Effects of Heat Stress on Physiology and Livelihoods: Implications for Human Capital Accumulation*

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Abstract

We present estimates of the effects of extreme temperatures on human capital accumulation in India. Short-run temperature reduces math but not reading test scores through a physiological mechanism. However this effect is temporary; hot days prior to the day of the test have no effect on performance. Longer-run temperature, in contrast, reduces both math and reading test scores through an agricultural 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, substantially weakens the link between longer-run temperature and test scores. Our results indicate that (1) extreme temperatures can affect a single economic outcome through multiple channels over different time horizons requiring multiple policy instruments to combat rising heat stress and (2) that absent social protection programs, climate change will have disproportionate and large negative impacts on human capital accumulation of poor populations in agrarian economies.

JEL Codes: H41, I0, Q5, Q54
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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*b*). 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 effects of short- and longer-run temperature on 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 math and reading tests of primary and secondary school children as an output measure of human capital accumulation to examine how extreme temperatures affect test performance. We identify two distinct mechanisms of impact - physiological effects of short-run temperature and reduced agricultural productivity from longer-run temperature and estimate impacts of policy interventions designed to offset fluctuations in agricultural income. In developed countries, temperature affects performance primarily through exposure to higher temperatures on the day of the test and the sensitivity of certain parts of the brain to those higher temperatures, effects that can likely be offset by climate-controlled classrooms and test centers (Graff-Zivin, Hsiang and Neidell, 2015; Park, 2017). 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 mechanism.[1]

We first estimate the effect of short-run temperature – measured as the average tempera-

[1]While 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 (Basu and Samet, 2002; IPCC, 2014; Deschenes and Moretti, 2009; Deschênes and Greenstone, 2011; Barreca et al., 2016). 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 (Deschenes and Moretti, 2009; Deschênes and Greenstone, 2011). 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 (Almond, Edlund and Palme, 2009; Almond and Currie, 2011; Sanders, 2012; Black et al., 2013; Isen, Rossin-Slater and Walker, 2015; Bharadwaj, Løken and Neilson, 2013; Bharadwaj et al., 2017). For instance, Isen, Rossin-Slater and Walker (2015), find that early childhood exposure to extreme heat causes a decrease in later-life earnings.

ture on the day of the test – on cognitive performance. We find that the day-of-test average temperature above 27C (80F) relative to day-of-test average temperature below 23C (73F) reduces math score performance by 0.3 standard deviations. Consistent with a physiological mechanism wherein the temperature sensitive part of the brain performs mathematical tasks, we find no effect of higher temperatures on reading scores (Hocking et al., 2001). Our estimates are remarkably similar to other estimates found in developed countries (Graff-Zivin, Hsiang and Neidell, 2015; Park, 2017; Cho, 2017). 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).[2]

Second, using math and reading test scores from multiple data sets – a rich longitudinal study from the state of Andhra Pradesh, and over 4 million tests from an annual survey of educational achievement conducted across India in the last decade – we show that over a longer-run horizon, measured as the number of hot days in the calendar year prior to the test, extreme temperatures affect both math and reading scores; in our individual panel data (repeated cross-sectional data) one extra day in a year with average *daily* temperature above 27C (29C) relative to less than 23C (15C-17C) reduces math and reading test performance by 0.007 (0.003) and 0.010 (0.002) standard deviations respectively.[3] These are large effects; an extra 40 hot days above 27C in a year, as is expected in India by the end of the 21st century, would reduce math and reading test scores by 0.28 and 0.4 standard deviations respectively, equivalent to wiping out 2-3 times the gains from the median educational intervention.[4]

We find strong evidence that the likely underlying mechanism is driven through the harmful effect of higher temperatures to agricultural yields: (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

[2]More permanent *economic* effects can still arise from short-term physiological effects of heat stress on performance when high stakes exams introduce path dependence in human capital accumulation as in the case of Park (2017). Ebenstein, Lavy and Roth (2016) demonstrate similar longer-term effects through short-run effects of ambient air pollution on test scores in Israel.

[3]We don't have information on the exact date of the tests in the all India repeated cross section and so we use the previous calendar year. We find comparable estimates across the sample of cognitive tests from the individual panel data set where we have the exact date and time of the test and the all India repeated cross section data where we only know the year of the test. We elaborate on this in the data and results section.

[4]See McEwan (2015) for a review of educational interventions in developing countries. The effect of the median educational intervention is between 0.08 and 0.15 standard deviations.

areas that grow below-median levels of heat resistant crops, and (c) extreme temperatures have large negative effects on agricultural yields and rural wages.[5] Moreover, we rule out alternative explanations such as heat stress affecting learning in schools, teacher attendance and disease prevalence that could, in theory, mediate the relationship between longer-run temperature and test scores.

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. Our NREGA results not only reinforce the underlying agricultural income mechanism linking hotter days to lower test scores, but also demonstrate the critical role of social protection programs in helping the poor cope with climate stressors.

In investigating how higher temperatures affect performance and human capital, we connect three distinct literatures. The first is the literature in climate and environmental economics that examines the relationship between hot weather and a variety of economic outcomes of interest including output (Burke, Hsiang and Miguel, 2015*b*; Somanathan et al., 2015; Burke and Emerick, 2016), mortality (Deschenes and Moretti, 2009; Barreca et al., 2016; Burgess et al., 2017) and conflict (Burke, Hsiang and Miguel, 2015*a*). A small number of new papers have considered the relationship between temperature and human capital (Graff-Zivin, Hsiang and Neidell, 2015; Park, 2017; Cho, 2017). In contrast to prior work, which has emphasized a single pathway between weather and an outcome of interest, we show that there can exist multiple mechanisms between weather and a single outcome of interest over different time scales. In the case of human capital as discussed in this paper,

[5] Higher wages increase human capital investments (Jacoby and Skoufias, 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 et al., 2017). 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.

we find that day-of-test effects are driven by physiological effects of heat stress, whereas the longer-run annual effects are driven by the effects of weather on livelihoods. Consequently, adaptation to a single climate stressor will require multiple policy instruments; climate-controlled classrooms or climate-cognizant test calendars will reduce the effects of short-run temperature, but income stabilizing social protection programs may be needed to reduce the damage from longer-run temperature. Importantly, 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 (Dell, Jones and Olken, 2012, 2014; Burke and Emerick, 2016). To the best of our knowledge, we are the first to provide evidence of different structural relationships over different time scales between temperature and a single economic outcome, suggesting that inferring the extent of adaptation from comparisons of the effects of short- and longer-run temperature may not be appropriate in all contexts.[6] In fact, if we were to compare our estimates of the effect of short- and longer-run temperature, we would incorrectly conclude that the rural poor were able to adapt almost perfectly (97%) within a year, masking the large effects of heat stress on both physiology and livelihoods and subsequently human capital accumulation.

Second, in public economics, we build on a vast literature on the effects of social protection programs (see, for e.g., Fiszbein et al. (2009) for an exhaustive review on conditional cash transfers). Even though there is considerable research on the level effects of such programs, little is known about the extent to which such social protection programs can attenuate the effect of weather shocks (Adhvaryu et al., 2015). Our paper is the first to provide evidence on the role of social protection programs in helping households in poor countries to cope contemporaneously with extreme temperatures. Furthermore, we isolate the distributional consequences of heat stress arising out of income differences from non-linearities in the so-called "damage function" (Hsiang, Oliva and Walker, 2017). The NREGA research design (employing an event-study framework and a triple differences approach) allows us to overcome the econometric challenge of non-random assignment of observable drivers of het-

[6] Recent work by Shrader (2016) provides a method to use informational interventions to quantify the ex-ante benefit of adaptation.

erogeneity (e.g., income) in the marginal effects of heat stress. As such we demonstrate that not only do social protection programs such as NREGA have level effects as demonstrated elsewhere in the literature (Liu and Barrett, 2013; Shah and Steinberg, 2015; Imbert and Papp, 2015; Khanna and Zimmermann, 2017), but they also reduce the temperature sensitivity of poor households, providing benefits that have previously received little consideration.[7] In doing so, we contribute to a long-standing literature on weather shocks and consumption smoothing amongst the rural poor (Rosenzweig and Stark, 1989; Rosenzweig and Wolpin, 1993; Paxson, 1993; Townsend, 1994; Deaton, 1997; Dercon and Krishnan, 2000; Dercon, 2005; Cole et al., 2013) and demonstrate that the ability of rural populations to smooth consumption over district-level aggregate weather shocks in agrarian areas will remain limited, absent social programs designed to offset fluctuations in agricultural income (Burgess et al., 2017).

Third, in the literature in development economics that examines the drivers of and barriers to human capital accumulation, we are the first to demonstrate the effects of heat stress on human capital accumulation in a developing country context. Our estimates of the physiological effects of heat stress compare to those found in the the US (Graff-Zivin, Hsiang and Neidell, 2015; Park, 2017) and South Korea (Cho, 2017). The remarkable similarity in the physiological effects of short-run temperature across developed and developing countries suggests that economic development may insulate countries from some but not all effects of climate change.

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 social protection programs in attenuating the marginal effect of temperature. Finally, in section 6 we provide concluding remarks.

[7] The closest work to us in this regard is Fetzer (2014) who shows that NREGA weakens the relationship between rainfall and conflict.

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 2005.[8] 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 India.[9] 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

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

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

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 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).[10] 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, 2006 and 2009 and 2013/14. 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

[10] Andhra 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.

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-longitude grid, from 1979 to present day.[11] To construct weather variables for each district or village, we construct an inverse-distance weighted average of all the weather grid points within a 100 kilometer 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 D.1 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), and data on NREGA. In this subsection we describe these data and the respective sources.

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

Agricultural Yields and Rural Wages

We use agricultural data from the Village Dynamics in South Asia Meso data set, 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). ICRISAT also provides data on district level averages of rural wages.

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 2006-2016 from the Management Information Systems (MIS).[12] In particular, we focus on the number of rural households enrolled in NREGA in a particular district in a given year.

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 temperature[13].

We perform our short-run analysis on data from the Young Lives Survey which provides

[12] We thank Cl'ement Imbert for sharing these data.

[13] There 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, Kala and Nyshadham, 2015). Exposure to heat has also been show to diminish attention, memory, information retention and processing, and the performance of psycho-perceptual tasks (Hyde et al., 1997; Vasmatzidis, Schlegel and Hancock, 2002)

the date of the cognitive test.[14] Since the YLS is an individual panel, we exploit within-child variation in exposure to temperature on the day of test on different waves of the survey. Given that the timing of the test is generally pre-arranged and invariant to short-run fluctuations in weather, an assumption we formally test, 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. We selected 23C as the cutoff since it represents the 25th percentile of the average daily temperatures in the state of Andhra Pradesh.

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

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 (α_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 within a district 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 the day-of-test temperature on performance is constant above and below 23C. We relax this assumption employ a second, more flexible specification that relaxes the constant marginal effect assumption over smaller temperature bins. The choice of temperature bins is motivated by 23C and 27C representing the 25th and 75th percentile of daily temperature distribution

[14] We 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.

with equally spaced bins in between.

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

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 4. 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 a 1C increase in average day-of-test temperature being above 23C reduces within-cohort math test performance by 0.17 standard deviations.[15] To allow for non-linearity in the marginal effects of temperature, we estimate our preferred specification is equation (2) as illustrated in figure 5(a). To the extent that other mechanisms such as income effects and cumulative learning manifest over a duration longer than a single day, the effects of short-run or day-of-test temperature is likely a 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.

[15] Our magnitudes are comparable to those found in developed countries. (Graff-Zivin, Hsiang and Neidell, 2015) find marginal effects of 0.2 standard deviations for every degree centigrade above 21C and (Park, 2017) finds a marginal effect of 0.1 standard deviations for every degree centigrade above 23C.

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 5(b)). Our results are consistent those in prior work in developed countries (Graff-Zivin, Hsiang and Neidell, 2015). The subject-specific effect of day-of-test temperature on performance suggests that the underlying mechanism is likely physiological rather than behavioral.

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.1).[16]

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

[16] 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 (table A.2). 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.

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, 2017). In our study, however, we evaluate the effects of temperature on low-stakes cognitive tests and abstract away from this pathway. While we acknowledge the possibility of this pathway, we will demonstrate that this is not the mechanism for the effects of longer-run temperature that we discuss in section 4.3.

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 lags on the effects of short-run temperature. We find no evidence for the persistence of the effects of short-run temperature on test scores; over the four days prior to the test, heat stress has no effect on test performance (figure 5). This pattern largely holds for at least up to 4 weeks of leads and lags (figures A.1 - A.3). 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 cognitive performance 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 cumulative heat exposure in classrooms or through lowering agricultural yields and income resulting in lower human capital investments. In the next section, we demonstrate that longer-run temperature affects human capital accumulation through the agricultural income channel and rule out competing explanations.

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 reduction in agricultural income and subsequently rule out alternative channels.

4.1 Research Design

To examine the effect of temperature on test scores in the longer-run, we employ the YLS and ASER data sets. While the YLS data set provides an individual level panel but with coverage limited to a single state. In contrast, the ASER data set has the advantage of national coverage with greater spatial variation in temperature exposure with a repeated cross-section at the district level. With each data set we estimate both flexible and parsimonious models.

Individual Panel Data (YLS)

Using the YLS survey we first estimate the following flexible model of the effects of temperature on test scores:

$$\begin{aligned} Y_{ijdm,t} = \gamma_2 T(23-25C)_{j,t-1} + \gamma_3 T(25-27C)_{j,t-1} + \gamma_4 T(>27C)_{j,t-1} \\ + f\left(rain_{j,t-1}\right) + g\left(humidity_{j,t-1}\right) + \alpha_i + \mu_{1d} + \mu_{2m} + \mu_{3t} + \epsilon_{ijdmt} \end{aligned} \tag{3}$$

$Y_{ijdm,t+1}$ 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 $t+1$, standardized by year-age. We control for cumulative rainfall and relative humidity (both in terciles), and include fixed effects for child (α_i), day-of-week (μ_{1d}), month-of-year (μ_{2m}) and year of survey (μ_{3t}). $T(\cdot)$ is a count of the number of the days since the previous test with average daily temperature within the specified range. For example, $T(23-25C)$ is the number of days since the last test with average daily temperature between 23C and 25C. Since the YLS data covers a single state (Andhra Pradesh), the temperature distribution is narrower than in other data sets we use in this paper that cover all of India. Since the number of days in a year is fixed at 365, we normalize the coefficient on the "optimal" temperature bin, in this case $T(<23C_{jt})$, to zero making it the reference bin. Thus γ_4 is the marginal effect of an extra day since the last test with average temperature above 27C relative to a day with average temperature below 23C. Our four temperature bins have, on average, an equal density. We cluster standard errors at the district-week level to allow for arbitrary correlation in test scores in a district in a week and for conservative inference when multiple children are assigned the same temperature observation.[17] The identifying assumption is that changes in the number of hot days experienced by a student in a given bin between successive tests is exogenous to changes in the student's test scores. Importantly, by tracking the same students over time, we are able to account for prior human-capital accumulation and provide causal estimates of the effects of the daily temperature distribution between successive tests on changes in student test performance.

We also estimate a second parsimonious approach with a single temperature cut off instead of flexible evenly spaced temperature bins:

$$\begin{aligned} Y_{ijdmt} = {} & \gamma T(>23C)_{j,t-1} + f\left(rain_{j,t-1}\right) + g\left(humidity_{j,t-1}\right) \\ & + \alpha_i + \mu_{1d} + \mu_{2m} + \mu_{3t} + \epsilon_{ijdmt} \end{aligned} \tag{4}$$

The notation is the same as in equation (3) with the key difference that $T(>23C)_{jt}$ is a count of the number of days above 23C experienced by a student district j between successive tests. As is common practice in the literature on climate economics, our choice of 23C for the parsimonious approach follows the (approximation of the) nonparametric analysis (equation 3) that revealed a kink at that level (Hsiang, 2016).

All India Repeated Cross Sectional Data (ASER)

While the YLS is rich data set that has the advantage of tracking the same students over many years, the coverage is limited to a single state. To understand the relationship between longer-run temperature and test scores throughout India, we employ the ASER data set. As in the case of YLS, we first estimate a flexible model:

$$Y_{ijqt} = \sum_{k=1}^{10} \gamma_k TMEAN^k_{jq,t-1} + f\left(rain_{jq,t-1}\right) + g\left(humidity_{jq,t-1}\right) + \alpha_j + \mu_t + \epsilon_{ijqt} \tag{5}$$

Y_{ijqt} is math or reading test scores for child i, in district j, in state q, in year $t+$

[17] In the YLS data, the lowest geographic identifier that is available is the district and the survey covers only 7 districts making it infeasible to cluster standard errors at the district level. In subsequent analysis with the ASER data, we are able to provide even more conservative inference by clustering standard errors at the district and state levels.

1, standardized by year-age. As with previous YLS specifications, the main explanatory variables of interest capture the distribution of daily average temperatures in district j in state q in time t. $TMEAN^k_{jqt}$ is the k^{th} of 10 temperature bins. We estimate separate coefficients γ_k for each of these k bins. The coldest temperature bin is a count of the number of days with average temperature less than 13C and the hottest temperature bin is a count of the number of days with average temperature greater than 29C. The bins in between are evenly spaced two degrees apart. We normalize the coefficient on the number of days in the optimal bin 15C-17C, relative to which we interpret all other coefficients. For example, γ_{10}, the coefficient on the hottest bin, is 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), relative humidity (in terciles of annual averages), district fixed effects (α_j) and year fixed effects (μ_t).[18] 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 randomness of weather fluctuations and the inability of rural households in India to predict such fluctuations. 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 (Hsiang, 2016). As in the case of the YLS, we also estimate a parsimonious version of equation (5) with the threshold of 21C. Our choice of 21C for the parsimonious model was chosen based on the (approximation of the) nonparametric analysis (equation 5) that revealed a kink at that level.

$$Y_{ijqt} = \gamma TMEAN(>21C)^k_{jq,t-1} + f\left(rain_{jq,t-1}\right) + g\left(humidity_{jq,t-1}\right) + \alpha_j + \mu_t + \epsilon_{ijqt} \qquad (6)$$

There is one additional distinction between the YLS and the ASER data sets that is worth noting. The YLS data set has the advantage of recording the exact day of the test

[18] Our results are robust to alternative specifications of rainfall including linear and quadratic terms for total annual rainfall. Those results are available on request.

and therefore allows us to precisely capture the exact distribution of daily temperature between successive tests. However, the ASER data does not provide the exact date of the test. We do know that the test is conducted in a given district on a weekend between the end of September and the end of November. If heat stress affects cognitive performance through an agricultural income channel, there must be at least one full agricultural cycle prior to the test (see figure 6). Therefore, we use the daily temperature distribution of the prior calendar year.[19] Importantly, this also sets up a falsification test for competing explanations that do not adhere to an agricultural calendar; while temperature in the previous year could affect test scores through an agricultural income channel, temperature in the same year as the test (the "current year") would affect test scores through other channels as well (e.g. learning, teacher attendance, disease prevalence etc. as detailed in section 4.4).

4.2 Results

We estimate equations (3) and (4) and find that an extra day between successive tests above 27C relative to below 23C, reduce math and reading test scores by 0.007 and 0.01 standard deviations respectively (table 2, figure 7). An extra 40 days above 27C, as is expected in India by the end of the century, would reduce performance in math and reading scores by 0.28 and 0.4 standard deviations effectively erasing 2-3 times the gains from a median educational intervention.[20] To remove any spurious effects from day of test temperature that could be correlated with number of hot days in a year in a given district, we also control for day-of-test temperature while estimating equations (3) and (4). In appendix table A.3, we show that including day-of-test temperature as a control doesn't change the effects of longer-term temperature on performance. Additionally, our results are robust to the inclusion of state-specific linear and quadratic trends (see appendix section A.2.4).

Next, we estimate equation (5) 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 3). In fact, using our binned approach, we find that test

[19] Shah and Steinberg (2016) similarly use rainfall shocks in the calendar year prior to the test as a proxy for wages.

[20] See McEwan (2015) for a review of educational interventions. The median intervention has an effect between 0.08-0.15 standard deviations.

performance decreases linearly in temperatures above 17C (figure 8). As a falsification test, we find no effect of hotter days in the current year or next year on performance in the current year (table 4). 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.2.2).

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 damage to the livelihoods of agrarian households. In section 4.4 we rule out alternative explanations.

4.3 Mechanisms

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, we find strong evidence to support an income mechanism underscoring the effect of temperature on test scores. In this section we first provide evidence that agricultural yields and rural income respond negatively to higher temperatures. Next, we use the ASER data to provide two distinct tests to support the agricultural income hypothesis: a) comparing effects of hot days across the growing and non-growing seasons of the agricultural calendar (following Burgess et al. (2017)), and b) comparing effects of heat on test scores across the dispersion of geographic dispersion of heat resistant crops.[21]

Temperature, Agricultural Yields and Rural Wages

To demonstrate that longer-run temperature affects human capital accumulation by affecting the livelihoods of the rural poor, we first demonstrate that temperature affects agricultural yields and rural wages. We find that agricultural yields and rural wages are highly responsive to higher temperatures (figure 9; table 5). We use two different price weighted agricultural

[21] While we find strong evidence in favor of an income mechanism, we remain agnostic about why income matters. We take cue from the rich body of evidence exploiting experimental and quasi-experimental variation in income to study the impacts on academic performance and find suggestive evidence for nutrition as the relevant margin of adjustment. We discuss these in appendix B. For a comprehensive review of the impacts of cash transfer programs, see Fiszbein et al. (2009).

yield indices: a) the 6 major crops and b) the 5 major monsoon crops.[22] We find that yields respond non-linearly to temperature (figure 10(a), 10(b)); an extra day above 29C (relative to a day between 15 and 17C) decrease yields by 0.5% - 0.7%. Rural wages respond linearly to higher temperatures (figure 10(c)); an extra day above 29C (relative to a day between 15 and 17C) decreases rural wages by 0.4%.[23]

Growing v. Non-Growing Season

To isolate effects by growing and non-growing season, we subdivide each temperature bin in equation (5) into hot days in that bin in the growing season and hot days in that bin in the non-growing season.[24] We find that 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. Specifically, an 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 6). 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 scores (figure 10).

Additionally, we test the impact of temperature across the growing and non-growing season on agricultural yields in the 6 major crops as well as the 5 major monsoon crops. 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 season relative to a day between 15C and 17C reduces yields by 1% (table A.8) with no effect of temperature

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

[23] Our estimates are comparable to those found elsewhere in the literature (Burgess et al., 2017; Carleton, 2017; Taraz, 2017). Consistent with our finding of extremely cold days also reducing cognitive performance, cold days also reduce agricultural yields though to a lesser extent than hot days do.

[24] We broadly follow (Burgess et al., 2017) in partitioning every year's weather data for each district into the growing and non-growing season. However, while Burgess et al. (2017) 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 beings 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.

on yields in the non-growing season.[25] The large impact of temperature on yields in the growing but not in the non-growing season is consistent with a model where temperature affects test scores through declines in agricultural income. In section 4.4 we rule out four alternative explanations: (1) heat stress during the school year, (2) heat stress from working on the field, (3) teacher attendance and (4) malaria.

Heat Resistant Crops

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 crops.[26] Since we are interested in the interaction term on heat resistant crops and temperature, we estimate the parsimonious equation (6) to preserve power. We find that growing heat resistant crops erases most of the effect of longer-run temperature on test scores. An extra 10 hot days above 21C in districts that grow below-median levels of heat-resistant crops lowers math scores by 0.022 standard deviations compared with a near-null effect in districts that grow above-median levels of heat-resistant crops (table 7).

However, the decision to plant heat resistant crops is endogenous to, amongst other factors, long-term average temperature or the "climate normal". Therefore, the decision to grow heat resistant crops could be a proxy for underlying economic conditions that reflect adaptation to long-term average temperatures along agricultural (e.g., heat resistant crops) and non-agricultural (e.g., fans) margins. To investigate the differences in the effects of temperature on test scores across different long-term historical climates, we break down the relationship between temperature and test scores based on long-term average temperatures. We find that districts with higher long-term average temperature plant a larger fraction of their total cultivated area with heat resistant crops (figure 13(a)). In the lower and middle deciles, there is very little take up of heat resistant crops but in districts with the highest

[25] We are unable to observe differences in the responsiveness of rural wages to temperature since we have only annual average wages but not wages broken down by the growing and non-growing season.

[26] Following 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 crop district if it's long-run average of the proportion of C4 crops is above the median value (which is 23%). In appendix figure A.6 we show the geographic distribution of the take-up of heat resistant crops.

long term average temperatures, over 30% of the total cultivated area is covered by heat resistant crops. Furthermore, the relationship between hot days above 29C and test scores largely follows the take up of heat-resistant crops; the effects are present only in the middle climate deciles, where there are enough hot days to find a discernible effect but the take-up of heat resistant crops remains low, for both math (figure 13(b)) and reading scores (figure 13(c)).[27] In the hottest climate deciles, as expected, there is little effect of hot days in the previous year on test scores with high prevalence of heat resistant crops.[28]

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 four alternative explanations: (1) higher temperatures during the school year affect learning which subsequently affects performance, (2) kids working on the field are exposed to higher temperatures, (3) higher temperatures increase cost of attendance for teachers, resulting in teacher absenteeism and lower test performance by students, and (4) higher temperatures may increase disease incidence directly by favoring growth of disease carrying pathogens and thereby affecting learning and test performance.

4.4.1 Heat During the School Year

The effect of short-run heat stress on cognitive performance could also manifest physiologically into reduced learning. If children are repeatedly exposed to heat stress during the school, then the cumulative effect of that heat stress can affect performance as a result of impaired learning. Thus the effect of hot days in the previous year on performance in the current year could also be the cumulative physiological effect of heat stress on the learning. To rule out this explanation, we first show that only hot days in the previous calendar year affect performance in the current year with hot days in the current year having no effect

[27]It is possible that the effects of temperature are limited to the middle terciles for entirely mechanical reasons - cold deciles don't have enough hot days and the warmest deciles have only hot days. However, the number of days above 21C across all but the two coldest deciles are very similar, making it unlikely that the dominant effects of hotter days in the middle deciles relative to other deciles are a result of a mechanical relationship.

[28]These results are consistent with earlier work that has found crop yields in hot regions are less sensitive to higher temperatures, due to agricultural adaptation (Taraz, 2017).

on test scores (table 4). If the physiological mechanism were driving the relationship between longer-run temperature and test scores, we would see the effects on performance of hot days in both the current year and previous year. As explained in figure 6, only hot days in the previous calendar year should affect test scores in the current through the agricultural income channel.

Second, the physiological channel, unlike the agricultural income channel, should not be contingent on the agricultural calendar. However, as noted previously, we see strong effects of hot days in the previous year's growing season on test score performance but no effect of hot days in the non-growing season (figure 10). To rule out concerns of overlapping agricultural and schooling calendars, we further split the growing season by months when the school is in session and when students are on break.[29] Our hypothesis is that the physiological effects of heat on learning should be limited to hot days in the school year whereas the agricultural income mechanism should be in play during school and non-school months. Consistent with an agricultural income mechanism, we find that hot days in school and non-school months have similar effects on performance (figure 13) suggesting that the relationship between higher temperatures in the prior year and test scores is not driven by reduced learning due to heat stress in the classroom.

4.4.2 Heat Exposure on the Field

In addition to the income mechanism, the large effects of heat in the growing season juxtaposed against the negligible effects of heat during the non-growing season, could also be explained by heat exposure to agricultural workers from working in the field. However, we find two pieces of evidence inconsistent with this possibility. First, heat stress during the concurrent year as the test has no effect on test scores (table 4). If heat stress from working on the field were driving the result, we would also expect to see effects in the concurrent year. Second, our test score results are limited to children between the ages of 5-16 and don't include adults who typically work the fields. Importantly, we see no effect of heat stress on the time spent by children working outdoors (appendix table B.5). Furthermore,

[29]Within the growing season that lasts from June through December, June and December typically have summer and winter holidays, with school in session more or less continuously from July through November.

if the on-field heat-exposure explanation were true, we would expect larger effects on older and male children who are the more likely to work on the field. In contrast, we find that the effects of temperature on test scores are largest for younger children (figure 14) with no discernible differences between the effects of heat on test scores of boys and girls (figure A.5).

4.4.3 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, 2014*a*,*b*). Hot temperatures can increase the cost of effort required to attend school, and lead to teacher absenteeism and consequently impact of human capital accumulation.[30] However, we find two pieces of evidence that are inconsistent with such a hypothesis. First, if teachers were skipping school or expending less effort in classrooms in response to heat stress, we would see the effects on performance of only hot days during the school year (figure 13). The near-identical effects of heat in the school and non-school year suggest that teacher effort and attendance cannot explain our results.

Second, we explicitly test 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.

[30]This problem is notable in India. 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.

4.4.4 Disease Prevalence

An alternative explanation to the longer-run temperature test score relationship could be through increased disease incidence (Patz et al., 2005). To the extent that health affects performance, temperature could affect performance through an increase in the population of disease carrying pathogens, particularly those carrying malaria. Importantly, we consider this mechanisms distinct from the agricultural income channel where reduced household income affects health status including vulnerability to disease (through, for e.g., nutrition). However, given the lifecycle of disease pathogens, we would expect that more recent higher temperatures to have a larger effect on health and therefore performance than similar days in previous years. Malaria, for example, is transferred through the *Anopheles* mosquito which typically has a lifecycle of about 2-4 weeks so if malarial incidence was driving our result, we should see an impact of hot days in the current year as well. In table 4, we show that temperature in the current year has no effect on test score performance.[31]

Second since some of the rainiest months of the year are in the growing season, the growing season v. non-growing season results may not rule out the malaria channel since rainfall and humidity favor *Anopheles* growth. Not only do we control for rainfall and humidity in our main specification (tables 3 and 5), we also show that when accounting for state-by-year fixed effects, rainfall has no measurable effect on test scores while hot days in the previous year have a stable effect (appendix table A.11). This suggests that the disease ecology of malaria is not driving the temperature-test score relationship.

Third, we follow Shah and Steinberg (2016) and exploit the geographic differences in prevalence of malaria across India and show that the effects of temperature don't vary across those states (Chhatisgarh, Jharkhand, Orissa, Karnataka and West Bengal). In figure A.7 we compare all other states against these malaria-prone states. Importantly, we show that during the growing season, there is no meaningful difference in the effects of temperature on test scores across malaria-prone and other states suggesting that malaria is unlikely to be the driving factor behind the negative relationship between higher temperatures and test scores.

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

5 Role of Social Protection Programs

In the results so far, we have established that longer-run temperature affects human capital through the agricultural income channel. The immediate implication of this finding is that social protection programs designed to offset fluctuations in agricultural income should 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 C.1.

5.1 Research Design

Our hypothesis is that reductions in agricultural income adversely affect cognitive performance. If NREGA modulates this relationship, it must be the case that NREGA in the agrarian year prior to the test 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 test both these hypothesis by performing an event study of the introduction of NREGA on the marginal effect of an extra hot day above 29C (relative to between 15-17C).

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.

We estimate the following equation:

$$
\begin{aligned}
Y_{ijqt} = & \sum_{k=1}^{10} \gamma_k TMEAN_{jq,t-1}^{k} + \sum_{\tau=-3,\tau\neq -1}^{\tau=2} \theta_\tau NREGA(t - T_j^* = \tau)_{jq,t-\tau} * TMEAN_{ijq,t-1}^{10} \\
& + \sum_{\tau=-3,\tau\neq -1}^{\tau=2} \beta_\tau NREGA(t - T_j^* = \tau)_{jq,t-\tau} + f(rain_{ijq,t-1}) + g(humidity_{ijq,t-1}) \\
& + \alpha_j + \mu_{qt} + \epsilon_{ijqt}
\end{aligned} \tag{7}
$$

The equation is identical to equation (5) with two additional sets of terms. The first $NREGA(t - T_j^* = \tau)_{jq,t-\tau} * TMEAN_{ijq,t-1}^{10}$ captures the interaction of NREGA roll-out with the number of days in the hottest temperature bin. Specifically, we estimate separate coefficients on the hottest temperature bin for the periods before and after the introduction of NREGA in district j in state q. The omitted period is the year before NREGA is introduced in a district and we interpret the coefficient of interest θ_τ relative to the period just before NREGA was introduced. In our baseline specification, we include district (α_j) and state-by-year (μ_{qt}) fixed effects. Since the implementation of NREGA was left up to the states, including state-by-year fixed effects removes any confounders that vary by state over time (e.g., state-level administrative capabilities, corruption in state government, taxation rules etc.) allowing us to compare districts within NREGA to each other before and after the introduction of NREGA (Chakraborty, 2007). In appendix C we provide a number of different robustness checks including using a triple-differences design to estimate the effect of NREGA on the marginal effect of an extra hot day in the previous calendar year.

5.2 Results

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 8). Figure 15 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.[32]

We note that the effects of NREGA represent "intent-to-treat" (ITT) estimates since not all households in a district will respond by taking up NREGA. Importantly, only those households will sign up for NREGA for whom the opportunity cost of labor is lower than the NREGA wage. As such we are likely underestimating the effect of NREGA in reducing the sensitivity of test scores to higher temperatures.

Since workfare requires individuals to sign up for work, it would be reasonable to expect NREGA take up to contemporaneously respond to higher temperature if it is indeed being used to offset declines in agricultural incomes. We find that NREGA take-up responds to temperature. We obtain annual NREGA take-up and expenditure data from 2006-2016 and show that hotter days in the current year drive NREGA take up and expenditures (figure 9; appendix table C.1). Specifically, an extra hot day with average temperature above 29C in a district (relative to a day between 15C and 17C), increases NREGA take up by nearly 1.3%. For the same extra hot day in a year, households are 3.4% more likely to use all 100 days of eligibility in the program. For each extra day above 29C, district NREGA expenditure increases by 2% on labor and nearly 3% on materials. These results suggest that households use NREGA to stabilize damage to agricultural income in hotter years.

The remarkable effect of NREGA in attenuating the 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 social protection programs can attenuate the negative effects of higher temperatures. The implication is that in poor countries where large parts of the population are dependent on agriculture, social protection programs can play a central role in shielding the poor from weather and facilitating adaptation to climate change.

Second, while there is considerable work on the benefits of conditional cash transfers and similar social protection programs, we know relatively little about the role of such

[32] In 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 C.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 (2015). 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 (2015).

programs in combating vulnerability.[33] If the susceptibility of cognitive performance (or another measure of productivity) to temperature can be characterized as vulnerability, social protection programs can not only have direct effects, but also indirect benefits in reducing vulnerability. Simultaneously, as governments around the world prepare to tackle climate change, any reasonable strategy should account for the increased dependence of the poor on social protection programs as they face aggregate shocks that informal risk sharing practices are unable to mitigate.

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 day-of-test "short-run" temperature affects test performance through a physiological effect. However, longer-run temperature affects human capital through an agricultural income mechanism. The separation of the pathways through which temperature affects human capital in the short- and longer-run has important implications for both climate economics research and climate policy.

First, the different structural relationships connecting short- and longer-run temperature to economic outcomes highlights the limitations of existing approaches in quantifying ex-post adaptation by comparing the effects of short- and longer-run temperatures. This is especially likely to be the case when considering low and middle-income countries, where the majority of the world's population lives, and where the propagation of defensive investments (e.g., air-conditioners) is limited and livelihoods remain climate-exposed. Importantly, the existence of multiple structural relationships implies that modeling and projecting the impact of climate change in poor countries will require not only understanding how these existing relationships will change over time through adaptation but also how new structural relationships will emerge over the next century.

Second, the presence of multiple pathways linking heat stress and a single economic outcome suggests adaptation to higher temperatures will be required along multiple margins.

[33] See Fiszbein et al. (2009) for a review on the impacts of cash transfer programs.

Effects of short-run temperature, driven by physiology, can likely be corrected through defensive investments such as air-conditioners, or changing the test calendar. For instance, India's main board for primary and secondary education has decided to move the important school leaving exams that are often the sole criterion in college admissions, from March and April when the average temperatures in India are 22C and 26C respectively to February when average temperatures are 17C (Gohain, 2017). While this change is not being made explicitly as a response to heat stress, it provides an opportunity to understand how adjustments to the testing calendar can alter the effects of short-run temperature.

By contrast, the effects of longer-run temperature are driven by damage to livelihoods that, in agrarian poor settings, are vulnerable to weather. Importantly, these effects of longer-run temperature reduce human capital accumulation by adversely affecting agricultural income and therefore may require social protection programs that can protect the livelihoods of the poor from weather and climate. Consequently, governments and policy makers should expect the dependence on their social protection programs to increase in the face of climate change. Governments around the world will have to carefully allocate scarce resources in adapting to different margins of damage from 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 protection programs also likely perpetuate persistent poverty.

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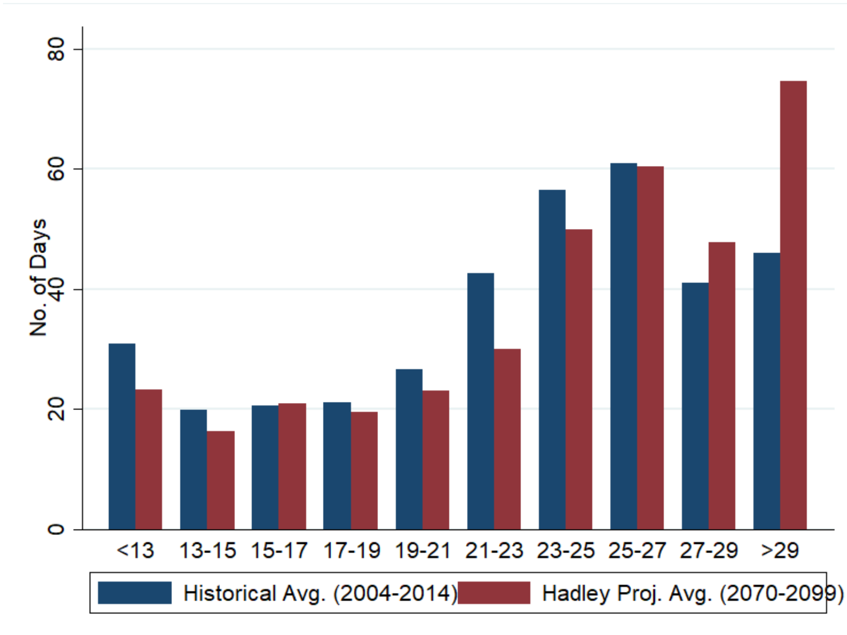
Figures

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



Notes: The figure shows the study period (2006-2014) distribution of days in the respective temperature windows alongside projections from the Hadley CM3 model under business as usual A1F1 scenario.

Figure 2: Average Daily Temperature by District

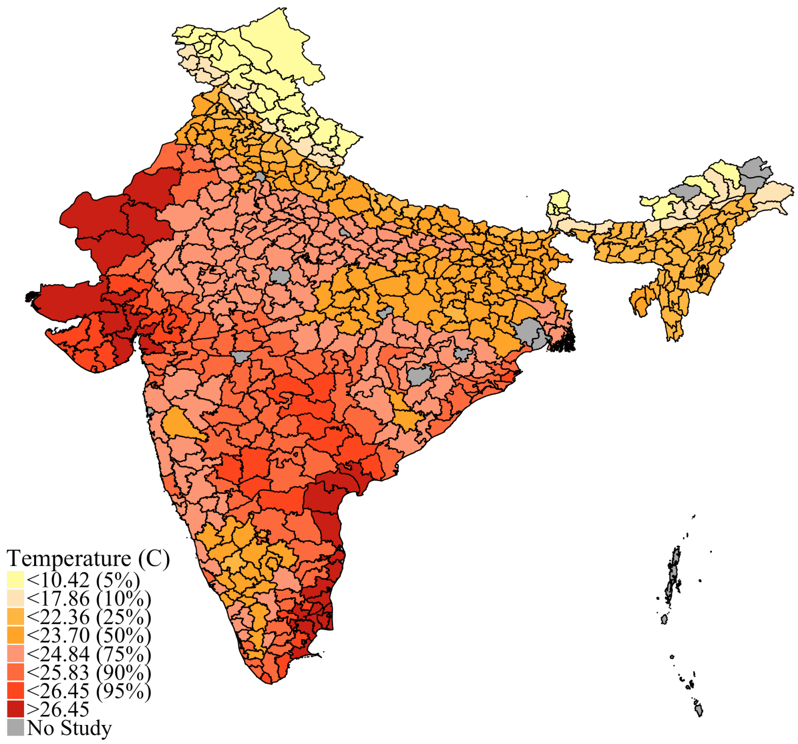


Figure 3: Distribution of Daily Temperatures for India and Andhra Pradesh

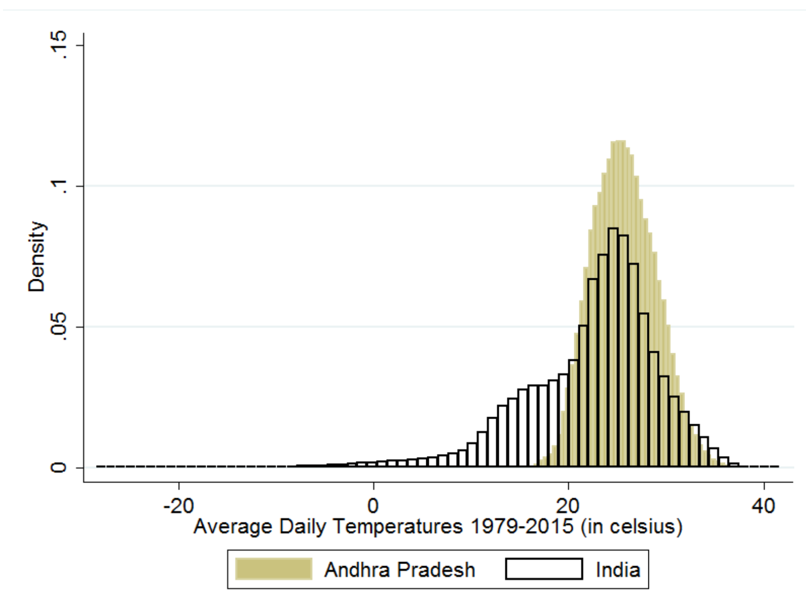
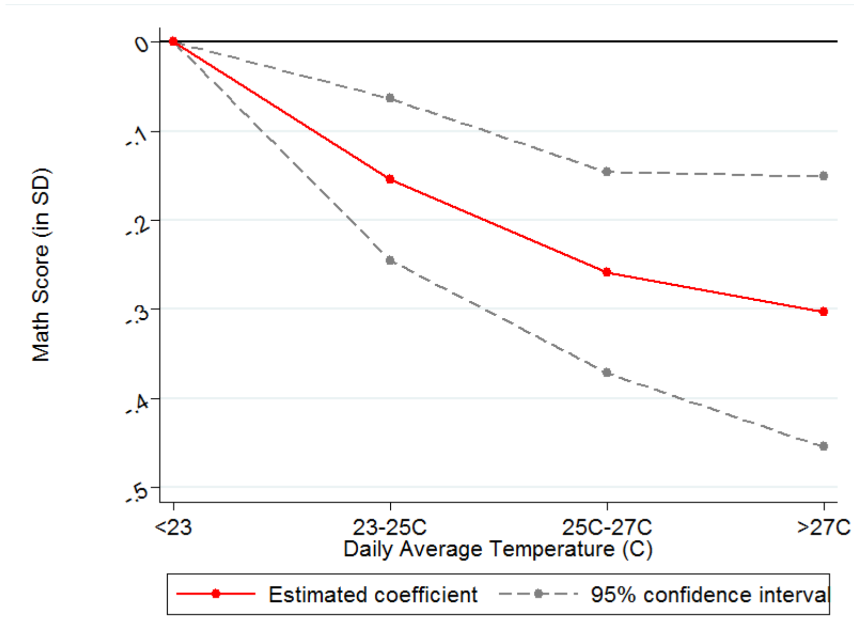
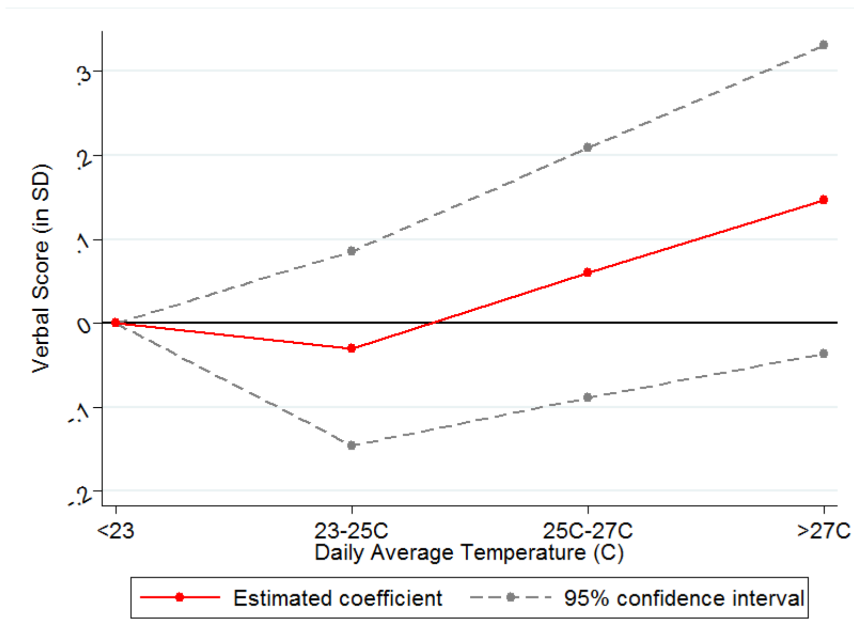


Figure 4: Short Run Temperature and Test Scores (YLS)



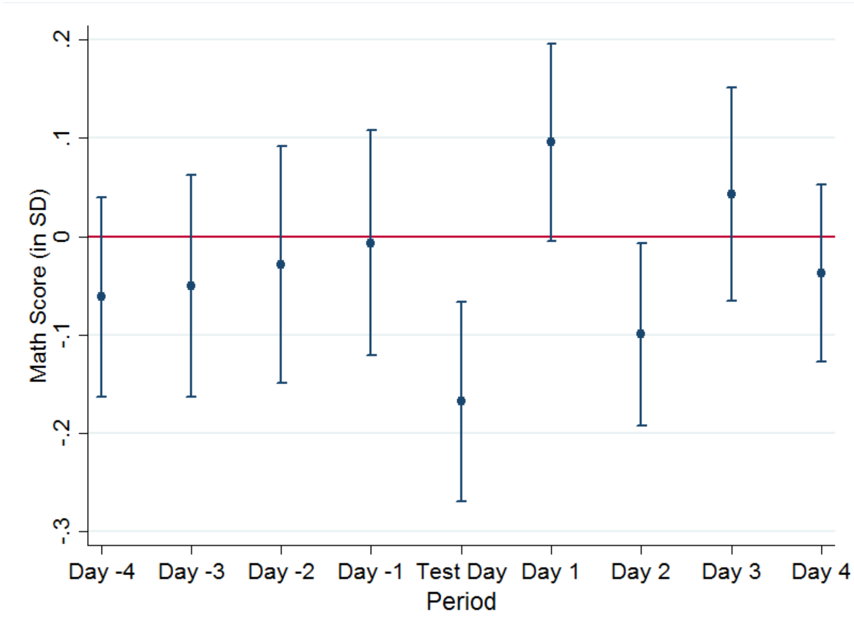
(a) Math Scores



(b) Reading Scores

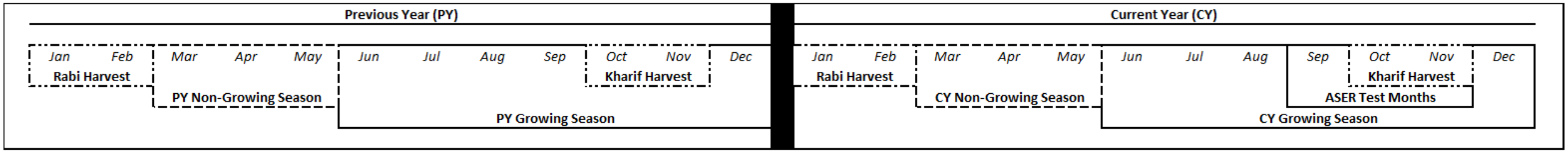
Notes: The figure shows the effect of day-of-test temperature on math and reading performance. The effect of temperature below 23C is normalized to zero and all other coefficients are interpreted relative to below 23C. The regressions include day of individual, week, month and survey round fixed effects. We control for precipitation. 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 5: Leads and Lags in Days: Short Run Temperature and Math Scores

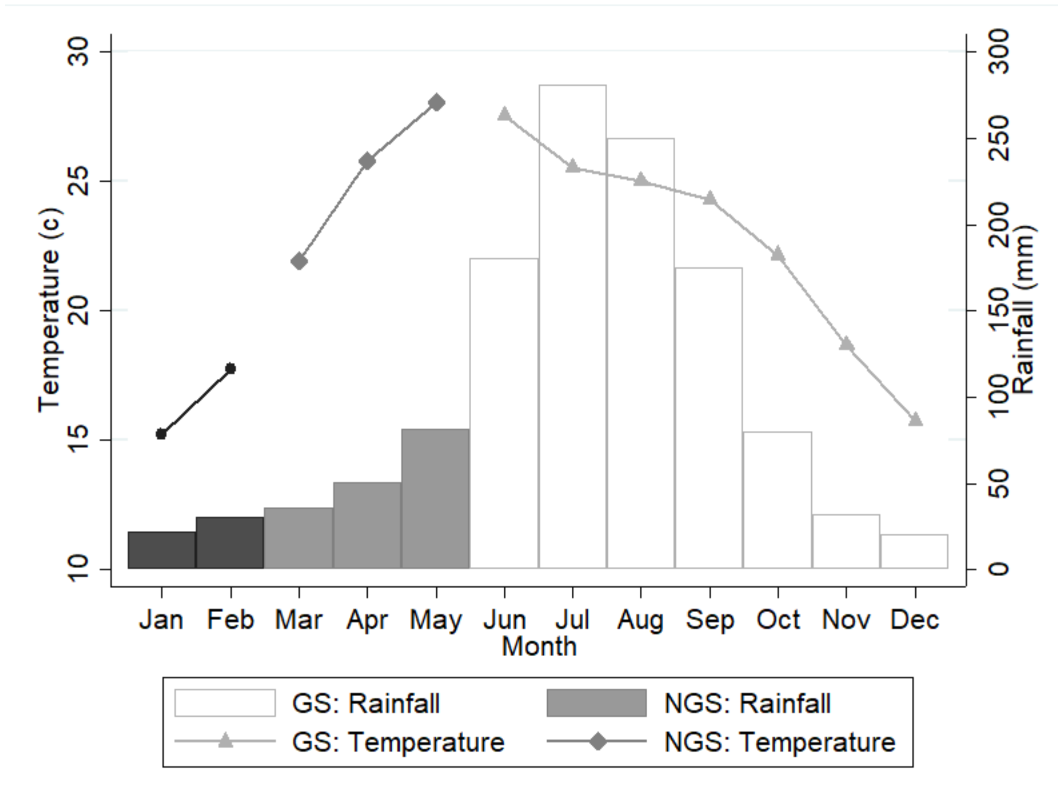


Notes: The figure present the impact of short-run temperature from 4 weeks before test day to 4 weeks after the test. Temperature is captured as 1 if temperature is > 23 on the day of the test for 'Test Day', 0 otherwise. Includes individual, day of week, month and survey round fixed effects. We control 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 6: Timeline of Effects of Longer-Run Temperature and Average Temperatures by Month and Season



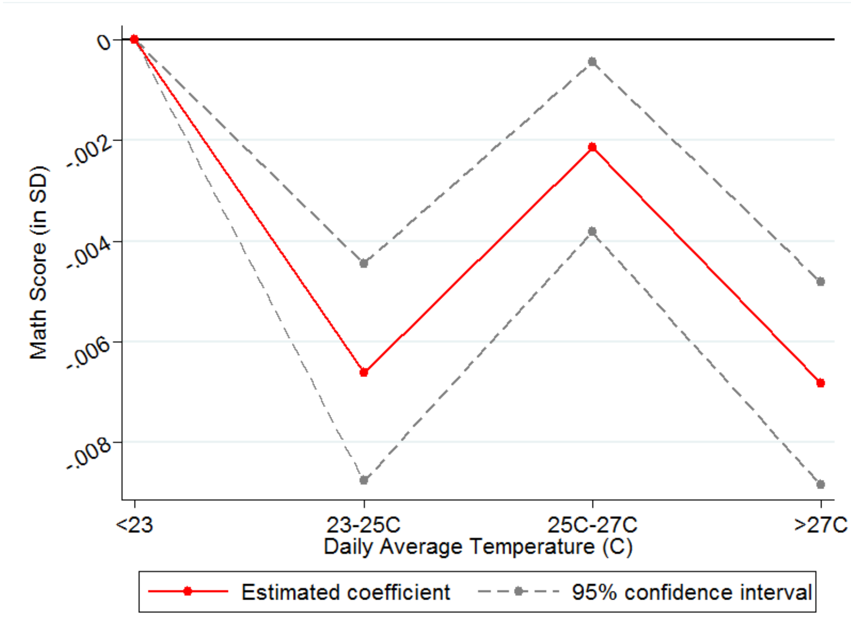
(a) Timeline of Effects of Longer-run Temperature



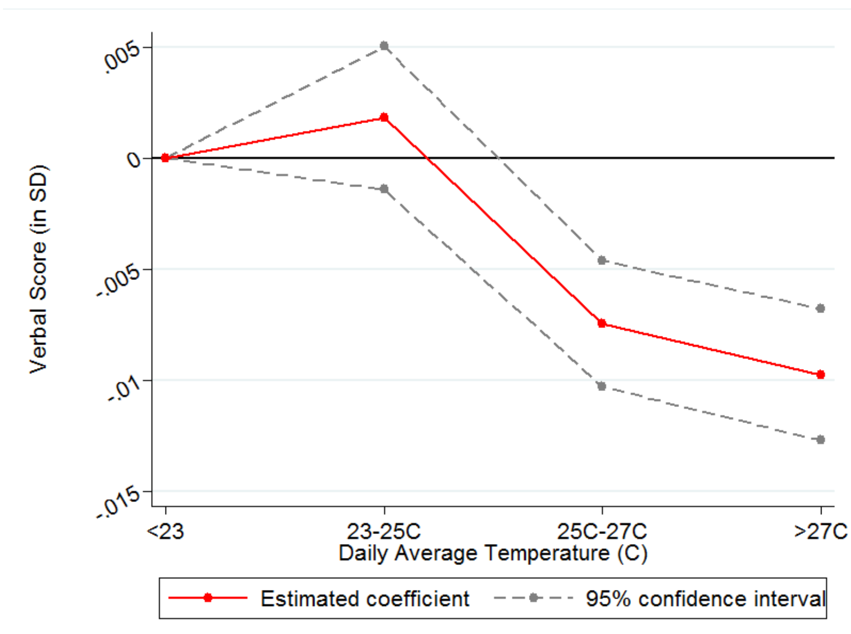
(b) Average Temperatures By Month and Season

Notes: Figure (a) demonstrates the timeline over which the effects of longer-run temperature manifest. Figure (b) shows the average temperature by month over the 2006-2014 time period along with average total rainfall in each month. The non-growing season is characterized by low rainfall whereas the growing season is characterized by high rainfall.

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



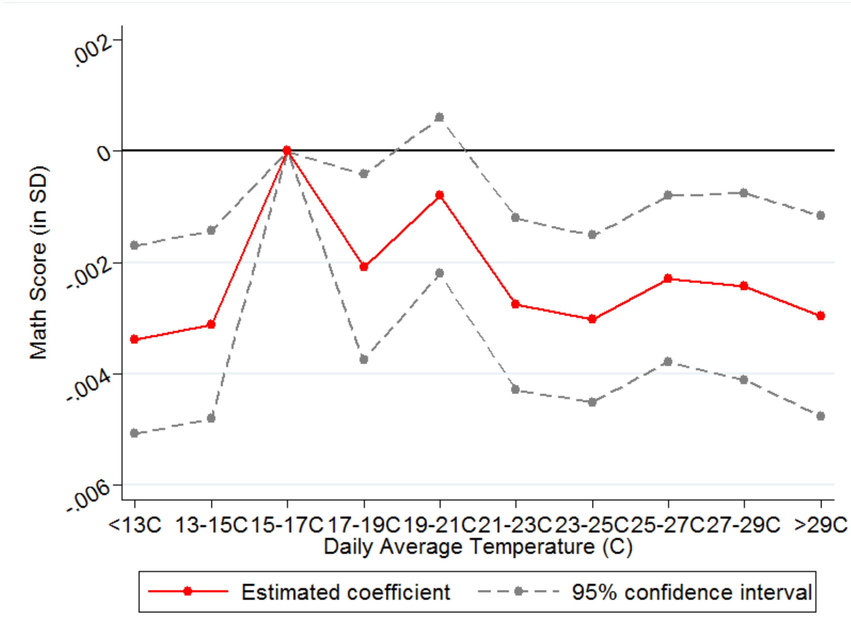
(a) Math Scores



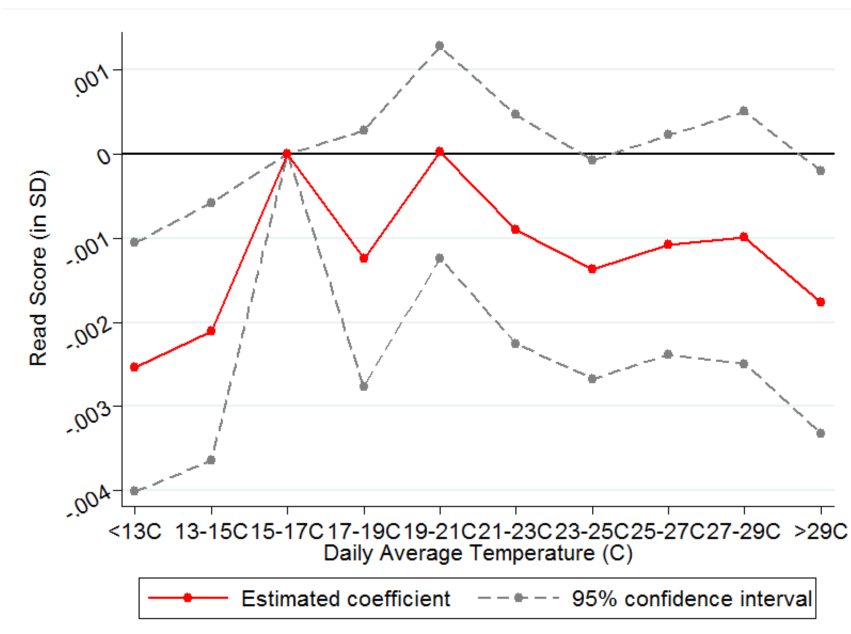
(b) Reading Scores

Notes: The figure shows the effect of longer-run temperature (defined as number of days in a given bin between successive tests) on math and reading performance. The effect of days below 23C is normalized to zero and all other coefficients are interpreted relative to below 23C. The regressions include individual, day of week, month and survey round fixed effects. We control for precipitation. 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 8: Long Run Temperature and Test Scores (ASER)



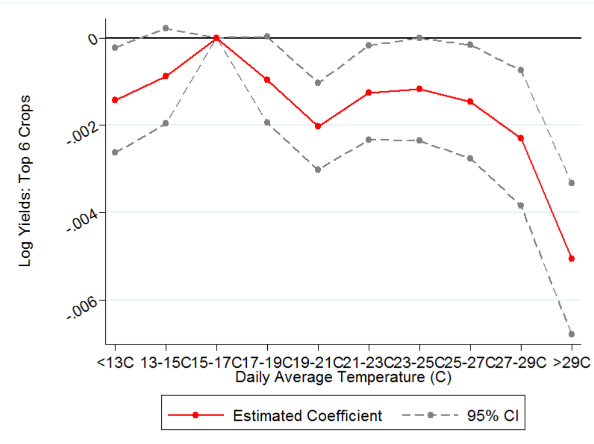
(a) Math Scores



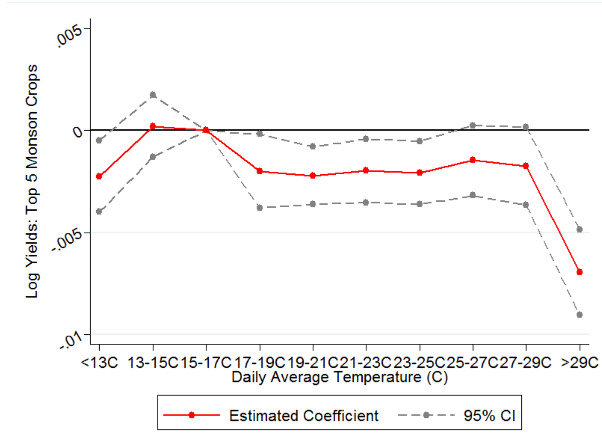
(b) Reading Scores

Notes: The figure shows the effect of longer-run temperature (defined as number of days in the previous calendar year - see figure) on math and reading performance. The effect of days between 15C-17C is normalized to zero and all other coefficients are interpreted relative to 15C-17C. The regressions include district and year fixed effects. We control flexibly for precipitation and humidity. Standard errors are in parentheses, clustered by district level.

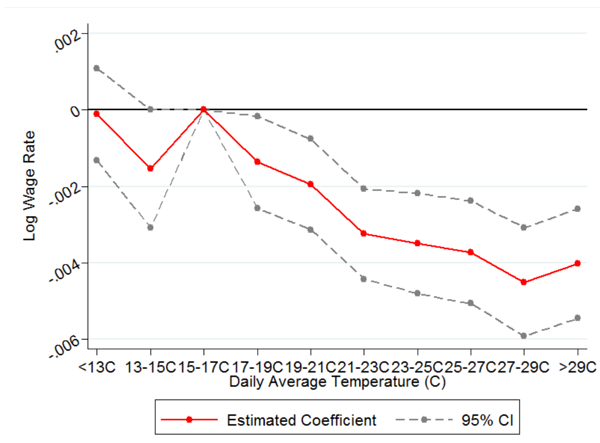
Figure 9: Effect of Temperature on Agricultural Yields and Rural Wages



(a) Temperature and Yields (6 Major Crops)



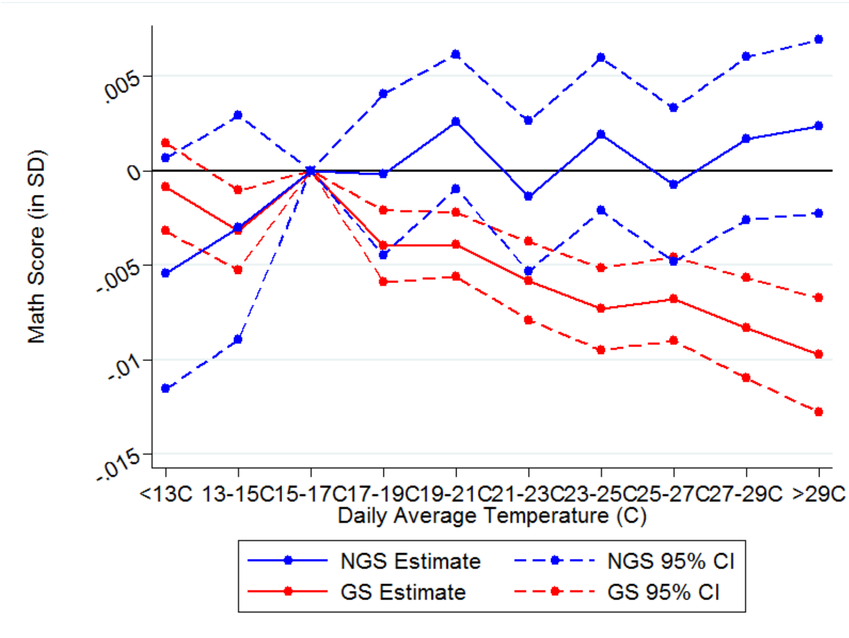
(b) Temperature and Yields (Main Monsoon Crops)



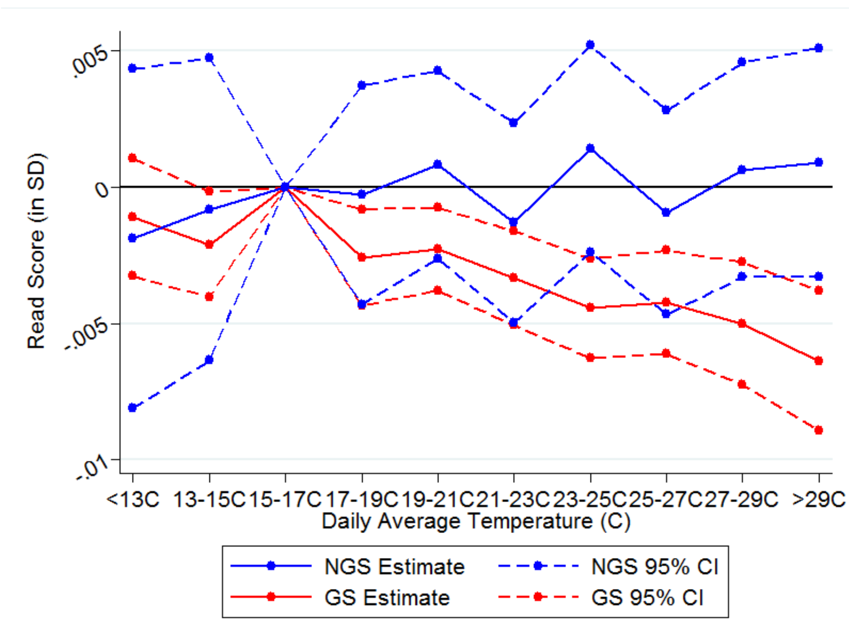
(c) Temperature and Rural Wages

Notes: The figure shows the effect of longer-run temperature (defined as number of days in the previous calendar year - see figure) on agricultural yields and rural wages from 1980 - 2014. The effect of days between 15C-17C is normalized to zero and all other coefficients are interpreted relative to 15C-17C. The regressions include district and year fixed effects. We control flexibly for precipitation and humidity. Standard errors are in parentheses, clustered by district level.

Figure 10: Growing vs. Non-Growing Season: Long Run Temperature and Test Scores (ASER)



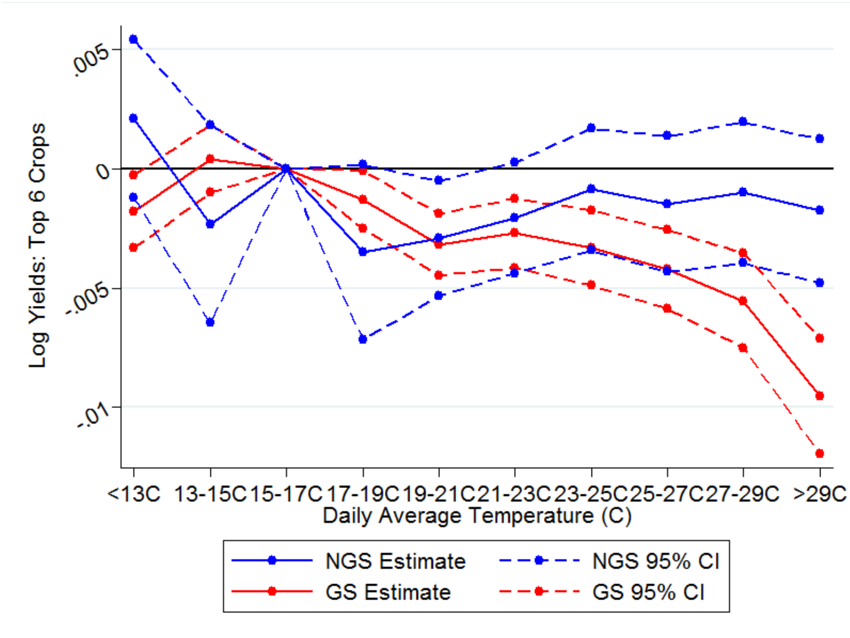
(a) Math Scores



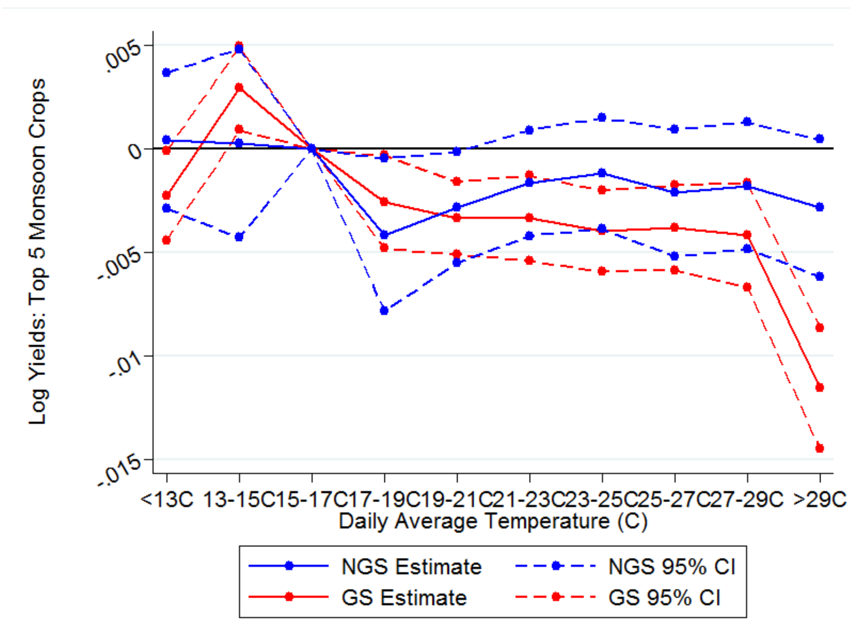
(b) Reading Scores

Notes: The figure shows the effect of longer-run temperature (defined as number of days in the previous calendar year - see figure) on math and reading performance divided amongst the growing season (June - Dec) and the non-growing season (March-May). The effect of days between 15C-17C is normalized to zero and all other coefficients are interpreted relative to 15C-17C. The regressions include district and year fixed effects. We control flexibly for precipitation and humidity. Standard errors are in parentheses, clustered by district level.

Figure 11: Growing vs. Non-Growing Season: Current Year Temperature and Yields



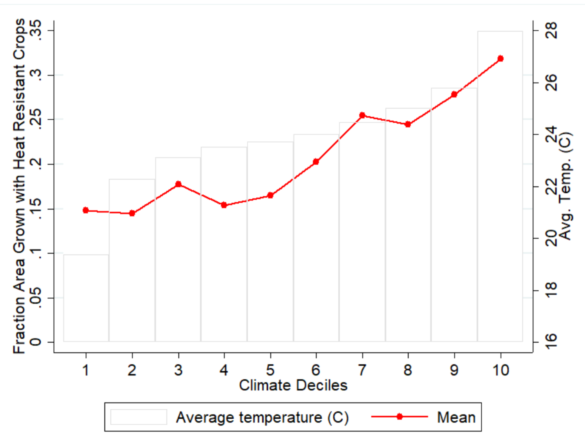
(a) 6 major crops



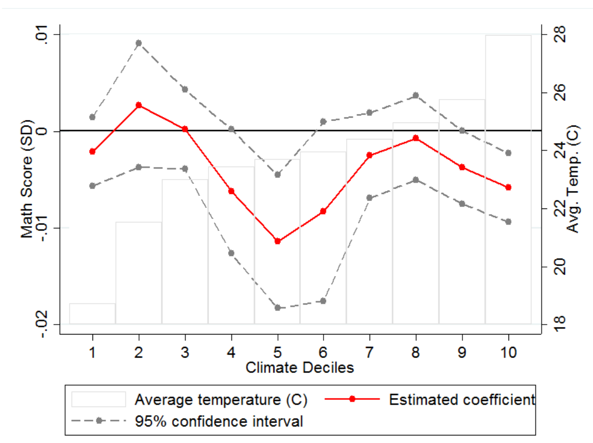
(b) 5 major monsoon crops

Notes: The figure shows the effect of longer-run temperature (defined as number of days in the previous calendar year - see figure) on agricultural yields from 1979 - 2014 divided amongst the growing season (June - Dec) and the non-growing season (March-May). The effect of days between 15C-17C is normalized to zero and all other coefficients are interpreted relative to 15C-17C. The regressions include district and year fixed effects. We control flexibly for precipitation and humidity. Standard errors are in parentheses, clustered by district level.

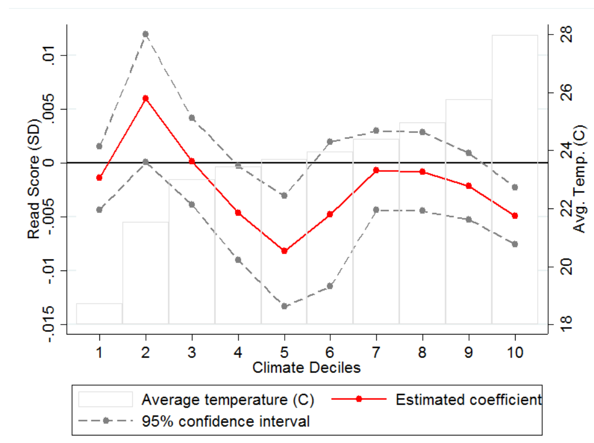
Figure 12: Heat Resistant Crops and Effect of Temperature on Test Scores by Average Temperature Deciles (ASER)



(a) Heat Resistant Crop Area as a Fraction of Total Cultivated Area



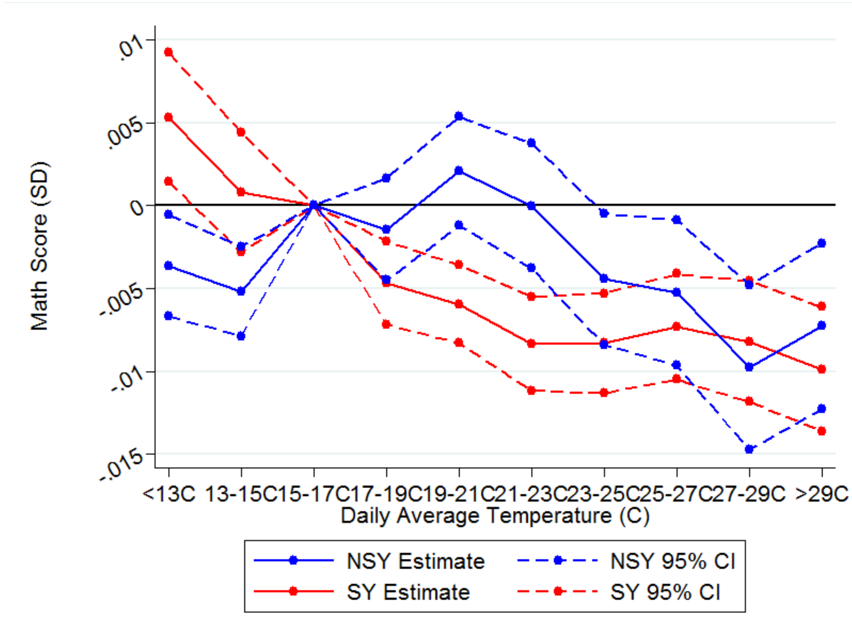
(b) Math Scores



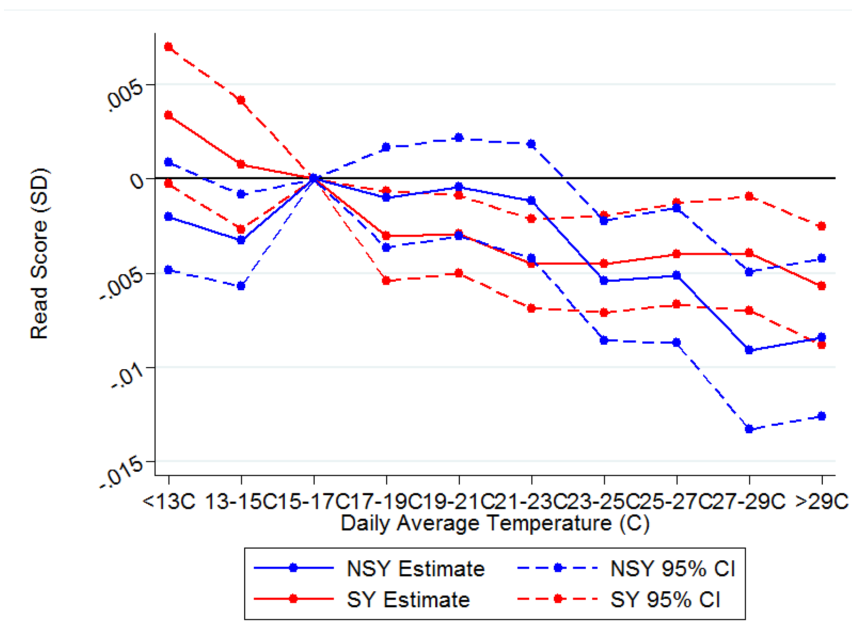
(c) Reading Scores

Notes: Figure (a) shows the average proportion of area within each district that is used to grow heat-resistant crops by deciles of average long-term temperature or the climate normal. Figures (b) and (c) show the the marginal effects of an additional hot day in the previous calendar year above 21C on math and reading performance respectively by deciles of average long-term temperature or the climate normal. The regressions include district and year fixed effects. We control flexibly for precipitation and humidity. Standard errors are in parentheses, clustered by district level.

Figure 13: Long Run Temperature and Test Scores: School Year v. Non-School Year (ASER)



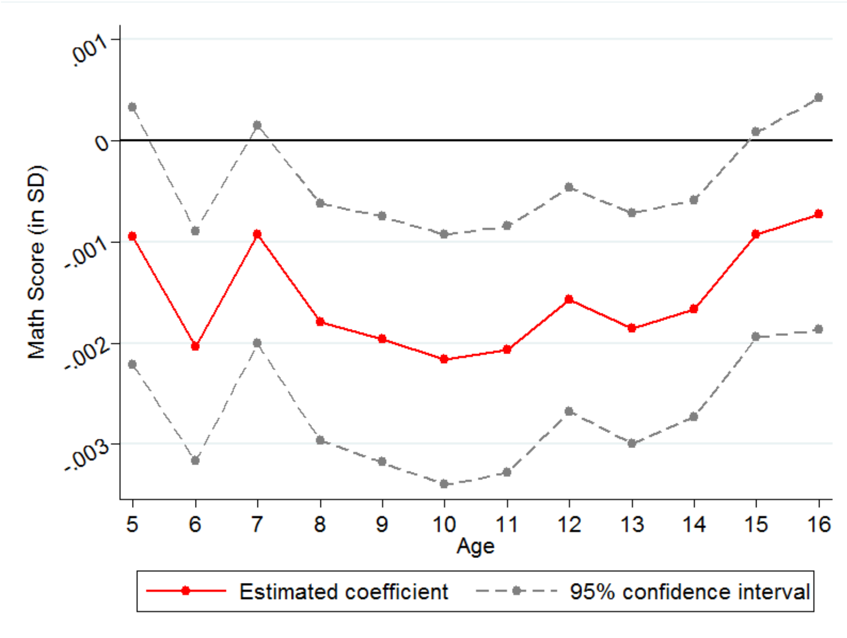
(a) Math Scores



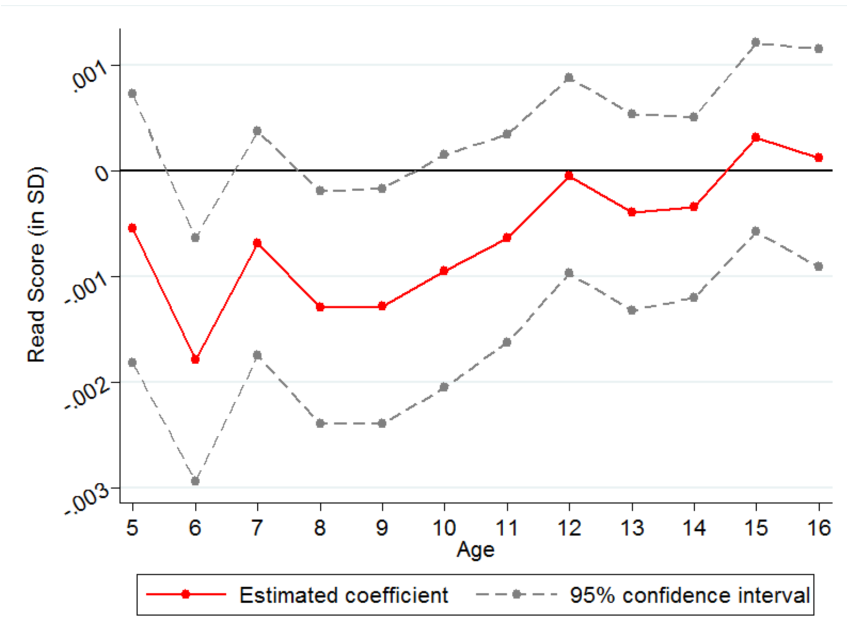
(b) Reading Scores

Notes: The figure shows the effect of longer-run temperature (defined as number of days in the previous calendar year - see figure) on math and reading performance divided amongst the school year (July-November) and the non-school year (June, December) within the growing season (June-December). The effect of days between 15C-17C is normalized to zero and all other coefficients are interpreted relative to 15C-17C. The regressions include district and year fixed effects. We control flexibly for precipitation and humidity. Standard errors are in parentheses, clustered by district level.

Figure 14: Effect of Long Run Temperature on Test Scores by age (ASER)



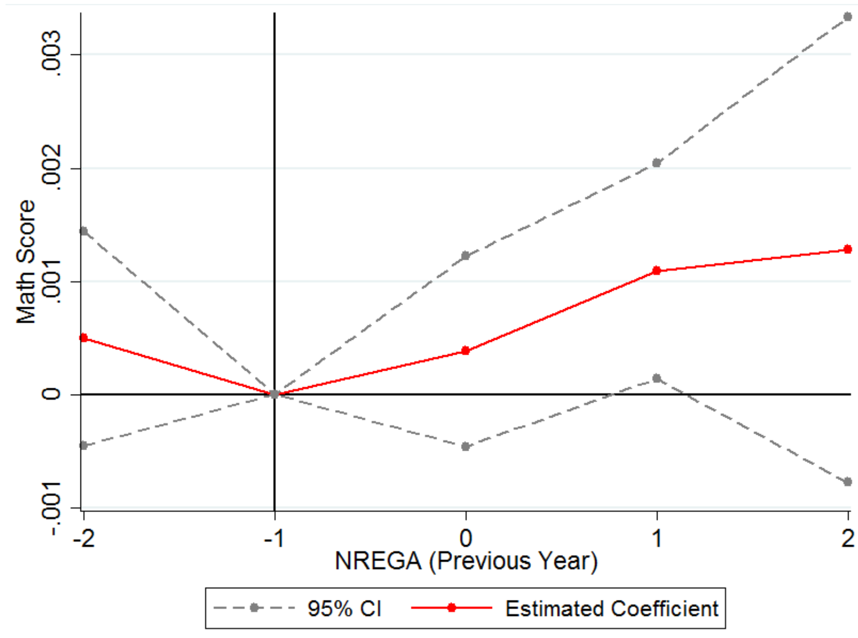
(a) Math Scores



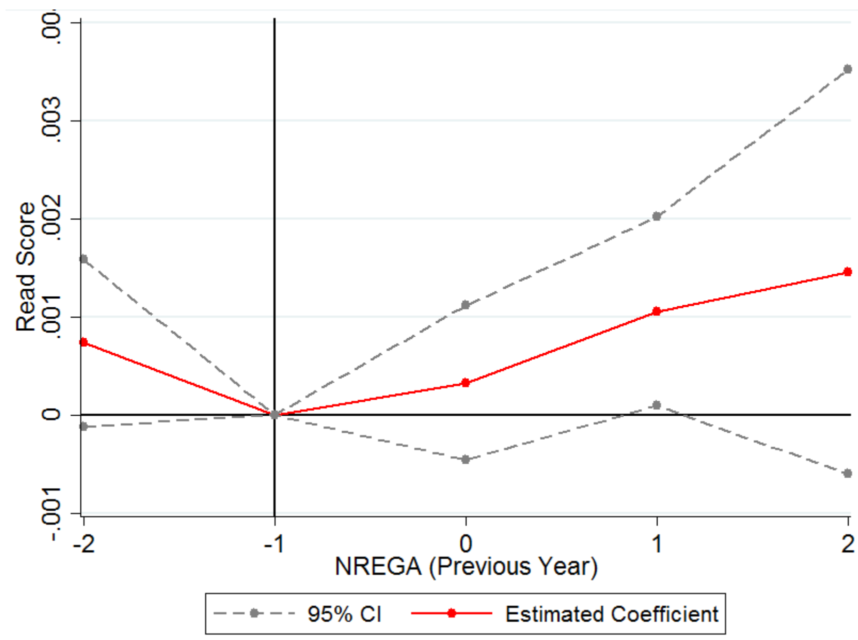
(b) Reading Scores

Notes: The figure shows the marginal effect of an additional hot day in the previous calendar year above 29C relative to 15C-17C on math and reading performance by age. The regressions include district and year fixed effects. We control flexibly for precipitation and humidity. Standard errors are in parentheses, clustered by district level.

Figure 15: Event Study: Long Run Temperature, NREGA and Test Scores



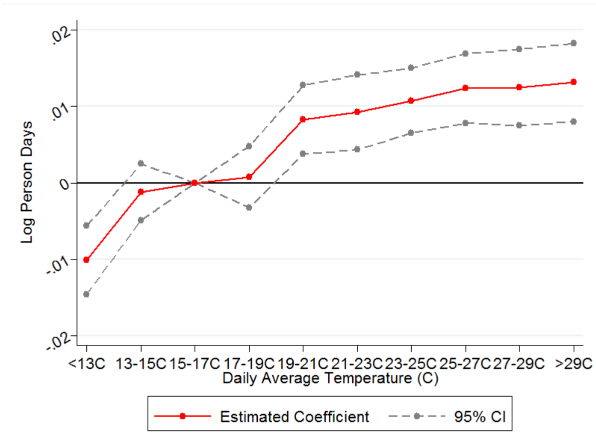
(a) Math Scores



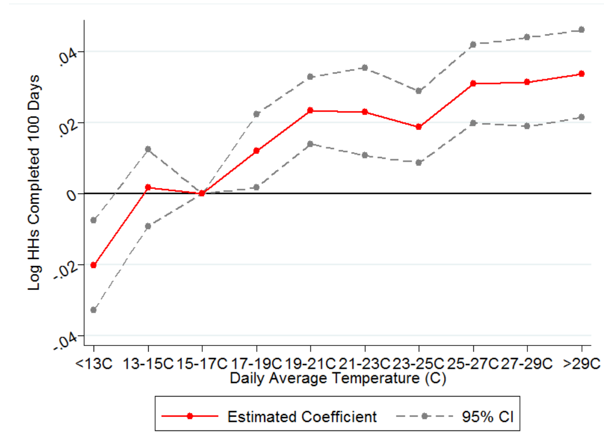
(b) Reading Scores

Notes: The figure shows the marginal effect of an additional hot day in the previous calendar year above 29C relative to 15C-17C on math and reading performance in an event study around the introduction of NREGA. The omitted variable is the days above 29C in the year prior to the introduction of NREGA ($\tau = -1$). The regressions include district and year fixed effects. We control flexibly for precipitation and humidity. Standard errors are in parentheses, clustered by district level.

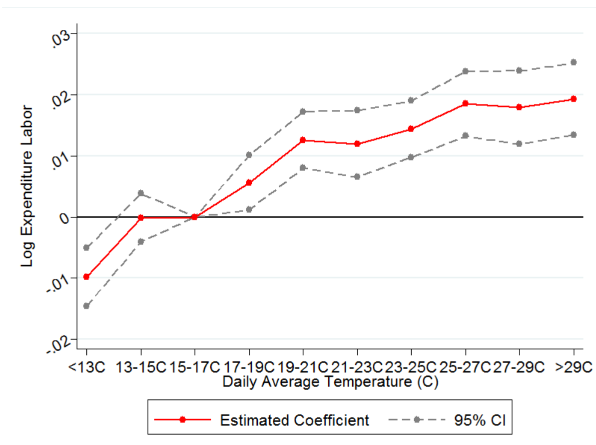
Figure 16: Effect of Temperature on NREGA Take-up



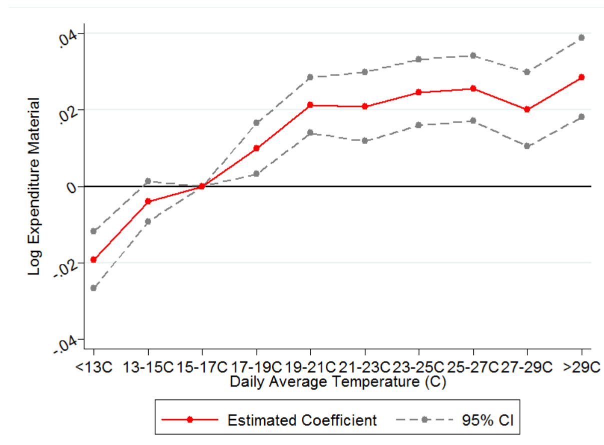
(a) Person Days



(b) HH's Completed All 100 Days



(c) Labor Expenditure



(d) Material Expenditure

Notes: The figure shows the effect of an extra hot-day on NREGA take-up, completion, and program expenditures using data from 2006-2016. The effect of days between 15C-17C is normalized to zero and all other coefficients are interpreted relative to 15C-17C. The regressions include district and year fixed effects. We control flexibly for precipitation and humidity. Standard errors are in parentheses, clustered by district level.

Tables

Table 1: Short 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
Day >23C	-0.168***		-0.012	
	(0.046)		(0.058)	
Day 23-25C		-0.154***		-0.030
		(0.046)		(0.059)
Day 25-27C		-0.259***		0.060
		(0.057)		(0.076)
Day >27C		-0.303***		0.147
		(0.077)		(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 (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***		-0.005***	
	(0.001)		(0.001)	
Days 23-25C		-0.007***		0.002
		(0.001)		(0.002)
Days 25-27C		-0.002**		-0.007***
		(0.001)		(0.001)
Days >27C		-0.007***		-0.010***
		(0.001)		(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 3: 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***		-0.0019***	
	(0.0006)		(0.0006)	
Days >21C	-0.0016***		-0.0007*	
	(0.0005)		(0.0004)	
PY Days <13C		-0.0034***		-0.0025***
		(0.0009)		(0.0008)
PY Days 13-15C		-0.0031***		-0.0021***
		(0.0009)		(0.0008)
PY Days 17-19C		-0.0021**		-0.0012
		(0.0009)		(0.0008)
PY Days 19-21C		-0.0008		0.0000
		(0.0007)		(0.0006)
PY Days 21-23C		-0.0027***		-0.0009
		(0.0008)		(0.0007)
PY Days 23-25C		-0.0030***		-0.0014**
		(0.0008)		(0.0007)
PY Days 25-27C		-0.0023***		-0.0011
		(0.0008)		(0.0007)
PY Days 27-29C		-0.0024***		-0.0010
		(0.0009)		(0.0008)
PY Days >29C		-0.0030***		-0.0018**
		(0.0009)		(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 4: Falsification Test: Temperature Test Scores (ASER)

	(1) Math Score (in SD) β / SE	(2) Read Score (in SD) β / SE
PY Days <15C	-0.0030***	-0.0027***
	(0.0007)	(0.0006)
PY Days >21C	-0.0020***	-0.0008*
	(0.0005)	(0.0005)
CY Days <15C	-0.0004	-0.0008
	(0.0007)	(0.0006)
CY Days >21C	0.0012*	0.0002
	(0.0006)	(0.0005)
NY Days <15C	-0.0006	-0.0017***
	(0.0007)	(0.0006)
NY Days >21C	0.0007	0.0001
	(0.0006)	(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 5: Current Year Temperature, Agricultural Yields and Rural Wages

	(1) Log Yield: Top 6 Crops β / SE	(2) Log Yield: Top 5 Monsoon Crops β / SE	(3) Log Wage Rate β / SE
Days <13C	-0.0014**	-0.0022**	-0.0001
	(0.0006)	(0.0009)	(0.0006)
Days 13-15C	-0.0009	0.0002	-0.0015*
	(0.0006)	(0.0008)	(0.0008)
Days 17-19C	-0.0010*	-0.0020**	-0.0014**
	(0.0005)	(0.0009)	(0.0006)
Days 19-21C	-0.0020***	-0.0022***	-0.0019***
	(0.0005)	(0.0007)	(0.0006)
Days 21-23C	-0.0013**	-0.0020**	-0.0032***
	(0.0006)	(0.0008)	(0.0006)
Days 23-25C	-0.0012*	-0.0021***	-0.0035***
	(0.0006)	(0.0008)	(0.0007)
Days 25-27C	-0.0015**	-0.0015*	-0.0037***
	(0.0007)	(0.0009)	(0.0007)
Days 27-29C	-0.0023***	-0.0017*	-0.0045***
	(0.0008)	(0.0010)	(0.0007)
Days >29C	-0.0051***	-0.0069***	-0.0040***
	(0.0009)	(0.0011)	(0.0007)
Observations	9479	9475	5516
R^2	0.882	0.875	0.959

Notes: This table presents the impact of temperature in the current year (captured via temperature bins) on agriculture yields and rural wages 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%.

Table 6: Growing vs. Non-Growing Season: Long Run Temperature and Test Scores (ASER)

	(1) Math Score (in SD) β / SE	(2) Read Score (in SD) β / SE
GS Days <13C	-0.0009	-0.0011
	(0.0012)	(0.0011)
GS Days 13-15C	-0.0032***	-0.0021**
	(0.0011)	(0.0010)
GS Days 17-19C	-0.0040***	-0.0026***
	(0.0010)	(0.0009)
GS Days 19-21C	-0.0039***	-0.0023***
	(0.0009)	(0.0008)
GS Days 21-23C	-0.0058***	-0.0033***
	(0.0011)	(0.0009)
GS Days 23-25C	-0.0073***	-0.0044***
	(0.0011)	(0.0009)
GS Days 25-27C	-0.0068***	-0.0042***
	(0.0011)	(0.0010)
GS Days 27-29C	-0.0083***	-0.0050***
	(0.0013)	(0.0012)
GS Days >29C	-0.0097***	-0.0064***
	(0.0015)	(0.0013)
NGS Days <13C	-0.0055*	-0.0019
	(0.0031)	(0.0032)
NGS Days 13-15C	-0.0030	-0.0008
	(0.0030)	(0.0028)
NGS Days 17-19C	-0.0002	-0.0003
	(0.0022)	(0.0020)
NGS Days 19-21C	0.0026	0.0008
	(0.0018)	(0.0018)
NGS Days 21-23C	-0.0014	-0.0013
	(0.0020)	(0.0019)
NGS Days 23-25C	0.0019	0.0014
	(0.0021)	(0.0019)
NGS Days 25-27C	-0.0008	-0.0009
	(0.0021)	(0.0019)
NGS Days 27-29C	0.0017	0.0006
	(0.0022)	(0.0020)
NGS Days >29C	0.0023	0.0009
	(0.0023)	(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 7: Heat Resistant Crops: Long Run Temperature and Test Scores (ASER)

	(1) Math Score (in SD) β / SE	(2) Read Score (in SD) β / SE
Days <15C	-0.0026***	-0.0020***
	(0.0007)	(0.0006)
Days >21C	-0.0030***	-0.0015***
	(0.0006)	(0.0005)
Days >21C * HRC	0.0021***	0.0009
	(0.0007)	(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 8: Event Study: Long Run Temperature, NREGA and Test Scores

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

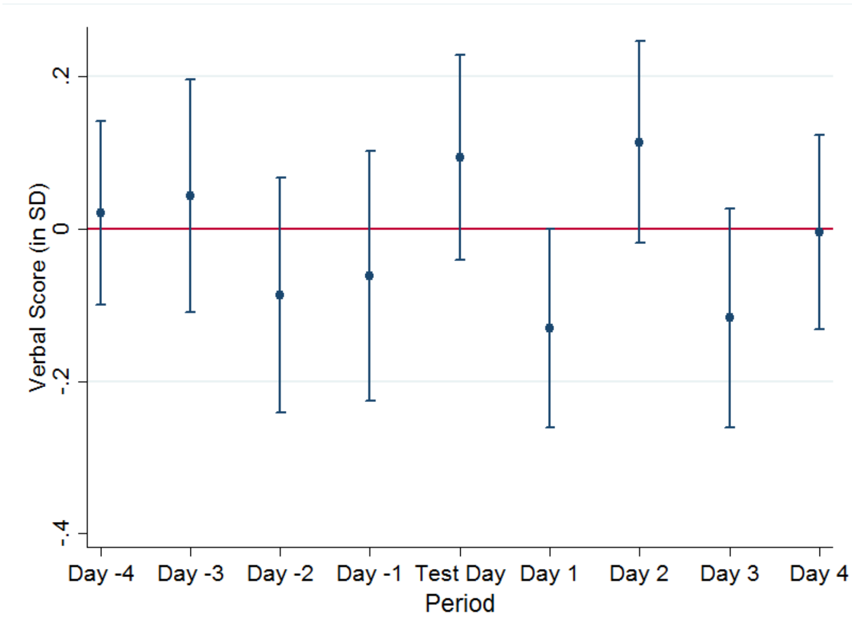
Notes: This table tests if the impact of last year's temperature were attenuated by NREGA roll-out in that year. To capture these effects, we have interacted the number of days in the previous year when the temperature was over 29C (bin 10) with the event time of NREGA roll-out. t=0 indicates if NREGA 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 Robustness Checks for the Effects of Short-Run Temperature

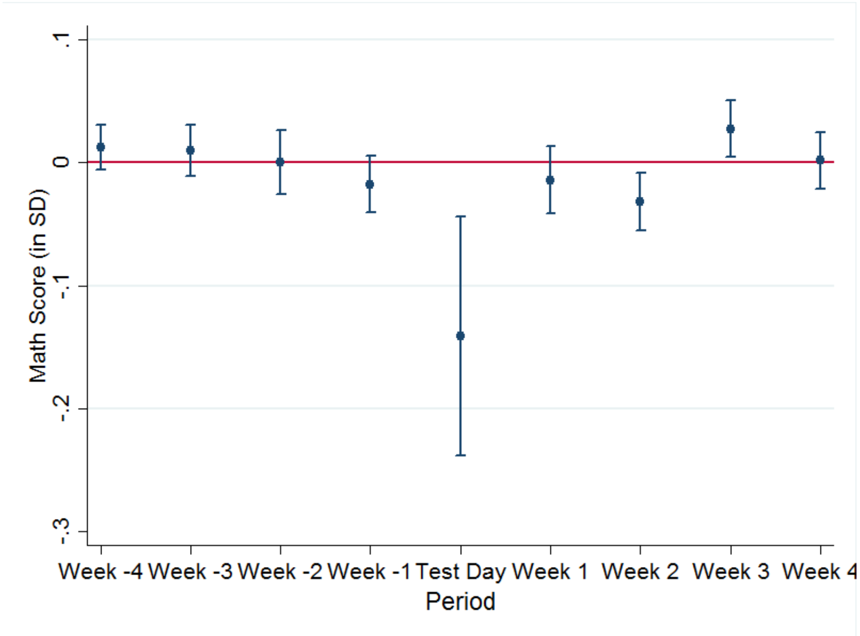
A.1.1 No Persistence in Short Run Physiological Effects

Figure A.1: Leads and Lags in Days: Short Run Temperature and PPVT Scores



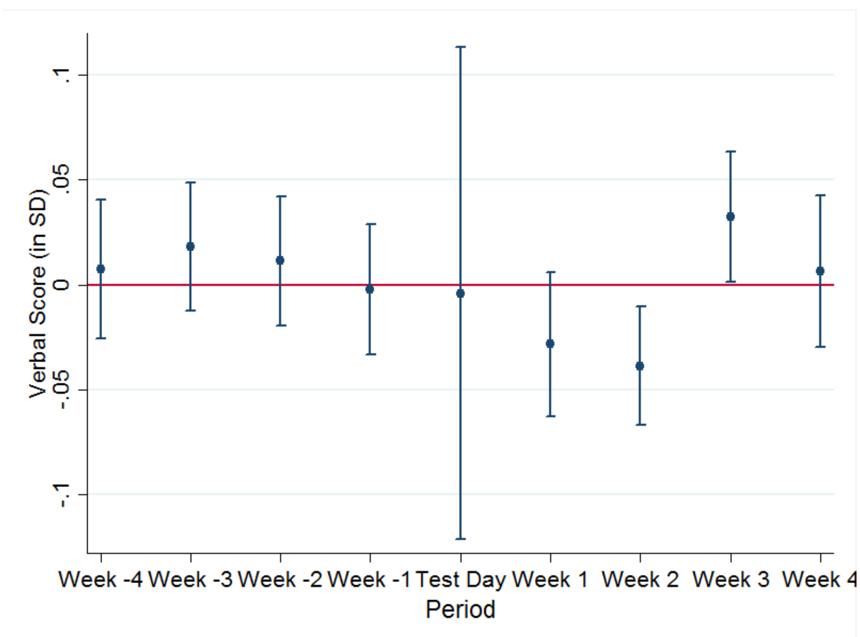
Notes: The figure present the impact of short-run temperature from 4 days before test day to 4 days after the test. Temperature is captured as 1 if temperature is > 23 on the day of the test for 'Test Day', 0 otherwise. Includes individual, day of week, month and survey round fixed effects. We control 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.2: 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 >23C 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.3: 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 >23C 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.1.2 Test Times and Timing of Test

Table A.1: Short Run Temperature and Test Timing

	(1) Math Start Time β / SE	(2) PPVT Start Time β / SE
Day 23-25C	0.187	-0.029
	(0.372)	(0.202)
Day 25-27C	0.211	-0.488
	(0.381)	(0.316)
Day >27C	0.449	-0.558
	(0.588)	(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%.

Table A.2: Short Run Temperature and Test Duration

	(1) Duration Math Test β / SE	(2) Duration PPVT Test β / SE
Day 23-25C	0.927	-2.331***
	(0.626)	(0.710)
Day 25-27C	0.657	-1.420
	(0.781)	(0.868)
Day >27C	2.068**	0.930
	(1.040)	(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%.

A.2 Robustness Checks for Effects of Longer Run Temperature

A.2.1 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***		0.030	
	(0.042)		(0.058)	
Days >23C	-0.004***		-0.005***	
	(0.001)		(0.001)	
Day 23-25C		-0.100**		-0.005
		(0.045)		(0.056)
Day 25-27C		-0.178***		0.139*
		(0.056)		(0.075)
Day >27C		-0.169**		0.253***
		(0.073)		(0.097)
Days 23-25C		-0.007***		0.001
		(0.001)		(0.002)
Days 25-27C		-0.002**		-0.007***
		(0.001)		(0.001)
Days >27C		-0.007***		-0.009***
		(0.001)		(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.2.2 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***		-0.0021***	
	(0.0006)		(0.0005)	
Days >21C	-0.0016***		-0.0007*	
	(0.0005)		(0.0004)	
PY Days <13C		-0.0041***		-0.0031***
		(0.0009)		(0.0007)
PY Days 13-15C		-0.0029***		-0.0018**
		(0.0008)		(0.0007)
PY Days 17-19C		-0.0017**		-0.0009
		(0.0009)		(0.0007)
PY Days 19-21C		-0.0010		-0.0003
		(0.0007)		(0.0006)
PY Days 21-23C		-0.0027***		-0.0009
		(0.0008)		(0.0007)
PY Days 23-25C		-0.0030***		-0.0014**
		(0.0008)		(0.0006)
PY Days 25-27C		-0.0022***		-0.0011*
		(0.0008)		(0.0006)
PY Days 27-29C		-0.0025***		-0.0013*
		(0.0008)		(0.0007)
PY Days >29C		-0.0028***		-0.0018**
		(0.0009)		(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.2.3 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*	0.0126*
	(0.0080)	(0.0073)
DD >21C	-0.0082	-0.0116**
	(0.0057)	(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	0.0094
	(0.0074)	(0.0063)
DD >21C	-0.0077	-0.0110**
	(0.0057)	(0.0045)
Observations	3446230	3446230
R^2	0.087	0.065

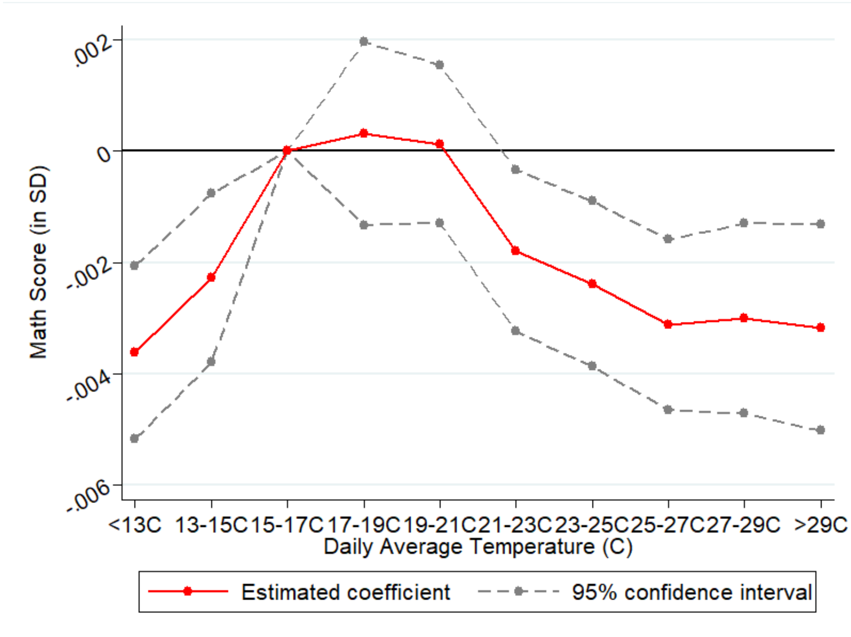
Notes: This table presents the impact of temperature in the previous year (captured via degree days) on test scores in the current year for children between the ages of 5-16 for 2006-2014. All specifications include district, year, and age fixed effects. We control for precipitation and humidity in all 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.2.4 ASER Results: Adding State-Specific Time Trends

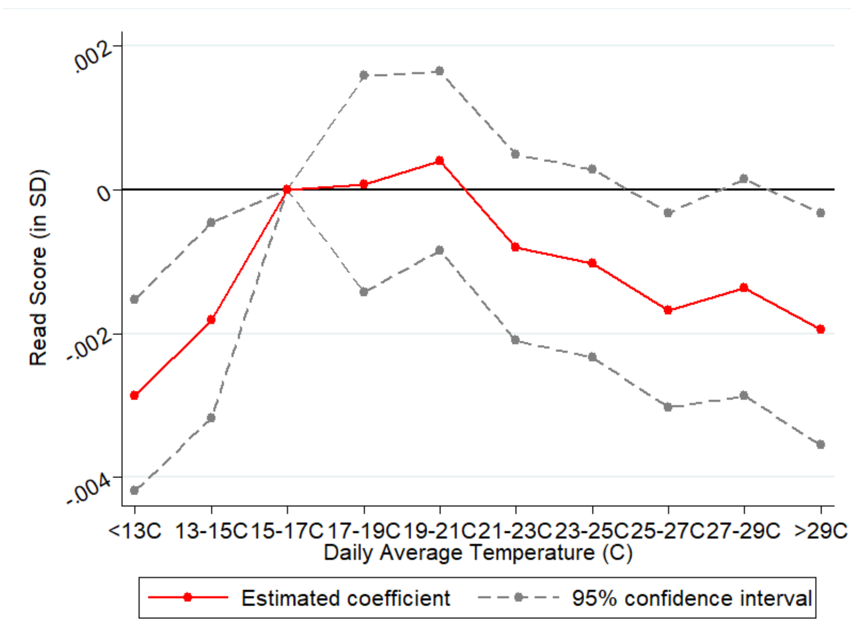
Table A.7: Long Run Temperature and Test Scores (ASER): Adding State-Specific Time Trends

	(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	-0.0032*** (0.0006)		-0.0026*** (0.0005)	
PY Days >21C	-0.0025*** (0.0004)		-0.0013*** (0.0004)	
PY Days <13C		-0.0036*** (0.0008)		-0.0029*** (0.0007)
PY Days 13-15C		-0.0023*** (0.0008)		-0.0018*** (0.0007)
PY Days 17-19C		0.0003 (0.0008)		0.0001 (0.0008)
PY Days 19-21C		0.0001 (0.0007)		0.0004 (0.0006)
PY Days 21-23C		-0.0018** (0.0007)		-0.0008 (0.0007)
PY Days 23-25C		-0.0024*** (0.0008)		-0.0010 (0.0007)
PY Days 25-27C		-0.0031*** (0.0008)		-0.0017** (0.0007)
PY Days 27-29C		-0.0030*** (0.0009)		-0.0014* (0.0008)
PY Days >29C		-0.0032*** (0.0009)		-0.0019** (0.0008)
Observations	4581616	4581616	4581616	4581616
R^2	0.097	0.097	0.076	0.076

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. Standard errors are in parentheses, clustered by district.
*Significant at 10%.
**Significant at 5%.
***Significant at 1%.



(a) Math Scores



(b) Reading Scores

Figure A.4: Long Run Temperature and Test Scores (ASER): Adding State-Specific Time Trends

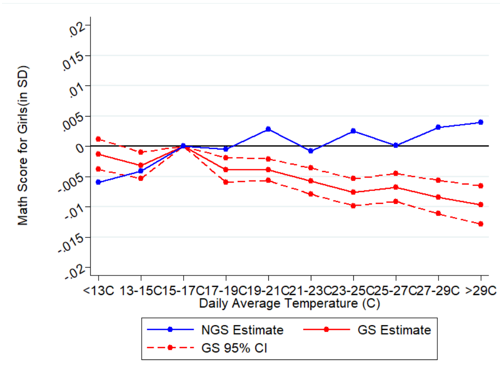
A.3 Robustness Checks: Agricultural Income Mechanism

Table A.8: Current Year Growing Season Temperature and Agriculture Yields

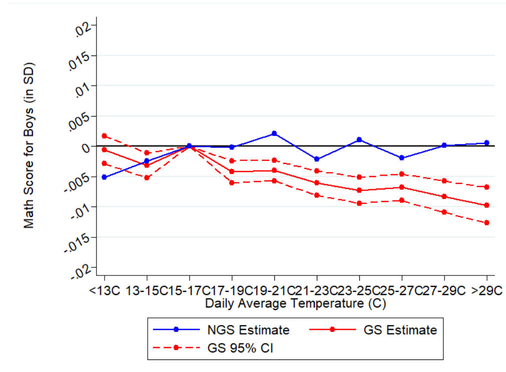
	(1) Log Yield: Top 6 Crops β / SE	(2) Log Yield: Top 5 Monsoon Crops β / SE
GS Days <13C	-0.0018**	-0.0023**
	(0.0008)	(0.0011)
GS Days 13-15C	0.0004	0.0029***
	(0.0007)	(0.0010)
GS Days 17-19C	-0.0013**	-0.0026**
	(0.0006)	(0.0011)
GS Days 19-21C	-0.0032***	-0.0033***
	(0.0007)	(0.0009)
GS Days 21-23C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

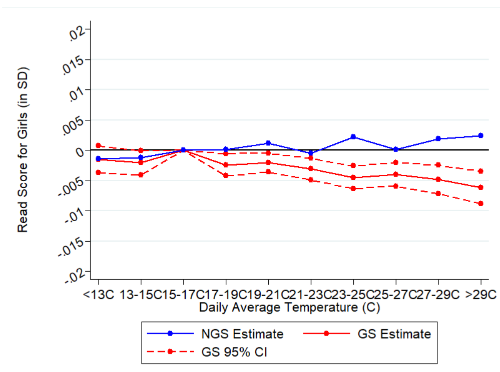
A.3.1 Heterogeneity - Gender



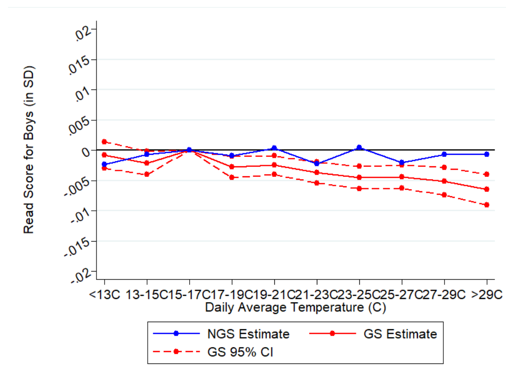
(a)
Girls(Math)



(b)
Boys(Math)



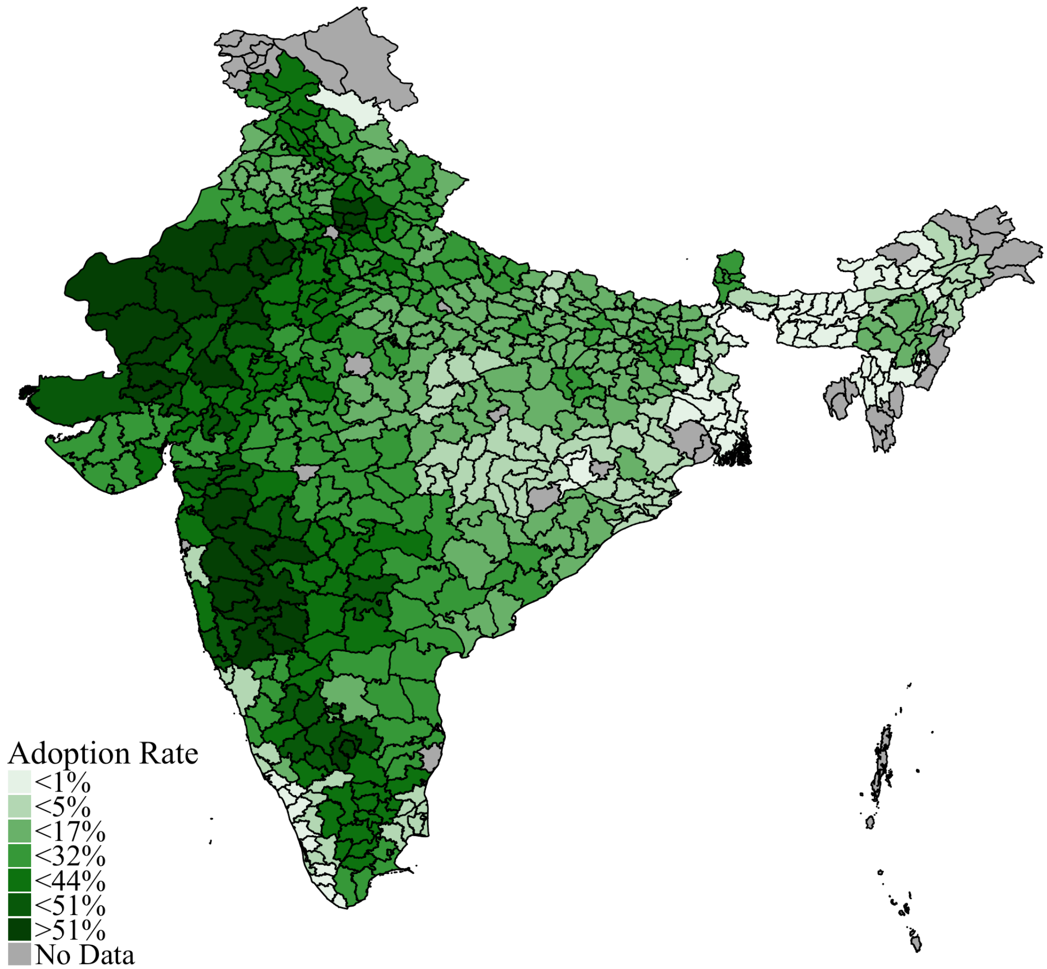
(c)
Girls(Read)



(d)
Boys(Read)

Figure A.5: Temperature and Test Scores (ASER): By Gender

Figure A.6: Average Take-Up of Heat Resistant Crops by District



A.3.2 Geographic Take-Up of Heat Resistant Crops

A.4 Alternative Explanations

A.4.1 Teacher Attendance

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*	-0.0028*	-0.0019
	(0.0006)	(0.0016)	(0.0013)
PY NGS Days >21C	0.0003	0.0008	0.0007
	(0.0003)	(0.0010)	(0.0009)
PY GS Days <15C	0.0006**	0.0016**	0.0013**
	(0.0003)	(0.0007)	(0.0006)
PY GS Days >21C	0.0001	0.0009*	0.0010**
	(0.0002)	(0.0005)	(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%.

A.4.2 Long Run Temperature and Dropouts, Grade Progression

Table A.10: 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		0.0001	
	(0.0000)		(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		-0.0002
		(0.0001)		(0.0003)
PY Days 19-21C		-0.0001		0.0003
		(0.0001)		(0.0002)
PY Days 21-23C		-0.0001		0.0002
		(0.0001)		(0.0003)
PY Days 23-25C		-0.0001		0.0004
		(0.0001)		(0.0003)
PY Days 25-27C		-0.0001		0.0001
		(0.0001)		(0.0003)
PY Days 27-29C		-0.0001*		0.0002
		(0.0001)		(0.0003)
PY Days >29C		-0.0001		0.0002
		(0.0001)		(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%.

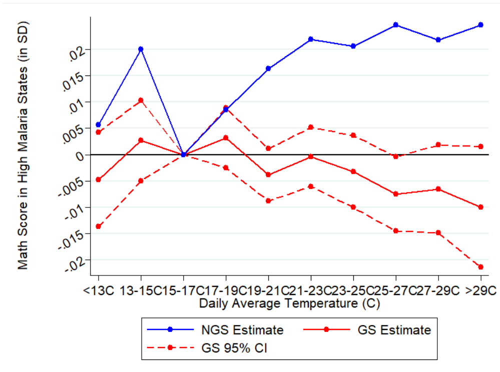
A.4.3 Temperature, Rainfall and Test Scores

Table A.11: Temperature, Rainfall and Test Scores

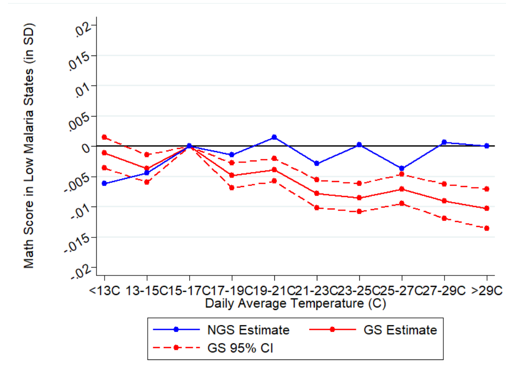
	(1) Math Score (in SD) β / SE	(2) Math Score (in SD) β / SE	(3) Read Score (in SD) β / SE	(4) Read Score (in SD) β / SE
PY Days <15C	-0.0020***	-0.0015*	-0.0017***	-0.0010
	(0.0006)	(0.0007)	(0.0006)	(0.0007)
PY Days >21C	-0.0021***	-0.0021***	-0.0011**	-0.0014**
	(0.0005)	(0.0006)	(0.0004)	(0.0006)
CY Days <15C	-0.0001	0.0000	-0.0006	-0.0006
	(0.0007)	(0.0008)	(0.0006)	(0.0007)
CY Days >21C	0.0018***	-0.0002	0.0004	-0.0000
	(0.0005)	(0.0006)	(0.0004)	(0.0005)
PY Rain Bottom Terc.	0.0078	-0.0006	0.0108	0.0015
	(0.0111)	(0.0106)	(0.0100)	(0.0099)
PY Rain Top Terc.	-0.0258***	-0.0016	-0.0186**	0.0001
	(0.0091)	(0.0096)	(0.0078)	(0.0086)
CY Rain Bottom Terc.	0.0230**	-0.0024	0.0142	-0.0022
	(0.0099)	(0.0111)	(0.0089)	(0.0096)
CY Rain Top Terc.	-0.0512***	-0.0067	-0.0296***	-0.0012
	(0.0101)	(0.0104)	(0.0084)	(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%.

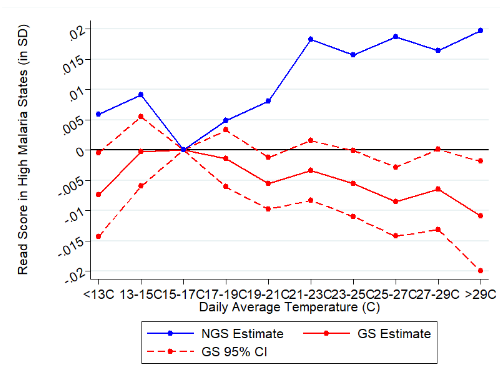
A.4.4 ASER Results: Results by Malaria Prone States



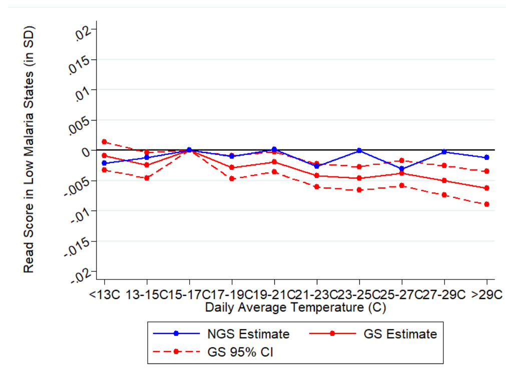
(a) Malaria Prone States



(b) Other States



(c) Malaria Prone States



(d) Other States

Figure A.7: Temperature and Test Scores (ASER): By Malaria Prone States

Table A.12: Long Run Temperature and Test Scores (ASER): Malaria Prone States

	(1) Math Score (in SD) Other States	(2) Math Score (in SD) Malaria Prone	(3) Read Score (in SD) Other	(4) Read Score (in SD) Malaria Prone
GS Days <13C	-0.0011	-0.0047	-0.0009	-0.0074**
	(0.0013)	(0.0046)	(0.0012)	(0.0035)
GS Days 13-15C	-0.0037***	0.0026	-0.0025**	-0.0003
	(0.0011)	(0.0039)	(0.0011)	(0.0029)
GS Days 17-19C	-0.0048***	0.0031	-0.0028***	-0.0014
	(0.0010)	(0.0029)	(0.0010)	(0.0024)
GS Days 19-21C	-0.0039***	-0.0039	-0.0019**	-0.0055**
	(0.0010)	(0.0025)	(0.0008)	(0.0022)
GS Days 21-23C	-0.0078***	-0.0004	-0.0042***	-0.0034
	(0.0012)	(0.0029)	(0.0010)	(0.0025)
GS Days 23-25C	-0.0085***	-0.0032	-0.0047***	-0.0055**
	(0.0012)	(0.0035)	(0.0010)	(0.0028)
GS Days 25-27C	-0.0071***	-0.0075**	-0.0038***	-0.0085***
	(0.0012)	(0.0036)	(0.0011)	(0.0029)
GS Days 27-29C	-0.0091***	-0.0065	-0.0050***	-0.0065*
	(0.0015)	(0.0043)	(0.0012)	(0.0034)
GS Days >29C	-0.0103***	-0.0100*	-0.0062***	-0.0109**
	(0.0016)	(0.0059)	(0.0014)	(0.0046)
NGS Days <13C	-0.0061*	0.0056	-0.0022	0.0059
	(0.0032)	(0.0089)	(0.0033)	(0.0068)
NGS Days 13-15C	-0.0044	0.0200**	-0.0013	0.0091
	(0.0031)	(0.0085)	(0.0029)	(0.0071)
NGS Days 17-19C	-0.0014	0.0085	-0.0010	0.0048
	(0.0022)	(0.0085)	(0.0021)	(0.0073)
NGS Days 19-21C	0.0015	0.0163***	0.0001	0.0080**
	(0.0019)	(0.0062)	(0.0018)	(0.0034)
NGS Days 21-23C	-0.0029	0.0219***	-0.0026	0.0183***
	(0.0021)	(0.0061)	(0.0020)	(0.0043)
NGS Days 23-25C	0.0003	0.0206***	-0.0001	0.0157***
	(0.0022)	(0.0054)	(0.0021)	(0.0036)
NGS Days 25-27C	-0.0037*	0.0246***	-0.0030	0.0187***
	(0.0022)	(0.0062)	(0.0020)	(0.0042)
NGS Days 27-29C	0.0006	0.0218***	-0.0003	0.0164***
	(0.0023)	(0.0061)	(0.0021)	(0.0044)
NGS Days >29C	0.0000	0.0246***	-0.0012	0.0197***
	(0.0025)	(0.0064)	(0.0023)	(0.0047)
Observations	3787102	794514	3787102	794514
R^2	0.089	0.065	0.071	0.060

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. Standard errors are in parentheses, clustered by district. The malaria prone states are Orissa, Chattisgarh, West Bengal, Jharkhand and Karnataka.
*Significant at 10%.
**Significant at 5%.
***Significant at 1%.

B Appendix: Why does income matter?

Given that longer-run temperature 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 households [34]. 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 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.

B.1 Additional Data Set

For this appendix, in addition to our datasets mentioned in the main paper, we also make use of the India Human Development Survey (IHDS), which is a nationally representative, multi-topic survey conducted across urban and rural areas. There are currently two waves of IHDS (2004-05 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.

B.2 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 B.2, columns 4-6). Consequently each additional hot day reduces value of household overall (home and market) consumption of grains by 0.6% (table B.2, 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.

[34] There 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).

Third, we do find hot days increase school absence modestly, and much of this is driven by increased sickness(table B.4). 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 (B.3).

We further corroborate this evidence from an additional survery with coverage for all of India - the India Human Development Survey (IHDS). We find that under extreme temperatures, overall grain consumption decreases (table B.7), sickness increases (table B.8) and medical expenditures increase (table B.9).

Time-Use

We find modest evidence to support the time-use hypothesis. We find that during extreme temperatures, households adjust their time use (table B.5,B.6). We find that an extra hot day above 23C increases time spent by children in caring for infants by 5% (table B.5, column 2) and a 7% increase in household chores (table B.5, column 3). Simultaneously, we observe a corresponding drop in self-study time by 4% (table B.6, column 2). Importantly however, we don't see any reduction in time spent in school (table B.6, 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.10).

Table B.1: 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***	-0.005***
	(0.003)	(0.002)
PY Days >27C	-0.006	-0.004*
	(0.003)	(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 B.2: 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	0.005***	-0.002	-0.002	-0.001	0.002
	(0.003)	(0.002)	(0.001)	(0.004)	(0.002)	(0.002)
PY Days 25-27C	-0.009*	0.014***	0.006**	0.010	-0.001	0.004
	(0.005)	(0.004)	(0.002)	(0.008)	(0.005)	(0.004)
PY Days >27C	-0.006	0.013***	0.005**	-0.016**	-0.005	-0.000
	(0.006)	(0.004)	(0.003)	(0.007)	(0.005)	(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%.

B.3 ASER: School Attendance

Table B.3: 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	0.0001	0.0021*
	(0.0005)	(0.0005)	(0.0011)
PY NGS Days >21C	0.0002	0.0002	0.0001
	(0.0004)	(0.0004)	(0.0008)
PY GS Days <15C	-0.0006***	-0.0006**	-0.0013**
	(0.0002)	(0.0002)	(0.0005)
PY GS Days >21C	-0.0004**	-0.0004**	-0.0004
	(0.0002)	(0.0002)	(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 B.4: Temperature and Student Health and Absenteeism

	(1) School Absence β / SE	(2) Reason: Illness β / SE
PY Days 23-25C	0.001	0.004**
	(0.002)	(0.002)
PY Days 25-27C	-0.001	-0.002*
	(0.002)	(0.001)
PY Days >27C	0.002	0.004***
	(0.002)	(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%.

B.4 Time Use

Table B.5: 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	0.055**	0.077*	-0.006
	(0.002)	(0.024)	(0.042)	(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 B.6: 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	-0.041*	-0.012
	(0.002)	(0.022)	(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%.

B.5 IHDS

Table B.7: 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	-0.0031	-0.0208**
	(0.0016)	(0.0073)	(0.0093)
Days >21C	-0.0020*	0.0036	-0.0073
	(0.0010)	(0.0040)	(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 B.8: Previous Year Temperature and Illness

	(1) Sick 0/1 β / SE	(2) Log Days Sick β / SE
Days <15C	0.0006	0.0002
	(0.0013)	(0.0021)
Days >21C	0.0021***	0.0023
	(0.0008)	(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 B.9: Previous Year Temperature and Health Expenditure

	(1) Log OutPatient Exp β / SE	(2) Log InPatient Exp β / SE
Days <15C	-0.0088	0.0051
	(0.0126)	(0.0135)
Days >21C	0.0208***	-0.0003
	(0.0064)	(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%.

C Appendix: NREGA

C.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.

C.2 Temperature and take-up of NREGA

Table C.1: NREGA Take-up and Temperature

	(1) Log Person Days β / SE	(2) Log HHs 100 Days β / SE	(3) Exp. Labor β / SE	(4) Exp. Material β / SE
Days <13C	-0.0101***	-0.0202***	-0.0098***	-0.0192***
	(0.0023)	(0.0064)	(0.0024)	(0.0038)
Days 13-15C	-0.0012	0.0016	-0.0001	-0.0040
	(0.0019)	(0.0055)	(0.0020)	(0.0027)
Days 17-19C	0.0008	0.0121**	0.0056**	0.0098***
	(0.0020)	(0.0053)	(0.0023)	(0.0034)
Days 19-21C	0.0082***	0.0235***	0.0126***	0.0212***
	(0.0023)	(0.0048)	(0.0024)	(0.0037)
Days 21-23C	0.0092***	0.0231***	0.0120***	0.0208***
	(0.0025)	(0.0063)	(0.0028)	(0.0046)
Days 23-25C	0.0108***	0.0188***	0.0143***	0.0246***
	(0.0022)	(0.0051)	(0.0024)	(0.0044)
Days 25-27C	0.0124***	0.0309***	0.0185***	0.0256***
	(0.0023)	(0.0057)	(0.0027)	(0.0044)
Days 27-29C	0.0125***	0.0315***	0.0179***	0.0201***
	(0.0025)	(0.0064)	(0.0030)	(0.0050)
Days >29C	0.0131***	0.0338***	0.0193***	0.0285***
	(0.0026)	(0.0063)	(0.0030)	(0.0053)
Observations	3519	3519	3519	3519
R^2	0.948	0.644	0.796	0.658

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 2006-2016. 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. This table uses annual data on NREGA take-up and expenditures.
*Significant at 10%.
**Significant at 5%.
***Significant at 1%.

C.3 Robustness: Triple Differences

Table C.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	-0.0037***	-0.0029***
	(0.0011)	(0.0010)
Days >21C	-0.0012	-0.0009
	(0.0009)	(0.0008)
NREGA PY	-0.1926***	-0.1322**
	(0.0622)	(0.0600)
NREGA PY*Days >21C	0.0005**	0.0003*
	(0.0002)	(0.0002)
Observations	1866623	1866623
R^2	0.098	0.081

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

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

	(1) Math Score (in SD) β / SE	(2) Read Score (in SD) β / SE
NREGA: T = -3	-0.0180	0.0160
	(0.0370)	(0.0342)
NREGA: T = -2	-0.0331	-0.0374
	(0.0345)	(0.0324)
NREGA: T = 0	-0.0754***	-0.0494*
	(0.0270)	(0.0254)
NREGA: T = 1	-0.1111***	-0.0901**
	(0.0366)	(0.0350)
NREGA: T = 2	-0.0675	-0.0748
	(0.0638)	(0.0598)
Days <13C	-0.0027*	-0.0009
	(0.0015)	(0.0014)
Days 13-15C	-0.0010	-0.0015
	(0.0019)	(0.0017)
Days 17-19C	0.0028*	0.0025
	(0.0017)	(0.0016)
Days 19-21C	0.0034**	0.0028**
	(0.0015)	(0.0014)
Days 21-23C	0.0021	0.0015
	(0.0014)	(0.0013)
Days 23-25C	0.0021	0.0017
	(0.0015)	(0.0013)
Days 25-27C	0.0003	0.0004
	(0.0016)	(0.0014)
Days 27-29C	0.0002	0.0003
	(0.0017)	(0.0015)
Days >29C	-0.0009	-0.0004
	(0.0018)	(0.0016)
NREGA: T = -3 * Days >29C	0.0007	0.0000
	(0.0005)	(0.0005)
NREGA: T = -2 * Days >29C	0.0006	0.0006
	(0.0005)	(0.0004)
NREGA: T = 0 * Days >29C	0.0002	0.0000
	(0.0004)	(0.0004)
NREGA: T = 1 * Days >29C	0.0008	0.0007
	(0.0005)	(0.0005)
NREGA: T = 2 * Days >29C	0.0003	0.0008
	(0.0010)	(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.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Figure C.1: Event Study: Long Run Temperature, NREGA and Math Scores

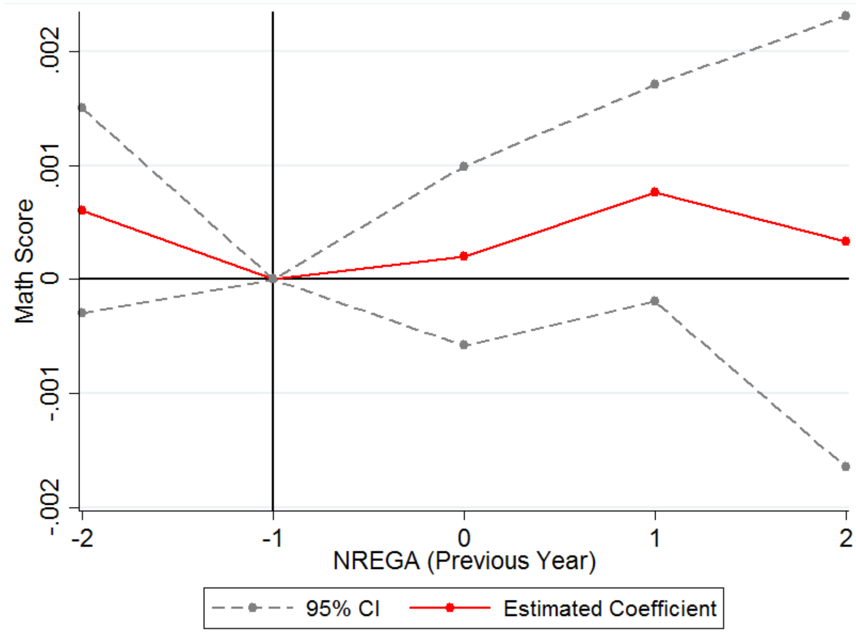
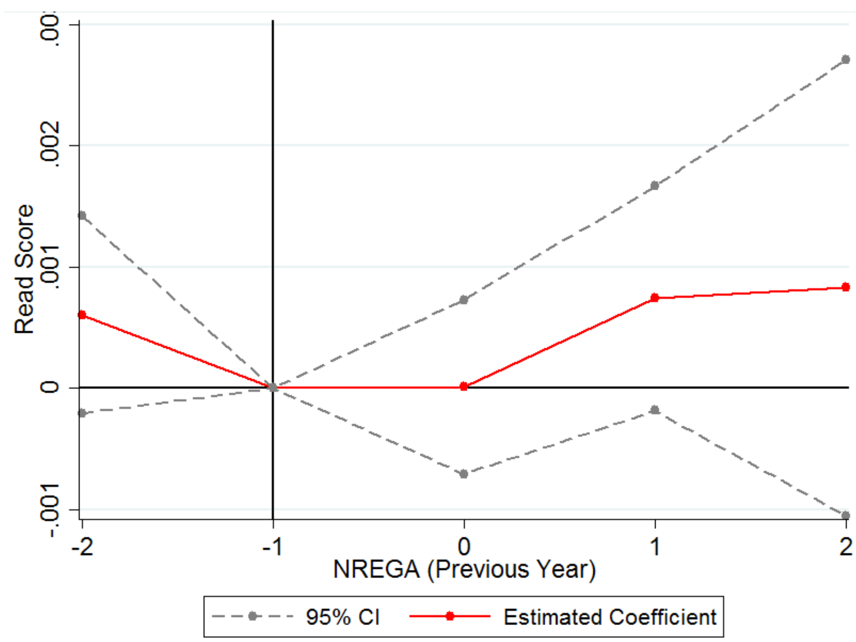


Figure C.2: Event Study: Long Run Temperature, NREGA and Reading Scores



C.5 Robustness: On-track Only

Table C.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***	0.1957**
	(0.0864)	(0.0823)
Time = -2	-0.0225	-0.0599
	(0.0846)	(0.0804)
Time = 0	-0.1399**	-0.1295**
	(0.0563)	(0.0534)
Time = 1	-0.2261***	-0.1936***
	(0.0802)	(0.0717)
Time = 2	-0.2924**	-0.2628**
	(0.1188)	(0.1047)
Days <15C	-0.0036***	-0.0024**
	(0.0011)	(0.0010)
Days >21C	-0.0011	-0.0007
	(0.0008)	(0.0007)
Time = -3 * Days >21C	-0.0011***	-0.0006**
	(0.0003)	(0.0003)
Time = -2 * Days >21C	0.0001	0.0002
	(0.0003)	(0.0003)
Time = 0 * Days >21C	0.0003*	0.0003*
	(0.0002)	(0.0002)
Time = 1 * Days >21C	0.0006**	0.0005**
	(0.0003)	(0.0002)
Time = 2 * Days >21C	0.0009**	0.0007**
	(0.0004)	(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 C.3: Event Study - On-Track Children: Long Run Temperature, NREGA and Math Scores

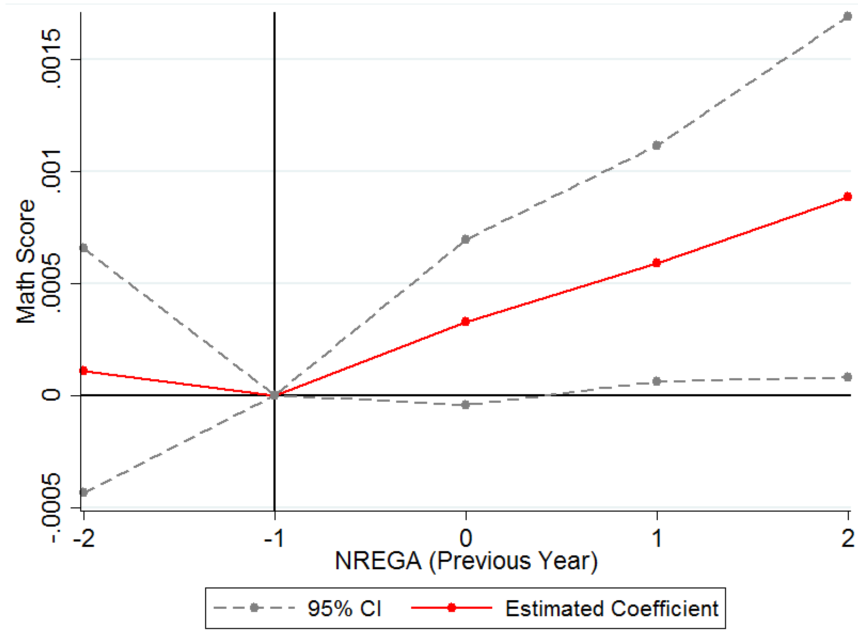


Figure C.4: Event Study - On-Track Children: Long Run Temperature, NREGA and Reading Scores

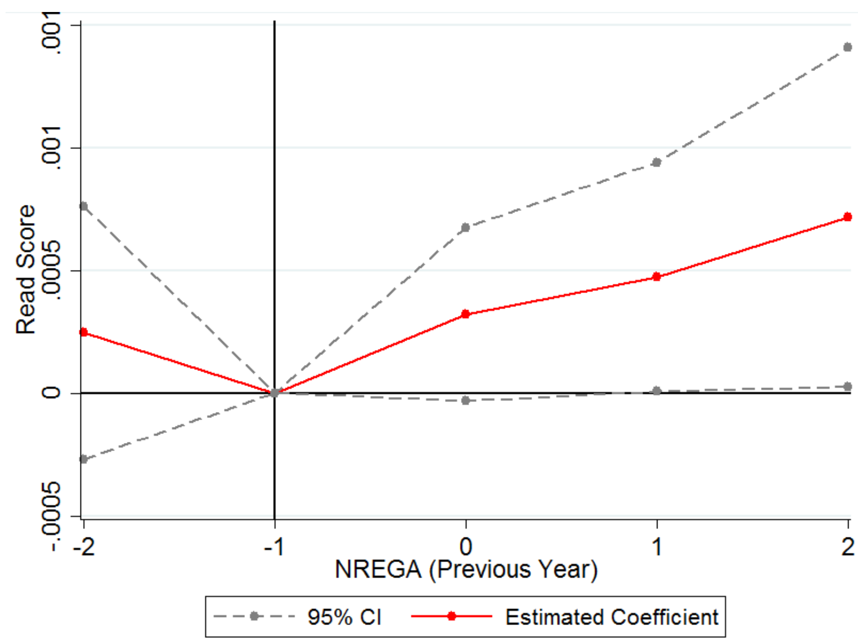


Table C.5: Difference in Difference - On-Track Children: Long Run Temperature, NREGA and Test Scores

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

D Appendix: Data

D.1 Weather Data

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

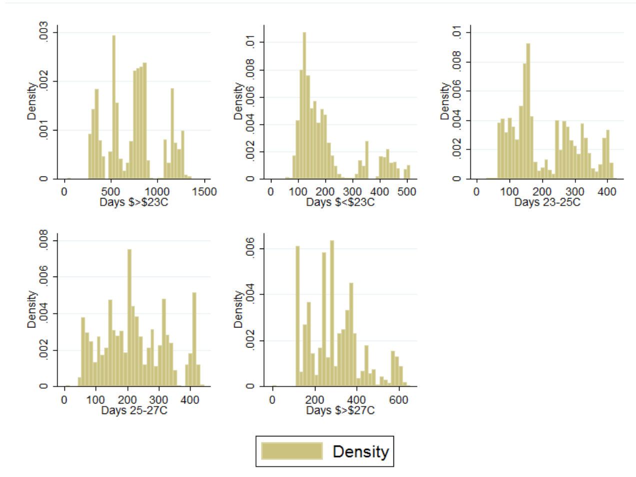
	All	2006	2007	2008	2009
Days >21C	250.49	249.75	257.84	245.86	247.68
	(87.46)	(83.67)	(88.98)	(89.34)	(91.98)
PY Days <13C	32.40	30.47	27.98	34.53	33.28
	(66.61)	(66.87)	(68.11)	(68.12)	(70.30)
PY Days 13-15C	16.48	18.39	15.12	16.94	17.29
	(15.14)	(15.81)	(15.37)	(15.65)	(15.73)
PY Days 15-17C	19.30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

Notes: Standard deviations are in parentheses.

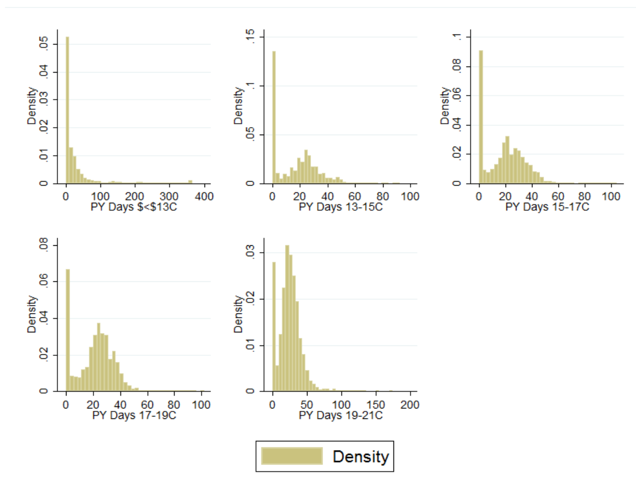
Table D.2: Summary Statistics: Yearly Temperature Bins - 2011-2014 (Mean no. of days)

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

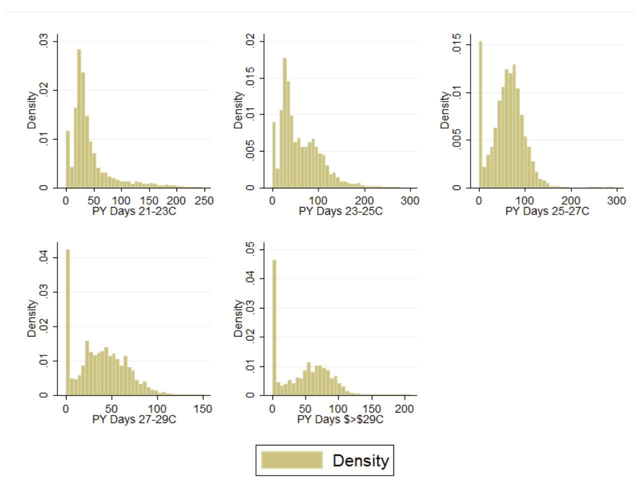
Notes: Standard deviations are in parentheses.



(a) Andhra Pradesh



(b) All India



(c) All India (continued)

Figure D.1: Long Run Temperature Variation