015)	-0.0021 (0.0016)
NGS Days 27-29C	-0.0010 (0.0015)	-0.0018 (0.0016)
NGS Days >29C	-0.0018 (0.0015)	-0.0028* (0.0017)
Observations	9479	9475
R^2	0.885	0.877

Notes: This table presents the impact of temperature in the current growing season (captured via temperature bins) on agriculture yields in the current year for 1980-2011. All specifications include district and year fixed effects. We control for precipitation in all specifications. Standard errors are in parentheses, clustered by district.

*Significant at 10%.

**Significant at 5%.

***Significant at 1%.

(a) 6 major crops

(b) 5 major monsoon crops

Figure A.4: Growing vs. Non-Growing Season: Current Year Temperature and Yields

A.7 ASER: School Attendance

Table A.8: Previous Year Temperature and Student Attendance

	(1) Stu. Attend Proportion β / SE	(2) Stu. Attend Proportion β / SE	(3) Stu. Attend Prop. > p50 β / SE
PY NGS Days <15C	0.0002 (0.0005)	0.0001 (0.0005)	0.0021* (0.0011)
PY NGS Days >21C	0.0002 (0.0004)	0.0002 (0.0004)	0.0001 (0.0008)
PY GS Days <15C	-0.0006*** (0.0002)	-0.0006** (0.0002)	-0.0013** (0.0005)
PY GS Days >21C	-0.0004** (0.0002)	-0.0004** (0.0002)	-0.0004 (0.0004)
Observations	93432	93432	93432
R^2	0.428		0.368

Notes: All specifications include district and year fixed effects. Standard errors are in parentheses, clustered by district. Specification (2) estimates a tobit model.

*Significant at 10%.

**Significant at 5%.

***Significant at 1%.

Table A.9: Previous Year Temperature and Teacher Attendance

	(1) Tch. Attend Proportion β / SE	(2) Tch. Attend Proportion β / SE	(3) Reg. Tch. Attend =100% β / SE
PY NGS Days <15C	-0.0010* (0.0006)	-0.0028* (0.0016)	-0.0019 (0.0013)
PY NGS Days >21C	0.0003 (0.0003)	0.0008 (0.0010)	0.0007 (0.0009)
PY GS Days <15C	0.0006** (0.0003)	0.0016** (0.0007)	0.0013** (0.0006)
PY GS Days >21C	0.0001 (0.0002)	0.0009* (0.0005)	0.0010** (0.0004)
Observations	75328	75328	75328
R^2	0.053		0.073

Notes: All specifications include district and year fixed effects. Standard errors are in parentheses, clustered by district. Specification (2) estimates a tobit model.

*Significant at 10%.

**Significant at 5%.

***Significant at 1%.

Table A.10: Temperature and Student Health and Absenteeism

	(1) School Absence β / SE	(2) Reason: Illness β / SE
PY Days 23-25C	0.001 (0.002)	0.004** (0.002)
PY Days 25-27C	-0.001 (0.002)	-0.002* (0.001)
PY Days >27C	0.002 (0.002)	0.004*** (0.002)
Observations	1736	1736
R^2	0.012	0.025

Notes: Includes individual, month and survey round fixed effects. We control for precipitation in all specifications. The sample includes only those children who were tested thrice in both Math and PPVT. Standard errors are in parentheses, clustered by district-week.

*Significant at 10%.

**Significant at 5%.

***Significant at 1%.

A.8 Time Use

Table A.11: Temperature and Child's Time Use (Work and Rest)

	(1) Ln Sleep β / SE	(2) Ln Child Care β / SE	(3) Ln HH Chores β / SE	(4) Ln Non-Pay Work β / SE
Days >23C	0.003 (0.002)	0.055** (0.024)	0.077* (0.042)	-0.006 (0.010)
Observations	1736	1736	1736	1736
R^2	0.051	0.030	0.319	0.029

Notes: Includes individual, month and survey round fixed effects. We control for precipitation in all specifications. The sample includes only those children who were tested thrice in both Math and PPVT. Time use variables are winsorized at the 1% level. Standard errors are in parentheses, clustered by district-week.

*Significant at 10%.

**Significant at 5%.

***Significant at 1%.

Table A.12: Temperature and Child's Time Use (Schooling)

	(1) Ln School β / SE	(2) Ln Study β / SE	(3) Ln Play β / SE
Days >23C	0.002 (0.002)	-0.041* (0.022)	-0.012 (0.009)
Observations	1736	1736	1736
R^2	0.237	0.027	0.153

Notes: Includes individual, month and survey round fixed effects. We control for precipitation in all specifications. The sample includes only those children who were tested thrice in both Math and PPVT. Time use variables are winsorized at the 1% level. Standard errors are in parentheses, clustered by district-week.

*Significant at 10%.

**Significant at 5%.

***Significant at 1%.

A.9 IHDS

Table A.13: Previous Year Temperature and Food Consumption

	(1) Log Grains Exp β / SE	(2) Log Ani Prd Exp β / SE	(3) Log Fruit Exp β / SE
Days <15C	0.0007 (0.0016)	-0.0031 (0.0073)	-0.0208** (0.0093)
Days >21C	-0.0020* (0.0010)	0.0036 (0.0040)	-0.0073 (0.0056)
Observations	16659	16659	16655
R^2	0.264	0.348	0.225

Notes: This table presents the impact of temperature in the previous year on food consumption for households with children between the ages 8-11. All specifications include district and round fixed effects. We control for precipitation in all specifications. Sample is restricted to only rural households. Standard errors are in parentheses, clustered by district.

*Significant at 10%.

**Significant at 5%.

***Significant at 1%.

Table A.14: Previous Year Temperature and Illness

	(1) Sick 0/1 β / SE	(2) Log Days Sick β / SE
Days <15C	0.0006 (0.0013)	0.0002 (0.0021)
Days >21C	0.0021*** (0.0008)	0.0023 (0.0014)
Observations	16656	16656
R^2	0.060	0.057

Notes: This table presents the impact of temperature in the previous year on illness for children between the ages 8-11. All specifications include district and round fixed effects. We control for precipitation in all specifications. Sample is restricted to only rural households. Standard errors are in parentheses, clustered by district.

*Significant at 10%.

**Significant at 5%.

***Significant at 1%.

Table A.15: Previous Year Temperature and Health Expenditure

	(1) Log OutPatient Exp β / SE	(2) Log InPatient Exp β / SE
Days <15C	-0.0088 (0.0126)	0.0051 (0.0135)
Days >21C	0.0208*** (0.0064)	-0.0003 (0.0072)
Observations	16655	16655
R^2	0.123	0.148

Notes: This table presents the impact of temperature in the previous year on health expenditure for households with children between the ages 8-11. All specifications include district and round fixed effects. We control for precipitation in all specifications. Sample is restricted to only rural households. Standard errors are in parentheses, clustered by district.

*Significant at 10%.

**Significant at 5%.

***Significant at 1%.

A.10 Long Run Temperature and Dropouts, Grade Progression

Table A.16: Long Run Temperature and Dropouts, Grade Progression

	(1) Dropout β / SE	(2) Dropout β / SE	(3) On-Track β / SE	(4) On-Track β / SE
Days <15C	-0.0000 (0.0000)		0.0000 (0.0002)	
Days >21C	-0.0001 (0.0000)		0.0001 (0.0001)	
PY Days <13C		0.0000 (0.0001)		-0.0001 (0.0003)
PY Days 13-15C		-0.0001* (0.0001)		0.0001 (0.0003)
PY Days 17-19C		0.0000 (0.0001)		-0.0002 (0.0003)
PY Days 19-21C		-0.0001 (0.0001)		0.0003 (0.0002)
PY Days 21-23C		-0.0001 (0.0001)		0.0002 (0.0003)
PY Days 23-25C		-0.0001 (0.0001)		0.0004 (0.0003)
PY Days 25-27C		-0.0001 (0.0001)		0.0001 (0.0003)
PY Days 27-29C		-0.0001* (0.0001)		0.0002 (0.0003)
PY Days >29C		-0.0001 (0.0001)		0.0002 (0.0003)
Observations	4581616	4581616	4581616	4581616
R^2	0.061	0.061	0.133	0.133

Notes: This table presents the impact of temperature in the previous year (captured via temperature bins) on probability of dropout and on-track status in the current year for children between the ages of 5-16 for 2006-2014. All specifications include district, year, and age fixed effects. We control for precipitation and humidity in all specifications. Standard errors are in parentheses, clustered by district.

*Significant at 10%.

**Significant at 5%.

***Significant at 1%.

A.11 Temperature, Rainfall and Test Scores

Table A.17: Temperature, Rainfall and Test Scores

	(1) Math Score (in SD) β / SE	(2) Math Score (in SD) β / SE	(3) Read Score (in SD) β / SE	(4) Read Score (in SD) β / SE
PY Days <15C	-0.0020*** (0.0006)	-0.0015* (0.0007)	-0.0017*** (0.0006)	-0.0010 (0.0007)
PY Days >21C	-0.0021*** (0.0005)	-0.0021*** (0.0006)	-0.0011** (0.0004)	-0.0014** (0.0006)
CY Days <15C	-0.0001 (0.0007)	0.0000 (0.0008)	-0.0006 (0.0006)	-0.0006 (0.0007)
CY Days >21C	0.0018*** (0.0005)	-0.0002 (0.0006)	0.0004 (0.0004)	-0.0000 (0.0005)
PY Rain Bottom Terc.	0.0078 (0.0111)	-0.0006 (0.0106)	0.0108 (0.0100)	0.0015 (0.0099)
PY Rain Top Terc.	-0.0258*** (0.0091)	-0.0016 (0.0096)	-0.0186** (0.0078)	0.0001 (0.0086)
CY Rain Bottom Terc.	0.0230** (0.0099)	-0.0024 (0.0111)	0.0142 (0.0089)	-0.0022 (0.0096)
CY Rain Top Terc.	-0.0512*** (0.0101)	-0.0067 (0.0104)	-0.0296*** (0.0084)	-0.0012 (0.0094)
Year Dummies	Yes	No	Yes	No
State-by-Year Dummies	No	Yes	No	Yes
Observations	4581616	4581616	4581616	4581616
R^2	0.085	0.102	0.069	0.079

Notes: This table presents the impact of temperature in the previous year, current year and next year (captured via temperature bins) on test scores in the current year for children between the ages of 5-16 for 2006-2014. Specifications 1 and 3 include district, year, and age fixed effects, while specifications 2 and 4 include district, state-by-year, and age fixed effects. We control for precipitation and humidity in all specifications. The sample includes children between the age 5-16. Standard errors are in parentheses, clustered by district.

*Significant at 10%.

**Significant at 5%.

***Significant at 1%.

A.12 Heterogeneity - Gender

(a) Math Scores

(b) Reading Scores

Figure A.4: Female vs. Male: Long Run Temperature and Reading Scores

B Appendix: NREGA

B.1 NREGA: Program Description

The National Rural Employment Guarantee Scheme (NREGS), also known as the Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA), is the largest work-fare program in the world. It legally guarantees each rural household up to 100 days of public-sector work a year at the minimum wage. The program was introduced using a backwardness index developed by the Planning Commission of India. First, it came into force in 2006 in 200 poorest districts in India; an additional 130 districts received the program in 2007, and all the remaining districts started NREGS in 2008. Any rural resident who is 18 or older can apply for work at any time of the year. Men and women are paid equally, though at least one-third beneficiaries must be women. Projects under NREGS involve construction of local infrastructure that improve water management through conservation, rain water collection and irrigation, as well as flood control, drought proofing, rural connectivity and land development. NREGS wages vary from state-to-state, but the floor as well as ceiling wage under the scheme are set by the central government.

B.2 Temperature and take-up of NREGA

Table B.1: Current and Previous Year Temperature and NREGA Take-up

	(1) Log NREGA Persons β / SE	(2) Log NREGA Persons GS β / SE	(3) Log NREGA Persons NGS β / SE
CY Days >21C	0.0164** (0.0082)	0.0119 (0.0083)	0.0185 (0.0151)
CY Days >21C	0.0384*** (0.0137)	0.0393*** (0.0134)	0.0365*** (0.0134)
PY Days <15C	-0.0029 (0.0067)	-0.0037 (0.0067)	0.0153 (0.0113)
PY Days >21C	0.0210 (0.0134)	0.0191 (0.0131)	0.0496*** (0.0142)
Observations	1578	1578	1578
R^2	0.611	0.615	0.669

Notes: This table presents the impact of temperature in the current and previous year (captured via temperature bins) on NREGA take-up in the current year for 2012-2015. All specifications include district and year fixed effects. We control for precipitation and humidity in all specifications. Standard errors are in parentheses, clustered by district.

*Significant at 10%.

**Significant at 5%.

***Significant at 1%.

B.3 Robustness: Triple Differences

Table B.2: Triple Differences: Long Run Temperature, NREGA and Test Scores

	(1) Math Score (in SD) β / SE	(2) Read Score (in SD) β / SE
Days <15C	-0.0023** (0.0011)	-0.0015 (0.0010)
Days >21C	-0.0015* (0.0008)	-0.0008 (0.0007)
NREGA Previous Yr	-0.2139*** (0.0518)	-0.1550*** (0.0496)
NREGA Previous Yr * Days >21C	0.0006*** (0.0002)	0.0004** (0.0002)
Observations	1417422	1417422
R^2	0.115	0.089

Notes: This table tests if the impact of last year's temperature were attenuated by NREGA roll-out in that year. All specifications include district, year and age fixed effects. We control for precipitation in all specifications. The sample includes children between the age 5-16. Standard errors are in parentheses, clustered by district.

*Significant at 10%. **Significant at 5%. ***Significant at 1%.

B.4 Robustness: State-by-Year FE v. Year FE

Table B.3: Event Study: Long Run Temperature, NREGA and Test Scores

	(1) Math Score (in SD) β / SE	(2) Read Score (in SD) β / SE
Time = -3	-0.0180 (0.0370)	0.0160 (0.0342)
Time = -2	-0.0331 (0.0345)	-0.0374 (0.0324)
Time = 0	-0.0754*** (0.0270)	-0.0494* (0.0254)
Time = 1	-0.1111*** (0.0366)	-0.0901** (0.0350)
Time = 2	-0.0675 (0.0638)	-0.0748 (0.0598)
Days <13C	-0.0027* (0.0015)	-0.0009 (0.0014)
Days 13-15C	-0.0010 (0.0019)	-0.0015 (0.0017)
Days 17-19C	0.0028* (0.0017)	0.0025 (0.0016)
Days 19-21C	0.0034** (0.0015)	0.0028** (0.0014)
Days 21-23C	0.0021 (0.0014)	0.0015 (0.0013)
Days 23-25C	0.0021 (0.0015)	0.0017 (0.0013)
Days 25-27C	0.0003 (0.0016)	0.0004 (0.0014)
Days 27-29C	0.0002 (0.0017)	0.0003 (0.0015)
Days >29C	-0.0009 (0.0018)	-0.0004 (0.0016)
Time = -3 * Days >29C	0.0007 (0.0005)	0.0000 (0.0005)
Time = -2 * Days >29C	0.0006 (0.0005)	0.0006 (0.0004)
Time = 0 * Days >29C	0.0002 (0.0004)	0.0000 (0.0004)
Time = 1 * Days >29C	0.0008 (0.0005)	0.0007 (0.0005)
Time = 2 * Days >29C	0.0003 (0.0010)	0.0008 (0.0010)
Observations	1866623	1866623
R^2	0.098	0.082

Notes: This table tests if the impact of last year's temperature were attenuated by NREGA roll-out in that year. To capture these effects, we have interacted the number of days in the previous year when the temperature was over 29C (bin 10) with the event time of NREGA roll-out. t=0 indicates if NREGA was implemented last year in that district. Because we are testing the effects of last year's temperature on current year's test scores, we interact previous year's NREGA roll-out with previous year's temperature, to capture attenuation. The reference temperature bin is 15-17C, and the omitted event time dummy is -1 (one year before NREGA was rolled-out in the previous year). The sample includes test scores in the current year for children between the ages of 5-16 for 2006-2009. All specifications include district, year and age fixed effects. We control for precipitation and humidity in all specifications. The sample includes children between the age 5-16. Standard errors are in parentheses, clustered by district.

Figure B.4: Event Study: Long Run Temperature, NREGA and Math Scores

Figure B.4: Event Study: Long Run Temperature, NREGA and Reading Scores

B.5 Robustness: On-track Only

Table B.4: Event Study - On-Track Children: Long Run Temperature, NREGA and Test Scores

	(1) Math Score (in SD) β / SE	(2) Read Score (in SD) β / SE
Time = -3	0.3286*** (0.0864)	0.1957** (0.0823)
Time = -2	-0.0225 (0.0846)	-0.0599 (0.0804)
Time = 0	-0.1399** (0.0563)	-0.1295** (0.0534)
Time = 1	-0.2261*** (0.0802)	-0.1936*** (0.0717)
Time = 2	-0.2924** (0.1188)	-0.2628** (0.1047)
Days <15C	-0.0036*** (0.0011)	-0.0024** (0.0010)
Days >21C	-0.0011 (0.0008)	-0.0007 (0.0007)
Time = -3 * Days >21C	-0.0011*** (0.0003)	-0.0006** (0.0003)
Time = -2 * Days >21C	0.0001 (0.0003)	0.0002 (0.0003)
Time = 0 * Days >21C	0.0003* (0.0002)	0.0003* (0.0002)
Time = 1 * Days >21C	0.0006** (0.0003)	0.0005** (0.0002)
Time = 2 * Days >21C	0.0009** (0.0004)	0.0007** (0.0004)
Observations	1430205	1430205
R^2	0.115	0.089

Notes: This table tests if the impact of last year's temperature were attenuated by NREGA roll-out in that year. To capture these effects, we have interacted the number of days in the previous year when the temperature was over 21C with the event time of NREGA roll-out. t=0 indicates if NREGA was implemented last year in that district. Because we are testing the effects of last year's temperature on current year's test scores, we interact previous year's NREGA roll-out with previous year's temperature, to capture attenuation. The reference temperature bin is 15-21C, and the omitted event time dummy is -1 (one year before NREGA was rolled-out in the previous year). The sample includes test scores in the current year for children between the ages of 5-16 for 2006-2009. All specifications include district, year and age fixed effects. We control for precipitation and humidity in all specifications. The sample includes children between the age 5-16. Standard errors are in parentheses, clustered by district. *Significant at 10%. **Significant at 5%. ***Significant at 1%.

Figure B.4: Event Study - On-Track Children: Long Run Temperature, NREGA and Math Scores

Figure B.4: Event Study - On-Track Children: Long Run Temperature, NREGA and Reading Scores

Table B.5: Difference in Difference - On-Track Children: Long Run Temperature, NREGA and Test Scores

	(1) Math Score (in SD) β / SE	(2) Read Score (in SD) β / SE
Days <15C	-0.0023** (0.0011)	-0.0014 (0.0010)
Days >21C	-0.0012 (0.0008)	-0.0007 (0.0007)
NREGA Previous Yr	-0.2055*** (0.0520)	-0.1496*** (0.0494)
NREGA Previous Yr * Days >21C	0.0006*** (0.0002)	0.0004** (0.0002)
Observations	1430205	1430205
R^2	0.114	0.089

Notes: This table tests if the impact of last year's temperature were attenuated by NREGA roll-out in that year. All specifications include district, year and age fixed effects. We control for precipitation in all specifications. The sample includes children between the age 5-16. Standard errors are in parentheses, clustered by district.

*Significant at 10%. **Significant at 5%. ***Significant at 1%.

C Appendix: Data

C.1 ASER Survey

Table C.1: Summary Statistics: Yearly Temperature Bins - 2006-2010 (Mean no. of days)

	All	2006	2007	2008	2009
Days >21C	250.49 (87.46)	249.75 (83.67)	257.84 (88.98)	245.86 (89.34)	247.68 (91.98)
PY Days <13C	32.40 (66.61)	30.47 (66.87)	27.98 (68.11)	34.53 (68.12)	33.28 (70.30)
PY Days 13-15C	16.48 (15.14)	18.39 (15.81)	15.12 (15.37)	16.94 (15.65)	17.29 (15.73)
PY Days 15-17C	19.30 (15.82)	18.46 (13.64)	16.44 (14.12)	18.23 (15.47)	19.38 (16.07)
PY Days 17-19C	21.22 (14.31)	22.96 (14.79)	20.03 (14.27)	23.35 (15.89)	21.44 (14.82)
PY Days 19-21C	25.32 (16.60)	24.98 (16.52)	27.58 (16.66)	26.08 (17.06)	26.93 (19.14)
PY Days 21-23C	42.87 (39.03)	39.58 (35.31)	45.81 (34.81)	43.98 (39.47)	47.54 (44.44)
PY Days 23-25C	60.30 (44.20)	56.48 (40.39)	59.98 (43.76)	60.63 (47.83)	67.36 (50.07)
PY Days 25-27C	61.43 (35.77)	60.97 (31.17)	60.51 (35.36)	57.59 (37.54)	66.55 (42.17)
PY Days 27-29C	38.59 (27.97)	40.44 (26.35)	44.34 (30.09)	39.67 (30.51)	31.87 (26.94)
PY Days >29C	47.30 (38.38)	52.28 (37.69)	47.20 (39.34)	43.99 (38.60)	34.35 (31.32)

Notes: Standard deviations are in parentheses.

Table C.2: Summary Statistics: Yearly Temperature Bins - 2011-2014 (Mean no. of days)

	2011	2012	2013	2014	2015
Days >21C	259.09 (84.50)	254.12 (89.84)	248.89 (88.67)	246.54 (81.46)	244.75 (87.12)
PY Days <13C	23.54 (58.18)	34.45 (68.93)	37.28 (67.21)	34.82 (61.96)	35.25 (68.00)
PY Days 13-15C	14.68 (15.45)	18.29 (15.42)	14.36 (13.80)	17.41 (14.06)	15.93 (14.29)
PY Days 15-17C	21.67 (18.16)	17.83 (13.68)	17.54 (15.37)	20.10 (14.47)	24.04 (19.06)
PY Days 17-19C	21.23 (14.91)	17.82 (12.36)	20.72 (14.27)	21.16 (11.87)	22.24 (14.34)
PY Days 19-21C	24.79 (16.58)	22.49 (15.72)	26.22 (16.71)	25.97 (13.71)	22.79 (16.05)
PY Days 21-23C	42.36 (36.68)	41.44 (40.27)	42.99 (41.21)	38.95 (36.64)	42.88 (40.64)
PY Days 23-25C	57.49 (41.00)	56.00 (41.56)	64.73 (46.61)	57.75 (40.65)	61.87 (43.42)
PY Days 25-27C	59.68 (33.42)	58.92 (33.65)	66.19 (37.75)	59.31 (31.86)	62.98 (36.40)
PY Days 27-29C	42.17 (27.23)	38.99 (27.52)	37.30 (27.60)	35.28 (24.55)	37.34 (28.47)
PY Days >29C	57.39 (42.69)	58.77 (42.00)	37.67 (32.50)	55.24 (38.43)	39.68 (32.87)

Notes: Standard deviations are in parentheses.