Temperature and Human Capital in India*

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Abstract

We estimate the effects of temperature on human capital production in India. We show that high temperatures reduce both math and reading test scores through an agricultural income mechanism—hot days during the growing season reduce agricultural yields and test scores with comparatively modest effects of hot days in the non-growing season. The roll-out of a workfare program, by providing a safety net for the poor, substantially weakens the link between temperature and test scores. Our results imply that absent social protection programs, climate change will have large negative impacts on human capital production of poor populations in agrarian economies.

JEL Codes: H41, I0, O13, O15, Q5, Q54
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1 Introduction

To what extent does the human condition vary with weather? This relationship has been of long-standing interest in the economics literature, and the fact that the earth's climate is warming has renewed interest in the effects of weather on economic outcomes (Mendelsohn, Nordhaus and Shaw, 1994; Dell, Jones and Olken, 2012, 2014; Burke, Hsiang and Miguel, 2015*b*). Because human capital is an important driver of economic growth (Nelson and Phelps, 1966; Romer, 1986; Barro, 2000), a critical yet understudied question is the impact of temperature on human capital production. This question is of particular interest in developing countries, which will experience disproportionately higher temperatures (Harrington et al., 2016), where predominantly agrarian livelihoods are climate-exposed, and where individuals are unable to consumption smooth over aggregate weather shocks (Rosenzweig and Stark, 1989; Rosenzweig and Wolpin, 1993; Paxson, 1993; Townsend, 1994; Deaton, 1997; Dercon and Krishnan, 2000; Dercon, 2005; Cole et al., 2013).

We use math and reading test scores for more than 4 million children in primary and secondary school to examine how high temperatures affect human capital production in India, where the number of extremely hot days is expected to double by the end of the 21st century (figure 1). We identify the mechanism of impact through reduced agricultural productivity 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).[1] However, in poor countries, human capital production 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.[2]

[1]We follow Graff-Zivin, Hsiang and Neidell (2015) to examine if similar effects exist in India. We find comparable estimates (appendix A).

[2]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; Deschênes 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 (Deschênes

First, using test scores from an India-wide repeated cross-section between 2006-2014, we show that over a longer-run horizon, measured as the number of hot days in the calendar year prior to the test, high temperatures affect both math and reading scores; 10 extra days in a year with average *daily* temperature above 29°C (85°F) relative to 15°C-17°C (59°F-63°F) reduce math and reading test performance by 0.03 and 0.02 standard deviations respectively.[3] These are large effects: an extra 40 hot days above 29°C in a year, as is expected in India by the end of the 21st century, would reduce math and reading test scores by 0.12 and 0.08 standard deviations respectively, equivalent to wiping out the gains from the median educational intervention.[4] We corroborate these findings using a rich longitudinal study from a large state in Southern India, Andhra Pradesh.

Second, we find strong evidence that the underlying mechanism is the harmful effect of higher temperatures on agricultural yields and incomes: (a) hot days during the agricultural growing season have large negative effects on test score performance whereas those in the non-growing season have minimal effects, (b) the effects of high temperatures are concentrated in warmer regions that grow below-median levels of heat resistant crops, and (c) high temperatures have large negative effects on both agricultural yields and rural wages.[5] 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)

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).

[3]We use the term "longer-run" temperature to distinguish these effects from those of day-of-test temperatures documented in appendix A.

[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.

[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). More recently, Shah and Steinberg (2017) have shown that higher wages can reduce human capital through an opportunity cost mechanism. If extreme weather affects household income, such income effects could be another potential channel through which extreme temperatures affect human capital production 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 mortality (Burgess et al., 2017). 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.

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%. We also 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 two distinct literatures. The first is the literature that examines the relationship between weather and economic outcomes, within which 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).[6] In contrast to prior work that 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 (e.g., human capital) over different time horizons. We find that day-of-test effects are likely driven by the physiological effects of heat stress (short-run temperature), whereas annual effects are likely driven by the effects of weather on livelihoods (longer-run temperature).[7] 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 day-of-test 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, 2014; Burke

[6] A rich literature considers the impacts of higher temperatures on a variety of economic outcomes including, but not limited to, output (Burke, Hsiang and Miguel, 2015*b*; Somanathan et al., 2015; Burke and Emerick, 2016), mortality (Deschênes and Moretti, 2009; Barreca et al., 2016; Burgess et al., 2017), and conflict (Burke, Hsiang and Miguel, 2015*a*).

[7] In appendix A, we estimate the effect of short-run temperature – measured as the average temperature on the day of the test – on cognitive performance. We find that the day-of-test average temperature above 27°C (80°F) relative to day-of-test average temperature below 23°C (73°F) 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 methodology and estimates are remarkably similar to related work in developed countries (Graff-Zivin, Hsiang and Neidell, 2015; Park, 2017; Cho, 2017). While these effects are temporary, we recognize that more permanent *economic* effects can arise from short-term physiological effects of heat stress and air pollution on performance when high-stakes exams introduce path dependence in human capital production, as in the cases of Park (2017) and Ebenstein, Lavy and Roth (2016), respectively.

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.[8]

Second, we build on a vast literature on the effects of social protection programs.[9] 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.[10] As such, we demonstrate that social protection programs such as NREGA reduce the temperature sensitivity of poor households, providing benefits that have previously received little consideration (Hsiang, Oliva and Walker, 2017).[11] In doing so, we identify an important policy instrument for adaptation, especially in developing countries where the rural poor are often unable to smooth consumption over district-level aggregate weather shocks (Rosenzweig and Stark, 1989; Rosenzweig and Wolpin, 1993; Paxson, 1993; Townsend, 1994; Deaton, 1997; Dercon and Krishnan, 2000; Dercon, 2005; Cole et al., 2013; Burgess et al., 2017).

The rest of the paper is organized as follows. Section 2 describes the data. In section 3 we outline the empirical strategy. In section 4 we describe our results and the underlying mechanism, and discuss competing explanations. 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.

[8] 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 production. Relatedly, recent work by Shrader (2016) provides a method to use informational interventions to quantify the ex-ante benefit of adaptation.

[9] See, for example, Fiszbein et al. (2009) and Parker and Todd (2017) for exhaustive reviews on conditional cash transfers.

[10] 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 heterogeneity (e.g., income) in the marginal effects of heat stress.

[11] 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 data sets 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

The Annual Status of Education Report 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.[12] The sample is a representative repeated cross section at the district level. The ASER surveyors ask each child, in his or her native language, four potential questions in math and reading. In each subject, the surveyors begin with the hardest of the four questions. If a child is unable to answer that question, they move on to the next hardest question, and so on and so forth.

The ASER is a valuable data set 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 more than 4 million tests across every rural district in India.[13] 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

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

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

administered each year on two or three weekends during the period 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 related to school attendance or access to schools. ASER tests children aged 5-16, who are currently enrolled, dropped out, or have never enrolled in school. In appendix E.1, we show average raw test scores for both math and reading from 2006-2014.

2.1.2 Young Lives Survey

While the ASER has the advantages of national coverage and a 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 the period between 2002 and 2011 in the state of Andhra Pradesh (unlike ASER, YLS is conducted in a single state in India).[14] The study has collected data on two cohorts of children: 1,008 children born between January 1994 and June 1995, and 2,011 children born between January 2001 and June 2002. We limit our sample to the younger cohort, since we have at least three survey rounds with test scores data for those children. Data was collected from children and their families using household visits in 2002, 2006, 2009, and in 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 children's age and cureent stage of education. In contrast to the ASER tests, the YLS tests are much longer and more comprehensive, with the math questionnaire containing 30 questions and the reading test covering close to 100 questions.

[14]Andhra Pradesh is the fourth-largest state in India by area and had a population of more than 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.

Further, YLS has particularly rich information about the socio-economic background of the children's households, child-specific data on time-use, nutritional intake data, health data, and data on medical expenditures.

2.2 Weather Data

In an ideal research setting, we would use observational weather 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 severely lacking. 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. Dee et al. (2011) provide more details about the methodology and construction of the ERA-Interim data set. 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 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 E.1 shows the long-run variation in temperature in Andhra Pradesh (panel A) and all India (panels 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) and data on NREGA.

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 (excludes wheat). ICRISAT also provides data on district-level averages of rural wages.

National Rural Employment Guarantee Act

The National Rural Employment Guarantee Act, also known as the Mahatma Gandhi National Rural Employment Guarantee Act, is the largest workfare program in the world. It legally guarantees each rural household up to 100 days of public-sector work each year at the prevailing minimum wage. It was rolled out non-randomly, in three phases, according to a backwardness index developed by the Planning Commission of India. The first phase began with 200 districts in February 2006; an additional 130 districts received the program in 2007. By April 2008 the scheme was operational in all rural districts in India. Any rural resident who is 18 years or older can apply for work at any time of the year. Men and women are paid equally, though at least one-third of the beneficiaries must be women. Projects under NREGA involve construction of local infrastructure that improves water management through conservation, rain water collection, and irrigation, as well as flood control, drought proofing, rural connectivity, and land development. NREGA wages vary from state to state, but the floor and ceiling wages under the scheme are set by the central government. We obtain data on NREGA participation for 2006-2016 from the Management Information Systems (MIS).[15] In particular, we focus on the number of rural households enrolled in NREGA in a particular district in a given year. In appendix E.3, we show summary statistics on NREGA participation, and labor as well as material expenditures from 2006-2014.

[15] We thank Clément Imbert for generously sharing these data.

3 Research Design

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

All India Repeated Cross-Sectional Data (ASER)

To understand the relationship between temperature and test scores throughout India, we use the ASER data set. Following Deschênes and Greenstone (2011) and Hsiang (2016), we first estimate a flexible model:

$$Y_{iajqt} = \sum_{k=1}^{10} \gamma_k TMEAN_{jq,t-1}^{k} + f\left(rain_{jq,t-1}\right) + g\left(humidity_{jq,t-1}\right) + \chi_a + \alpha_j + \mu_t + \epsilon_{ijqt} \quad (1)$$

Y_{iajqt} is math or reading test scores for child i, of age a, in district j, in state q, in year t, standardized by year-age. $TMEAN_{jq,t-1}^{k}$ 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 13°C, and the hottest temperature bin is a count of the number of days with average temperature greater than 29°C. We chose these endpoints because 13°C and 29°C are the 10th and 90th percentiles of average daily temperatures across India from 2006-2014. The bins in between are evenly spaced two degrees apart. The omitted bin is the 15°C-17°C bin, which we chose to omit because it has the maximum coefficient of all the bins (e.g., it has the most optimal effect on test scores). All other bins are interpreted relative to this bin. 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 29°C relative to a day with average temperature between 15°C and 17°C.

We control for rainfall (in annual cumulative terciles relative to district-specific historical averages), relative humidity (in terciles of annual averages), age fixed effects (χ_i), district fixed effects (α_j) and year fixed effects (μ_t).[16] We cluster standard errors at the district level to account for serial correlation within the district over time. Each coefficient γ_k is identified under the assumption that, after controlling for rainfall and humidity, changes in the number of hot days are exogenous to district-specific unobservable characteristics that vary over time. 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). We also estimate a parsimonious version of equation (1) with the upper threshold of 21°C and lower threshold of 15°C. Our choice of 15°C and 21°C for the parsimonious model is based on the (approximation of the) nonparametric analysis (equation 1) that revealed a kink at that level.

$$\begin{aligned} Y_{ijaqt} =& \gamma_1 TMEAN(>21°C)_{jq,t-1} + \gamma_2 TMEAN(<15°C)_{jq,t-1} \\ & f\left(rain_{jq,t-1}\right) + g\left(humidity_{jq,t-1}\right) + \chi_a + \alpha_j + \mu_t + \epsilon_{ijqt} \end{aligned} \tag{2}$$

An important limitation of the ASER data is that it does not provide the exact date of the test; we know only that the test is conducted in a given district on a single weekend between the end of September and the end of November. Since our hypothesis is that hot days affect test scores by affecting household income that relies on agricultural output, we must measure the effect of heat during at least one full agricultural cycle prior to the test. We discuss this timeline in figure 4. India's main agricultural season is the Kharif season, with the growing season from June through October and harvest in October and November. Given that our tests are conducted concurrently or before harvest, heat during the growing season in the same calendar year as the test should not directly affect test scores, because that income effect would not have transpired by the time of the test. Instead, we use the daily temperature distribution of the prior calendar year as our main independent variable. Importantly, this also sets up a falsification test for competing explanations that

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

do not adhere to an agricultural calendar. While temperature in the previous year could affect test scores through an agricultural income channel (and potentially other mechanisms), temperature in the same year as the test (the "current year") would affect test scores through only non-agricultural channels (e.g., learning, teacher attendance, disease prevalence, etc., as detailed in section 4.2). Next, we use the YLS data set, in which we have information on the exact date of the test to estimate the effect of hot days between successive tests (covering at least one full agricultural cycle) on test scores. We describe that strategy below.

Individual Panel Data (YLS)

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

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

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. We control for cumulative rainfall, and include fixed effects for child (α_i), day-of-week (μ_{1d}), month-of-year (μ_{2m}), and survey-round (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, $T(23°C - 25°C)$ is the number of days since the last test with average daily temperature between 23°C and 25°C. Since the YLS data covers a single state (Andhra Pradesh), the temperature distribution is narrower than in the other national data sets that we use. Furthermore, since the number of days in a year is fixed at 365, we normalize the coefficient on the "optimal" temperature bin, in this case $T(< 23°C_{jt})$, 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 27°C relative to a day with average temperature below 23°C. Our four temperature bins have, on average, an equal density with 23°C, 25°C, and 27°C representing the first, second and third quartiles of the temperature distribution in Andhra Pradesh during our study period. We cluster standard errors at the district-week level to allow for arbitrary correlation in test scores in a district in a given testing week and for conservative inference when multiple children are assigned the same temperature observation. Each γ_i is identified under the assumption that the number of hot days experienced by a child in a given bin between successive tests is exogenous to child-specific unobservable characteristics that vary over time. Importantly, by tracking the same children over time, we are able to account for prior human-capital production 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 cutoff instead of flexible temperature bins:

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

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

4 Results

We estimate equation (1) and find that an extra 10 days in a year with average daily temperature above 29°C relative to a day with average daily temperature between 15°C and 17°C reduce math performance by 0.03 standard deviations and reading performance by 0.02 standard deviations (figure 5, table 1). Using our binned approach, we find that test performance decreases in temperatures above 17°C. The results are similar to those estimated with our parsimonious approach: 10 days above 21°C reduce math and reading performances by 0.02 and 0.01 standard deviations respectively. These are economically meaningful effects: 40 extra hot days above 29°C, as is expected in India by the end of the 21st century, would eliminate the gains from a median educational intervention.[17] Importantly, these are our most conservative estimates and represent the lower bound.

We find qualitatively similar (though quantitatively larger) effects when we estimate equations (3) and (4) using the YLS individual panel data set. We find that 10 extra days between successive tests above 27°C relative to below 23°C, reduce math and reading test scores by 0.07 and 0.10 standard deviations respectively (table 2, figure 6). The YLS data allows for us to estimate the effects of temperature by controlling for individual fixed effects, removing any time invariant individual level characteristics correlated with temperature. With the YLS data, we can also account for prior human capital production. We can also remove any spurious effects arising from day-of-test temperature that could be correlated with number of hot days in a year in a given district by controlling for day-of-test temperature while estimating equations (3) and (4).[18] In appendix table B.1, we show that including day-of-test temperature as a control doesn't change the effects of year-of-test temperature on performance.

Additional robustness checks provide the following results. First, we find no effect of hotter days in the current year or the next year on performance in the current year, and including these does not appreciably change our primary coefficient of interest (table 3). Second, our point estimates are quantitatively similar for the limited sample of "on-track" students who are in the correct school grade-for-age (appendix B.1.2). Third, our results are robust to a degree-day specification (appendix B.1.3). Fourth, the addition of lags does not significantly affect our point estimates (appendix B.1.4). Fifth, our results remain unchanged with the inclusion of state-specific linear and quadratic trends (appendix B.1.5). And, sixth, our results remain unchanged with the inclusion of state-by-year fixed effects (appendix B.1.6).

4.1 Mechanisms

If higher temperatures have large, negative effects on agricultural income, it is possible that these effects have consequences for children's human capital production in the immediate

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

[18]In appendix A, we show that test performance is affected by day-of-test temperature.

future. We find strong evidence in support of such a pecuniary mechanism underscoring the effect of temperature on test scores. First, we provide evidence that agricultural yields and wages 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 geographic dispersion of heat-resistant crops.[19]

Temperature, Agricultural Yields, and Rural Wages

To demonstrate that temperature affects human capital production 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 7, table 4). We use two different price-weighted agricultural yield indices: (a) the six major crops, and (b) the five major monsoon crops.[20] We find that yields respond non-linearly to temperature (figures 8(a), 8(b)). An extra day above 29°C (relative to a day between 15°C and 17°C) decrease yields by 0.5%-0.7%. Rural wages respond linearly to higher temperatures (figure 8(c)). An extra day above 29°C (relative to a day between 15°C and 17°C) decreases rural wages by 0.4%.[21]

Growing Season v. Non-Growing Season

To isolate effects by growing and non-growing seasons, we subdivide each temperature bin in equation (1) into days in that bin in the growing season and days in that bin in the non-growing season.[22] We find that the effect of temperature on test scores is primarily driven

[19]While we find strong evidence in favor of an income mechanism, we remain agnostic about why income matters. We take our cue from the rich body of evidence exploiting experimental and quasi-experimental variations in income to study the impacts on academic performance and find modest suggestive evidence for nutrition as the relevant margin of adjustment. We discuss these in appendix C. For comprehensive reviews of the impacts of cash transfer programs, see Fiszbein et al. (2009) and Parker and Todd (2017).

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

[21]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 reducing performance, cold days also reduce agricultural yields, though to a lesser extent than hot days.

[22]We broadly follow Burgess et al. (2017) in partitioning every year's weather data for each district into growing and non-growing seasons. 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 December 31st, we define the non-growing season as lasting from March through May and the

through higher temperatures in the previous years' agricultural growing seasons: an extra hot day above 29°C in the growing season has an order of magnitude larger effect on test scores than a corresponding extra hot day above 29°C in the non-growing season. Specifically, an extra 10 days above 29°C in the growing season reduces math scores by 0.102 standard deviations and reading scores by 0.062 standard deviations, compared to negligible effects in the non-growing season (table 5). The differences between the effects of temperature on test scores across growing versus non-growing seasons increase with higher temperatures for both math and reading scores (figure 8).

Additionally, we test the impact of temperature across the growing and non-growing seasons on agricultural yields of the six major crops as well as the five major monsoon crops. Using district level yields data, we find that an extra day above 29°C in the growing season reduces yields by three times more than the same type of day in the non-growing season. In absolute terms, the magnitude is large; an extra day above 29°C in the growing season relative to a day between 15°C and 17°C reduces yields by 1% (table B.8), with no effect of temperature on yields in the non-growing season.[23] The large impact of temperature on yields in the growing season but not in the non-growing season is consistent with a model in which temperature affects test scores through declines in agricultural income.

Heat-Resistant Crops

To further explore the impact of temperature on agricultural yields and test scores, we analyze the role of 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.[24] Since we are interested in the interaction term on heat-resistant crops and temperature, we estimate the parsimonious equation (2) to preserve power. We find that

growing season as lasting from June through December. The southwest monsoon begins to arrive (from the south) on the Indian subcontinent around the start of June of every year, and covers all of north India by the start of July.

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

[24]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 its long-run average of the proportion of C4 crops is above the median value, which is 23%. In appendix figure B.2 we show the geographic distribution of the take-up of heat-resistant crops.

growing heat-resistant crops erases most of the effect of higher temperatures on test scores. An extra 10 hot days above 21°C 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 6).

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 temperature deciles. We find that districts with higher long-term average temperature plant a larger fraction of their total cultivated area with heat-resistant crops (figure 11(a)). In the lower and middle deciles, there is very little take-up of heat-resistant crops but in districts with the highest long-term average temperatures, more than 30% of the total cultivated area is covered by heat-resistant crops. Furthermore, the relationship between days with temperature above 29°C 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 11(b)) and reading scores (figure 11(c)).[25] 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.[26]

4.2 Alternative Explanations

In this section, we rule out alternative channels that could potentially explain the relationship between temperature and test scores. Specifically, we consider four alternative explanations: (1) high temperatures during the school year affect learning, which subsequently affects per-

[25]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. In appendix table B.9 we report fraction of child-by-year observations with deviations at least as large as five days over 21°C for each climate decile, averaged over the years 2006-2014. We have sufficient temperature variation in each decile (relative to the middle deciles) after removing district and year fixed effects.

[26]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).

formance; (2) high temperatures during the growing season affect child labor in agriculture, which subsequently affects performance; (3) high temperatures increase the cost of attendance for teachers, resulting in teacher absenteeism and lower test performance by students; and (4) high temperatures increase disease incidence by favoring growth of disease-carrying pathogens, thereby affecting learning and test performance.

4.2.1 Heat During the School Year

The effect of short-run heat stress on cognitive performance could also manifest physiologically into reduced learning, as documented in appendix A. If children are repeatedly exposed to heat stress during 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 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 on test scores (table 3). If the physiological mechanism were driving the relationship between annual (or longer-run) temperature and test scores, we would see the effects on performance of hot days in both the current year and the previous year. As explained in figure 4, only hot days in the previous calendar year should affect test scores in the current year through the agricultural income channel.

Second, the physiological channel, unlike the agricultural income channel, should not be contingent on the agricultural calendar. 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 8). 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.[27] 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 effect during both school and non-school months in the growing season. Consistent with an agricultural income mechanism, we find that hot days in school and non-school

[27] 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.

months have similar effects on performance (figure 11), suggesting that it is unlikely that the relationship between higher temperatures in the prior year and test scores is driven by reduced learning due to heat stress in the classroom.

4.2.2 Heat Exposure on the Field

In addition to the income mechanism, the combination of large effects of heat in the growing season, paired with the negligible effects of heat during the non-growing season, could also be explained by heat exposure of agricultural workers from working in the field. If these workers are the same children being tested, then the growing season heat effects could be physiological effects on the human body, rather than those driven through an agricultural income mechanism. However, we find two pieces of evidence inconsistent with this hypothesis. First, heat stress during the concurrent year as the test has no effect on test scores (table 3). India's main agricultural season lasts from June through November. Since ASER tests are conducted from late September to early November, physiological exposure to heat, for children contributing labor to agriculture, would have transpired by the time of the test. Thus, we would expect to see effects of heat exposure in the concurrent year. Importantly, we see no effect of heat stress on the time spent by children working outdoors (appendix table C.5). Furthermore, if the agricultural labor-heat-exposure explanation were true, we would expect larger effects on older male children, who plausibly spend more time on agricultural activities. In contrast, we find that the effects of temperature on test scores are largest for younger children (figure 12), with no discernible differences between the effects of heat on test scores of boys and girls (figure B.1).

4.2.3 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 to later-life outcomes (Chetty, Friedman and Rockoff, 2014*a*,*b*). High temperatures can increase the cost of effort required to attend school and lead to teacher absenteeism, and consequently impact human capital production.[28] 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 11). The near-identical effects of heat during the school and non-school parts of the 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 year and the current year do not affect teacher attendance (appendix table B.10). This is consistent across different formulations of teacher attendance (binary or continuous) and across different specifications (linear or tobit). Therefore, it is unlikely that teacher attendance is the operational channel of impact linking hotter days to reduced test score performance.

4.2.4 Disease Prevalence

An alternative explanation to the temperature-test score relationship could be through increased disease incidence (Patz et al., 2005). To the extent that health affects performance, temperature could affect test scores through an increase in the population of disease-carrying pathogens, particularly those carrying malaria. Some of the rainiest months of the year are during the growing season, and since rainfall and humidity favor *Anopheles* growth, our growing season versus non-growing season estimates cannot rule out the malaria channel. We consider this disease-prevalence mechanism to be distinct from the disease susceptibility effects that may occur via the agricultural income channel (the latter occurring when reduced household income affects health status, including disease vulnerability, through channels such as nutrition). Although we control for rainfall and humidity in our main specification (table 1), and our results remain robust to the inclusion of state-by-year fixed effects, insofar as higher temperatures independently increase the incidence of disease variably within a given state-year, our results might be a function of such a mechanism.

However, because of the life cycle of disease pathogens we would expect more recent higher

[28] This problem is notable in India. Using unannounced visits to measure attendance, a nationally representative survey found that 24% 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.

temperatures to have a larger effect on health, and therefore performance, than similar days in the previous calendar year. Malaria, for example, is transferred through the *Anopheles* mosquito, which typically has a life cycle of two to four weeks, so if malarial incidence were driving our result, we should see an impact of hot days in the current year as well. In table 3, we show that temperature in the current year has no effect on test score performance.[29] Prima facie, this suggests that the disease ecology of malaria is not driving the temperature-test score relationship. Additionally, we follow Shah and Steinberg (2017) and exploit the geographic differences in prevalence of malaria across India and show that the effects of temperature don't vary with malaria prevalence. In figure B.3 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.[30]

5 Role of Social Protection Programs

The results so far have established that temperature likely affects human capital through an agricultural income channel. The immediate implication of this finding is that social protection programs designed to offset fluctuations in agricultural income could ameliorate the effects of hot days on test scores. To test this hypothesis, we consider the largest workfare program in the history of the world – the National Rural Employment Guarantee Act of 2005 – which guarantees every person in rural India 100 days of paid employment. The majority of such work is manual labor on rural infrastructure projects, making NREGA a self-targeting conditional cash transfer program that has an income-stabilizing effect in the event of shocks to agricultural income.

[29] Hotter days in the current year have been associated with higher prevalence of malaria (Patz et al., 2005).

[30] The malaria-prone states are Chhatisgarh, Jharkhand, Orissa, Karnataka, and West Bengal.

5.1 Research Design

Our hypothesis is that insults to agricultural income adversely affect human capital production. If NREGA modulates this relationship, hotter days might increase NREGA take-up and attenuate the relationship between temperature and test scores, by compensating (at least partially) for heat-induced agricultural income losses. We test this hypothesis in an event study framework, by exploiting the staggered district-level roll-out of NREGA. To do so, we estimate the marginal effect of an extra hot day above 29°C (relative to between 15°C-17°C) for the same district before and after the introduction of NREGA. We estimate the following equation:

$$
\begin{aligned}
Y_{iajqt} = & \sum_{k=1}^{10} \gamma_k TMEAN^k_{jq,t-1} + \sum_{\tau=-3,\tau\neq-1}^{\tau=2} \theta_\tau NREGA(t - T^*_j = \tau)_{jq,t-\tau} * TMEAN^{10}_{jq,t-1} \\
& + \sum_{\tau=-3,\tau\neq-1}^{\tau=2} \beta_\tau NREGA(t - T^*_j = \tau)_{jq,t-\tau} + \chi_a \\
& + f(rain_{jq,t-1}) + g(humidity_{jq,t-1}) + \alpha_j + \mu_t + \epsilon_{iajqt} \qquad (5)
\end{aligned}
$$

The equation is identical to equation (1) with an additional term, $NREGA(t - T^*_j = \tau)_{jq,t-\tau} * TMEAN^{10}_{jq,t-1}$, which captures the interaction of the roll-out of NREGA 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. For the NREGA interaction terms, the omitted period is the year before NREGA is introduced in a district, and we interpret the coefficient of interest θ_τ relative to that period. In our baseline specification, we include district (α_j) and year (μ_t) fixed effects. Our specification compares the effect of a hot day on test scores before and after a district received NREGA, relative to the effect of that hot day in other districts that didn't receive NREGA in the same year. Furthermore, to account for the potential endogeneity of the age-for-grade or "on track" status (Shah and Steinberg, 2015) we show that our results are robust when limiting the sample to children who are "on track" (appendix D.4). NREGA was introduced in 2006 and, because all districts had received NREGA by 2008, we restrict the ASER sample to include only survey-rounds between 2006-2009.

5.2 Results

The main coefficient of interest is the interaction between NREGA and the number of days above 29°C. Consistent with an income mechanism, we find that NREGA attenuates the effect of an extra hot day above 29°C in the prior calendar year on math and reading scores by more than 50% (table 7).[31] Figure 13 pictorially depicts the event study and shows that the introduction of NREGA attenuates the effect of those extra 10 hot days above 29°C on test scores by 0.01 standard deviations on both math and reading.[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.[33] Our results are robust to a parsimonious model similar to equation (2), with an upper threshold of 21°C and a lower threshold of 15°C. Our coefficient of interest is the interaction of NREGA roll-out with number of days above 21°C (appendix figure D.1, appendix table D.2). Finally, our results are robust when limiting the sample to "on track" students, reducing the likelihood that the endogeneity of NREGA and age-for-grade status is confounding our results (appendix D.4).

Since workfare requires individuals to sign up for work, it would be reasonable to expect NREGA take-up to respond contemporaneously to higher temperatures to offset declines in agricultural incomes. Indeed, we find that NREGA take-up responds to higher temperatures. We obtain annual NREGA district level take-up and expenditure data from 2006-2016 and show that hotter days in the current year drive NREGA take-up and expenditures (figure 14, appendix table D.6). Specifically, an extra hot day with average temperature above 29°C in a district (relative to a day between 15°C and 17°C) 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 29°C, district NREGA

[31] We show that prior to NREGA roll-out in a district, an extra 10 days above 29°C (relative to between 15°C and 17°C) reduces math and reading scores by 0.02 and 0.01 standard deviations, respectively, although because we use only data from 2006-2009 we are relatively underpowered.

[32] We find that NREGA exposure has a negative level effect on math and reading scores, and this effect is statistically significant (table 7). These are the opportunity cost effects shown in Shah and Steinberg (2015).

[33] We also employ a triple-differences design (comparing the effects of a hot versus a cold day in districts with and without NREGA, before and after they receive NREGA) to estimate the effect of NREGA on the marginal effect of an extra hot day in the previous calendar year and find comparable estimates (appendix table D.1).

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 relationship between temperature and test scores is of considerable importance. First, the result reinforces the underlying income mechanism linking higher temperatures to lower test score performance. Not only do higher temperatures lower test performance by adversely affecting household agricultural income, but 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 programs in combating vulnerability.[34] If the susceptibility of cognitive performance (or another measure of productivity) to temperature can be characterized as vulnerability, social protection programs can have not only 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 dramatically impact the poor by limiting pathways out of poverty that depend on human capital production. We find that day-of-test "short-run" temperature affects test performance through a physiological effect. However, temperature in the calendar year prior to the test, or "longer-run" temperature, affects human capital production through an agricultural income mechanism. The separation of the pathways through which temperature affects human capital over different time horizons has important implications for both climate change research

[34] See Fiszbein et al. (2009) and Parker and Todd (2017) for reviews on the impacts of cash transfer programs.

and 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. 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 between temperature and economic outcomes 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. Effects of short-run temperature, driven by physiology, can likely be corrected through defensive investments such as air conditioners, or by 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 22°C and 26°C respectively, to February, when average temperatures are 17°C (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 production 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 production as a pathway out of poverty in poor countries (Barrett, Garg and

McBride, 2016), climate change will not only affect the livelihoods of the rural poor but also, absent social protection programs, likely perpetuate persistent poverty.

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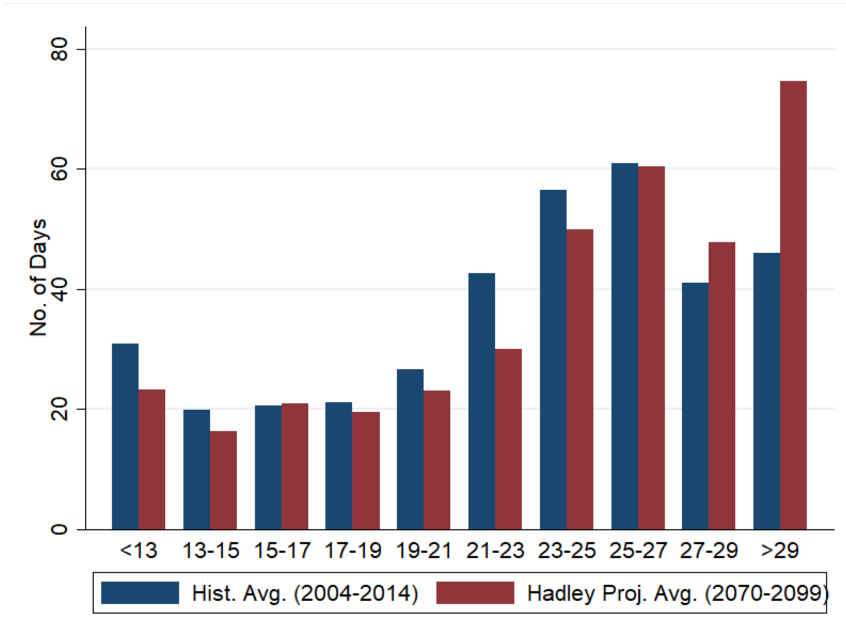
Figures

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

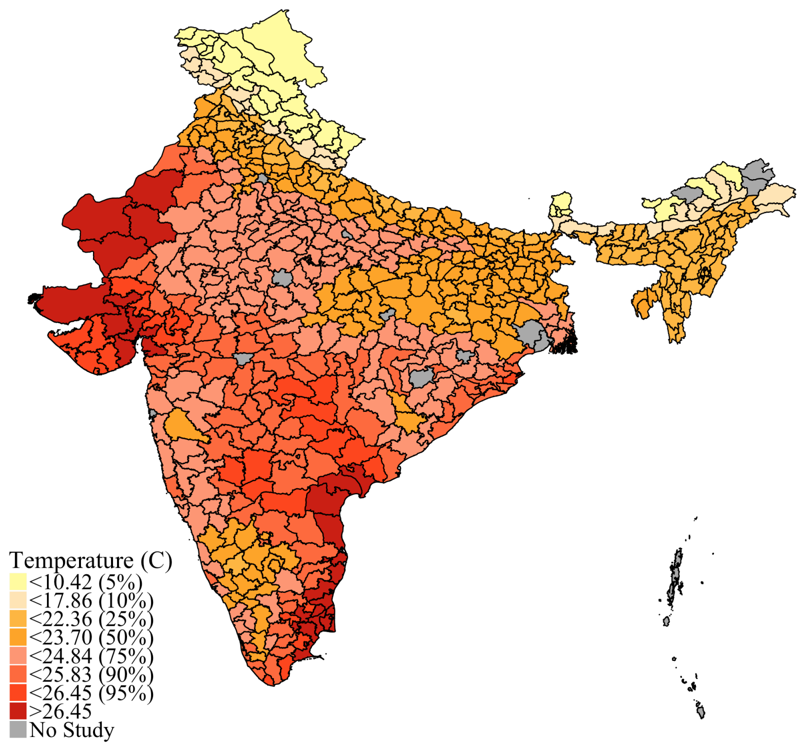


Figure 3: Distribution of Daily Temperatures for India and Andhra Pradesh

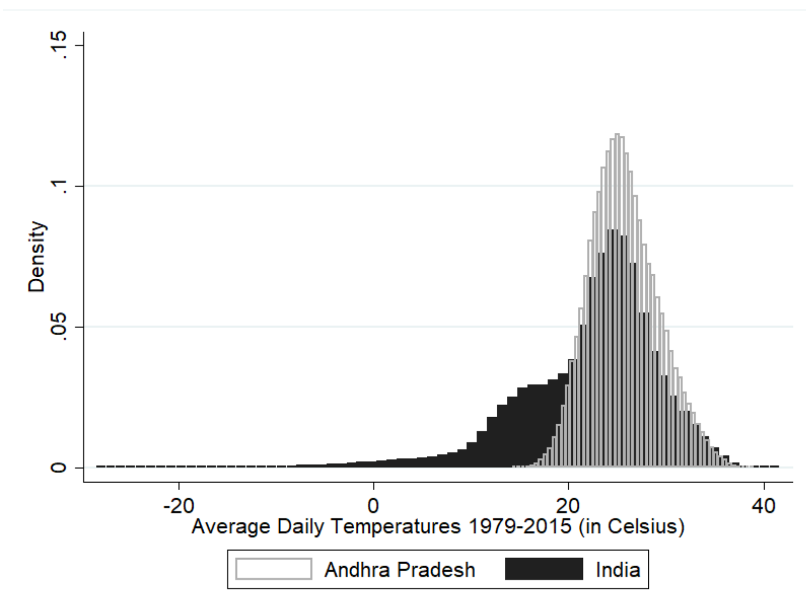
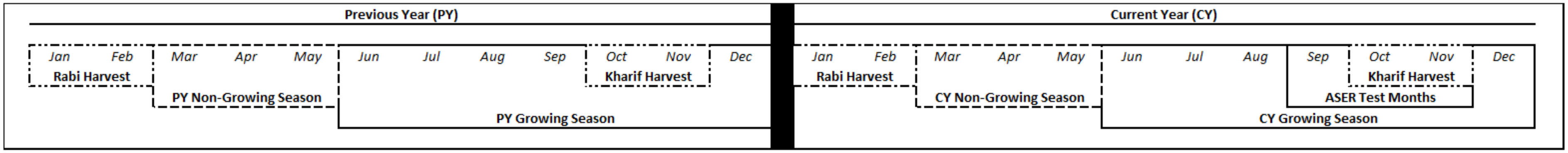
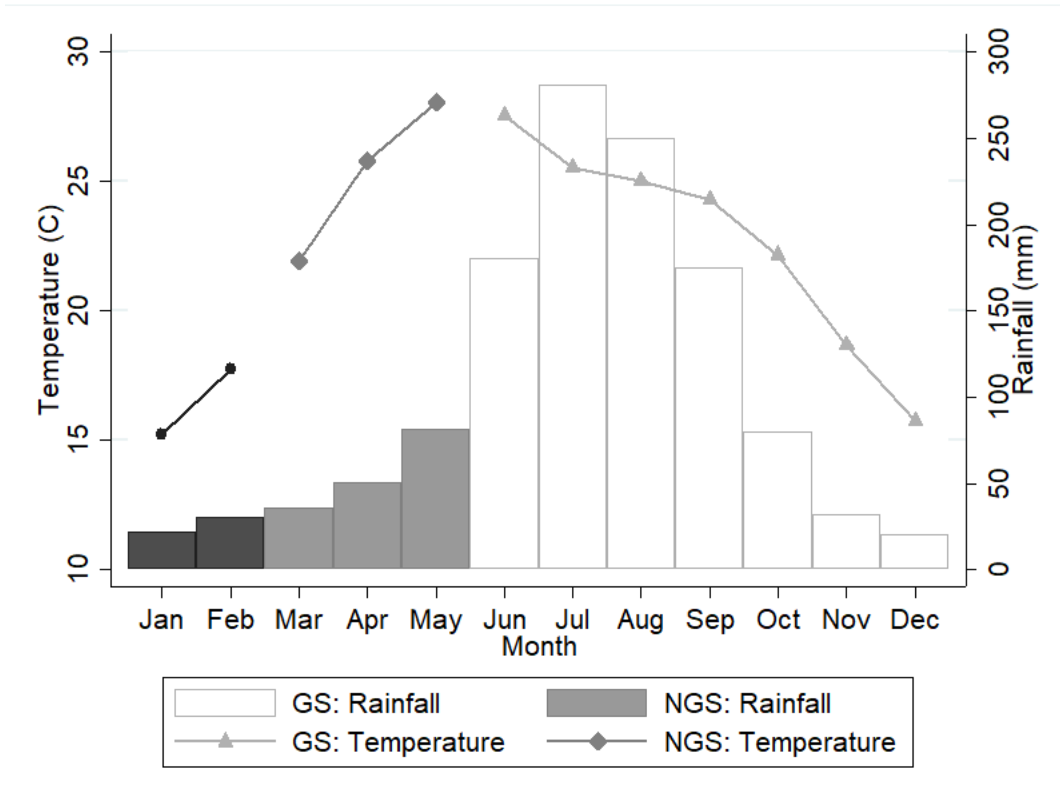


Figure 4: Timeline of Effects of Longer-Run Temperature and Average Temperatures by Month and Season



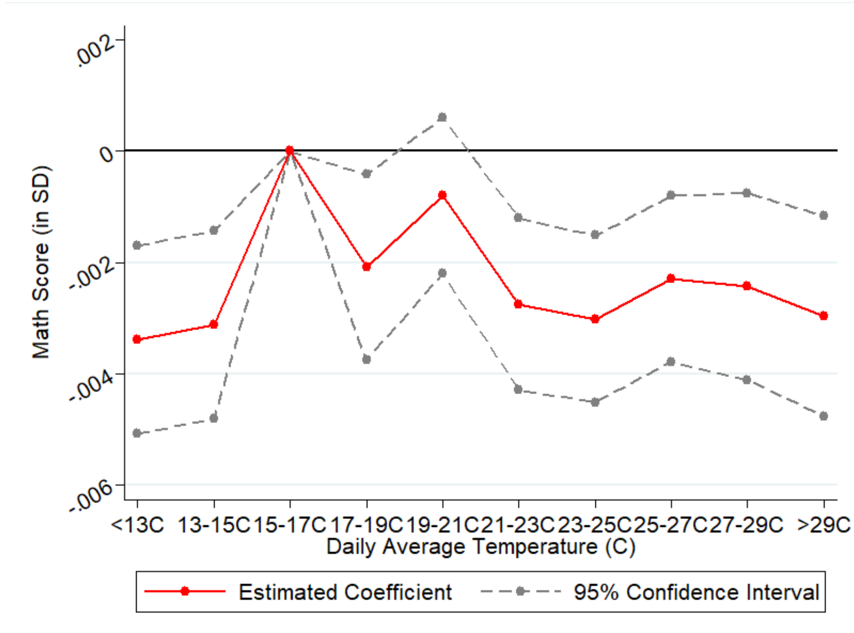
(a) Timeline of Effects of Longer-run Temperature



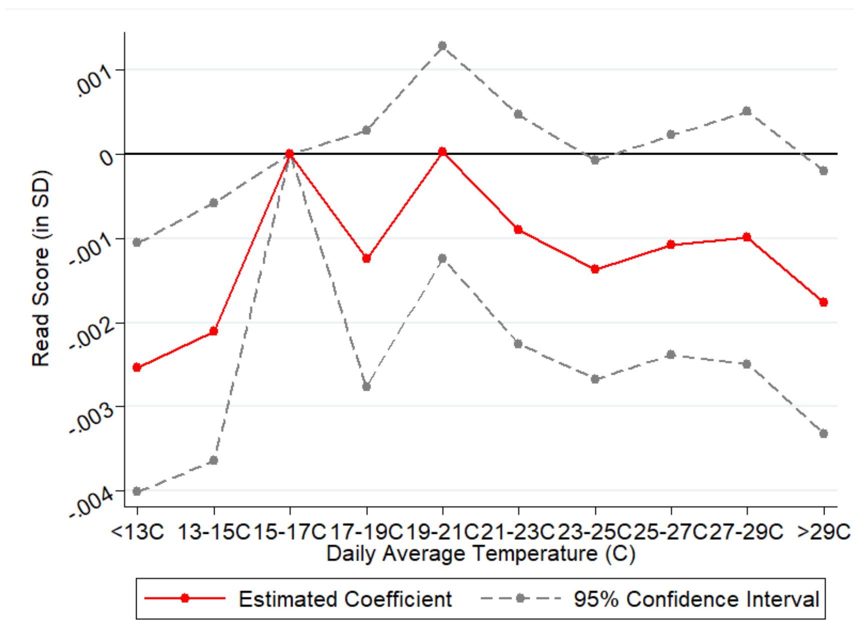
(b) Average Temperatures By Month and Season

Notes: Figure (a) demonstrates the timeline over which the effects of 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 5: Long-Run Temperature and Test Scores (ASER)



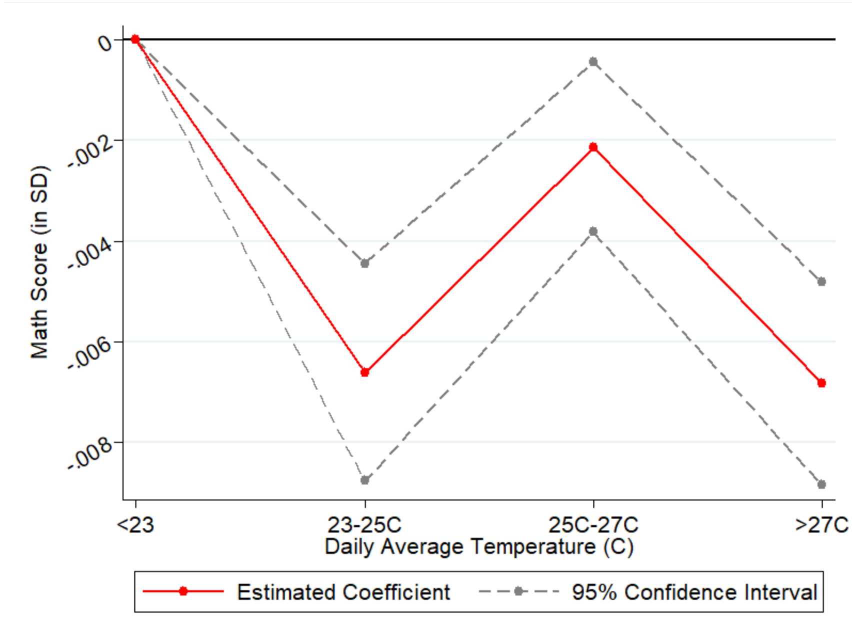
(a) Math Scores



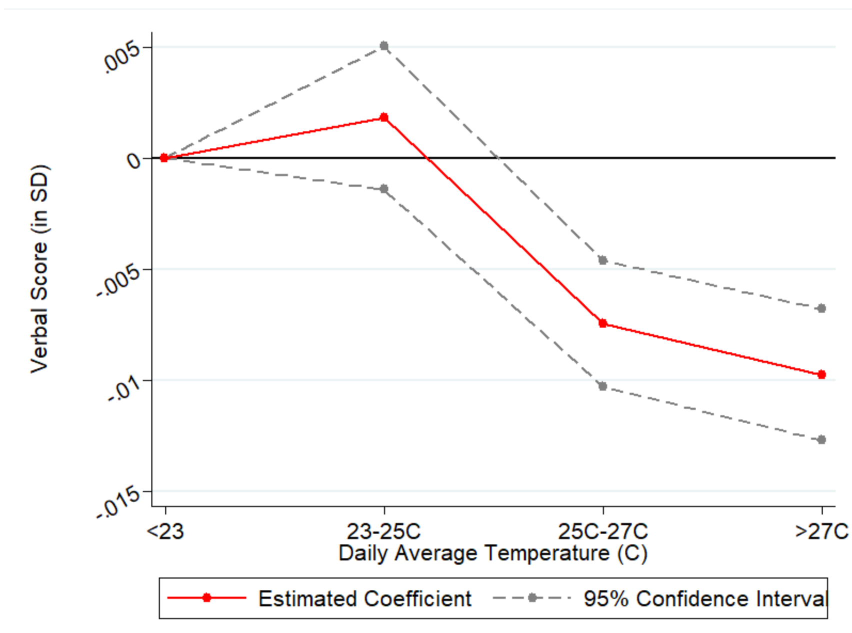
(b) Reading Scores

Notes: The figure shows the effect of longer-run temperature (defined as number of days in the previous calendar year - see figure 5(a)) on math and reading performance. The effect of days between 15°C-17°C is normalized to zero and all other coefficients are interpreted relative to 15°C-17°C. 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 6: Temperature and Test Scores (YLS)



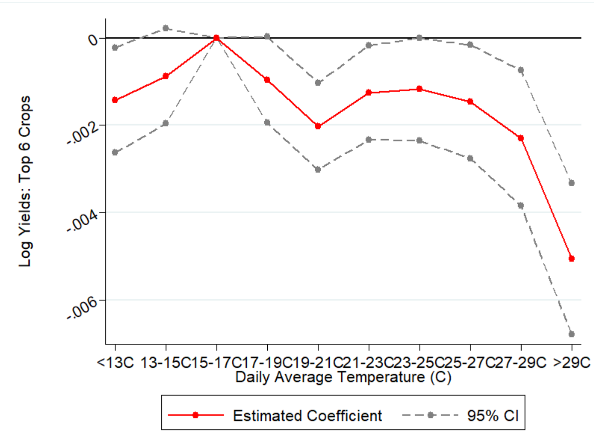
(a) Math Scores



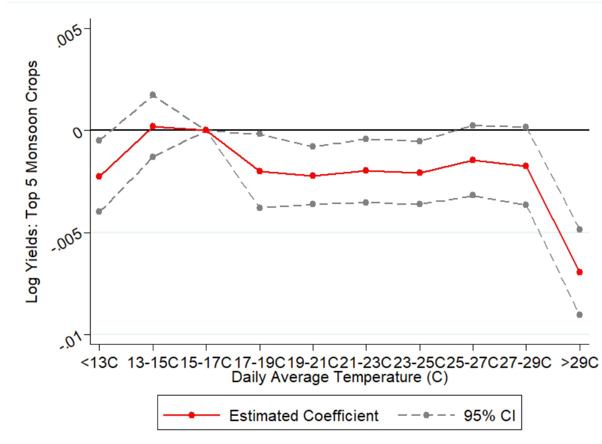
(b) Reading Scores

Notes: The figure shows the effect of temperature (defined as number of days in a given bin between successive tests) on math and reading performance. The effect of days below 23°C is normalized to zero and all other coefficients are interpreted relative to below 23°C. 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.

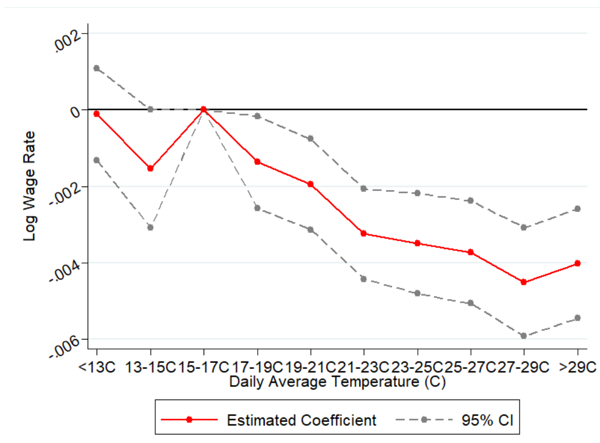
Figure 7: Effect of Temperature on Agricultural Yields and Rural Wages



(a) Temperature and Yields (6 Major Crops)



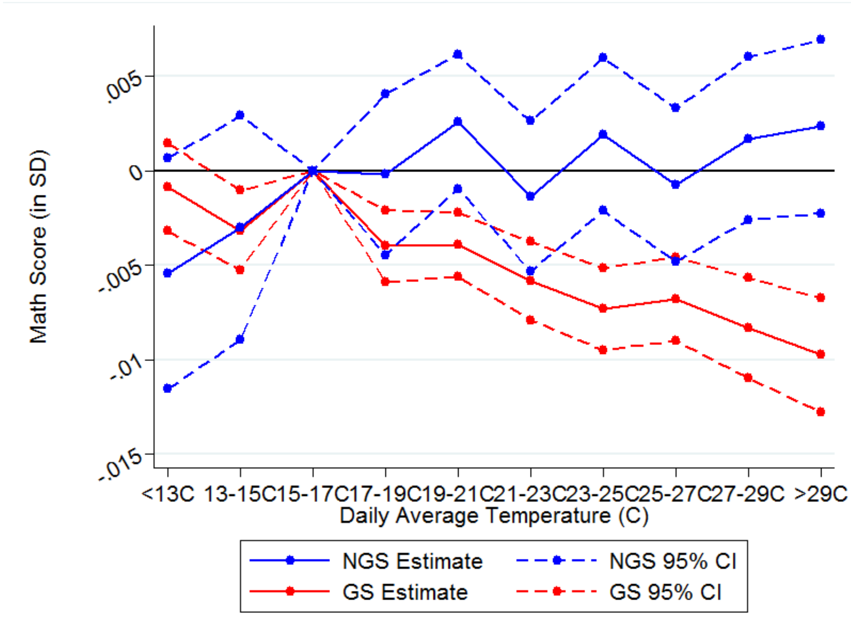
(b) Temperature and Yields (Main Monsoon Crops)



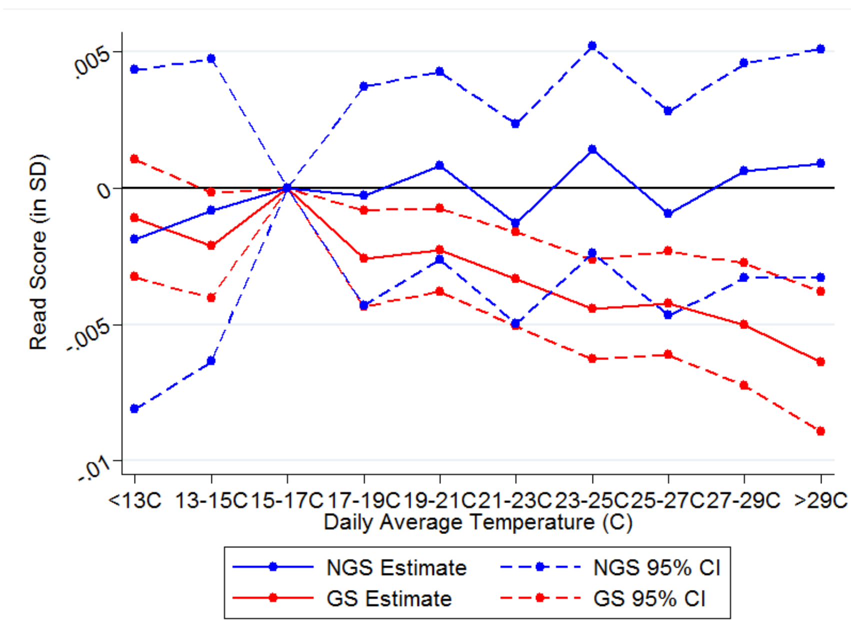
(c) Temperature and Rural Wages

Notes: The figure shows the effect of temperature (defined as number of days in the previous calendar year - see figure 5(a)) on agricultural yields and rural wages from 1980—2014. The effect of days between 15°C-17°C is normalized to zero and all other coefficients are interpreted relative to 15°C-17°C. 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 8: Growing Season v. Non-Growing Season: Temperature and Test Scores (ASER)



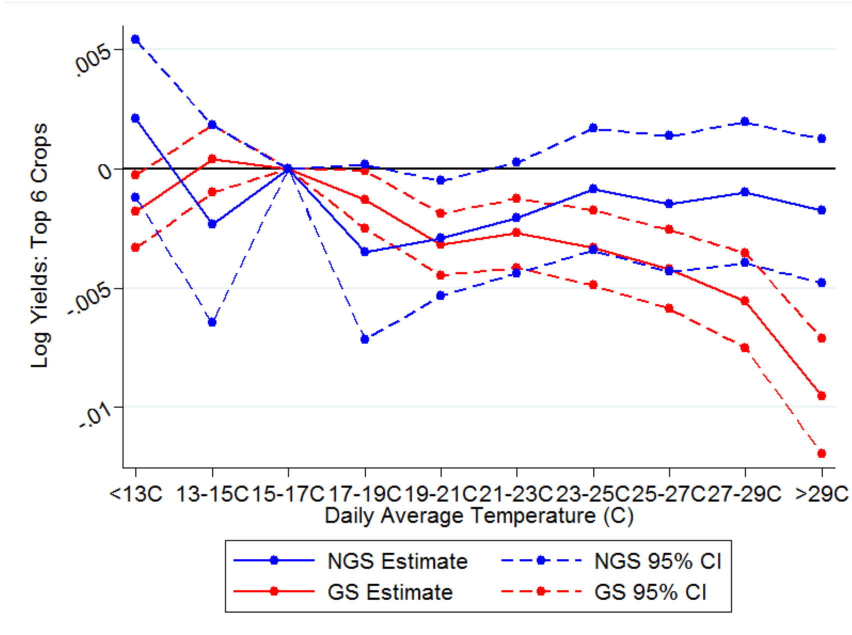
(a) Math Scores



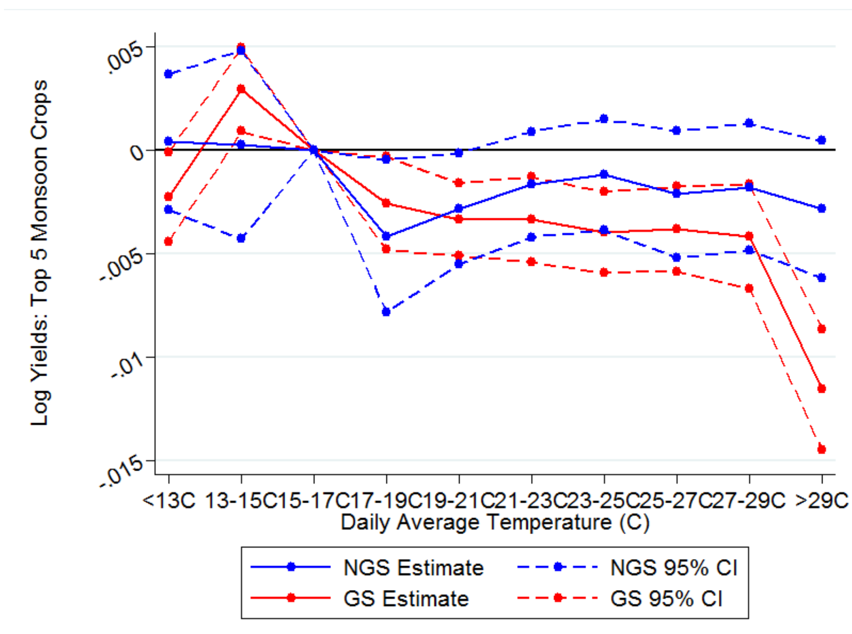
(b) Reading Scores

Notes: The figure shows the effect of longer-run temperature (defined as number of days in the previous calendar year - see figure 5(a)) on math and reading performance divided amongst the growing season (June—Dec) and the non-growing season (March—May). The effect of days between 15°C-17°C is normalized to zero and all other coefficients are interpreted relative to 15°C-17°C. 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: Growing v. Non-Growing Season: Current Year Temperature and Yields



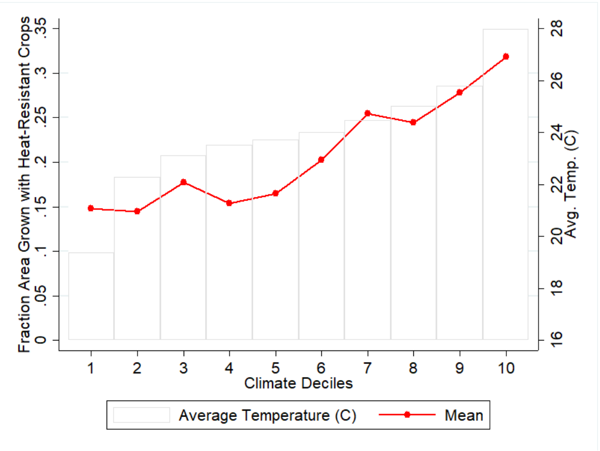
(a) 6 Major Crops



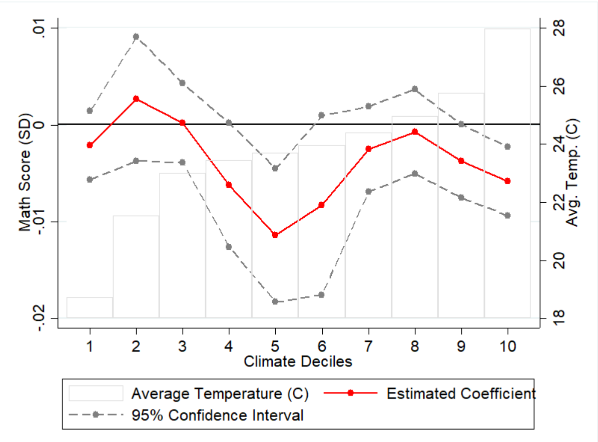
(b) 5 Major Monsoon Crops

Notes: The figure shows the effect of longer-run temperature (defined as number of days in the previous calendar year - see figure 5(a)) 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 15°C-17°C is normalized to zero and all other coefficients are interpreted relative to 15°C-17°C. The regressions include district and year fixed effects. We control flexibly for precipitation and humidity. Standard errors are in parentheses, clustered by district level.

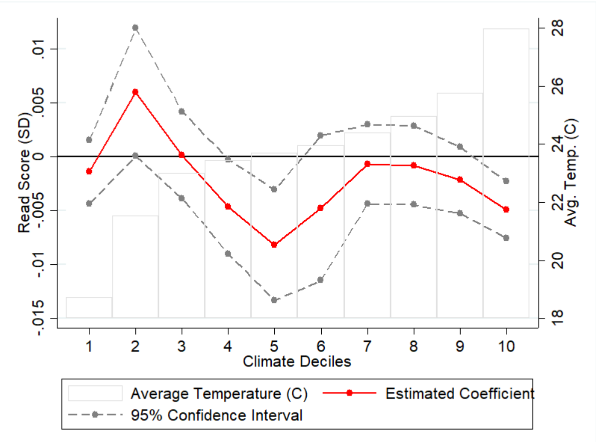
Figure 10: Heat-Resistant Crops and Effect of Temperature on Test Scores by Average Temperature Deciles (ASER)



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



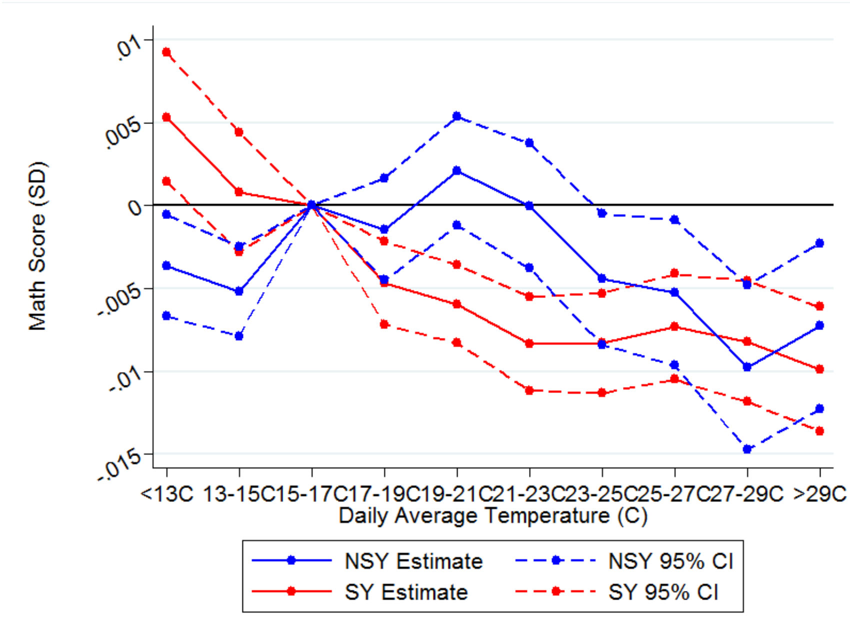
(b) Math Scores



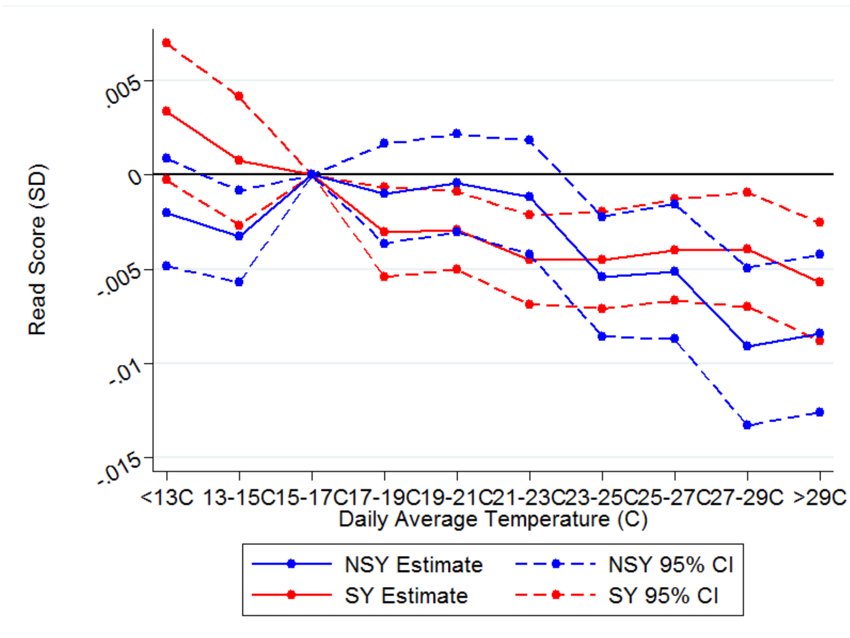
(c) Reading Scores

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 21°C 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 11: Temperature and Test Scores: School Year v. Non-School Year (ASER)



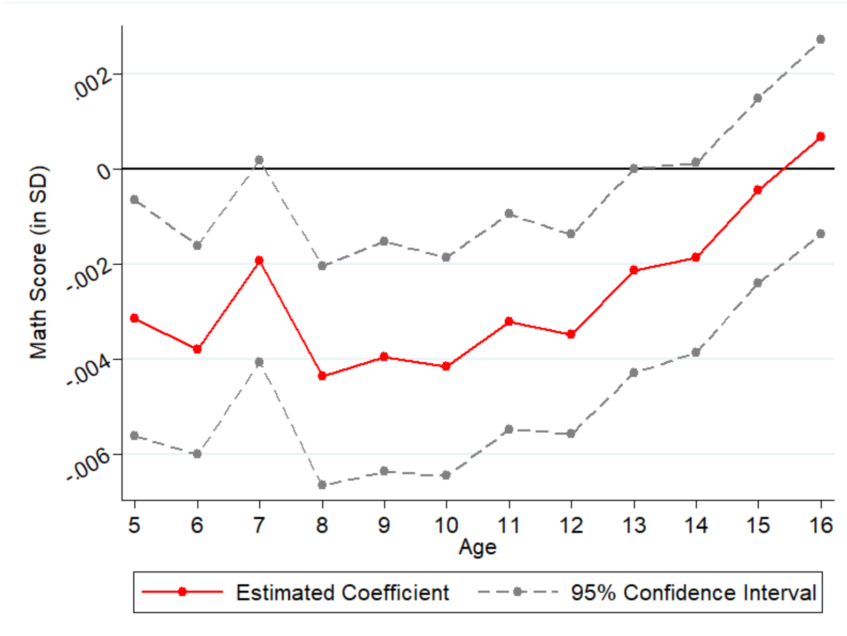
(a) Math Scores



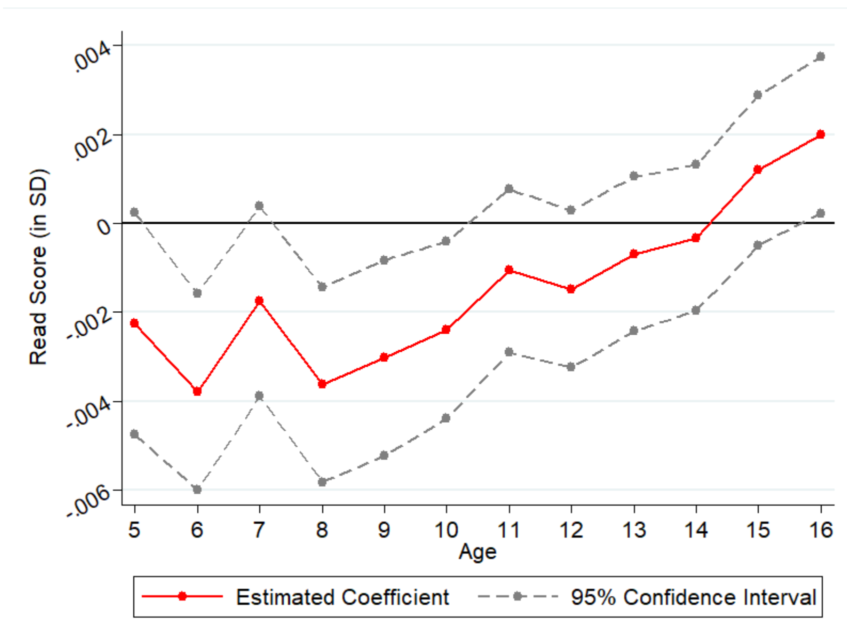
(b) Reading Scores

Notes: The figure shows the effect of longer-run temperature (defined as number of days in the previous calendar year - see figure 5(a)) 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 15°C-17°C is normalized to zero and all other coefficients are interpreted relative to 15°C-17°C. 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: Effect of Temperature on Test Scores by Age (ASER)



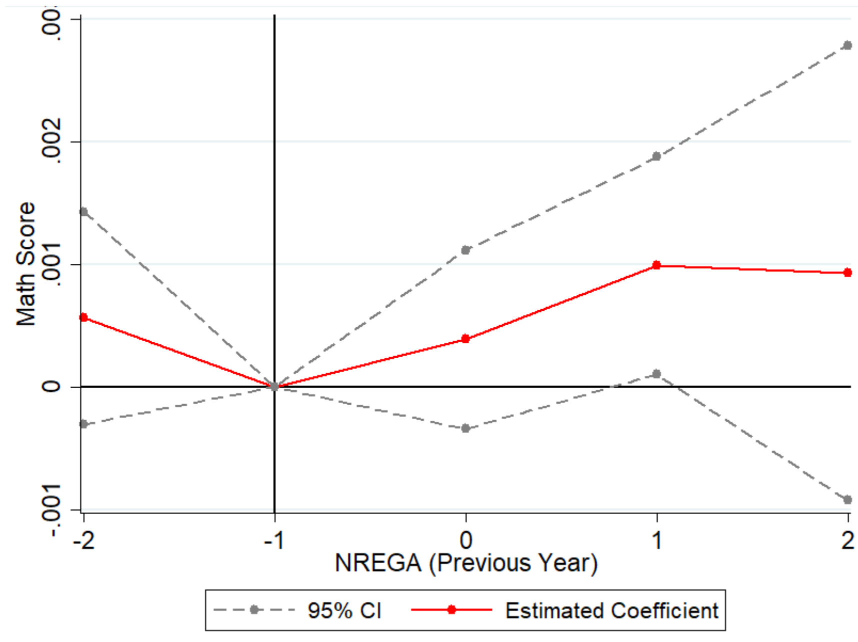
(a) Math Scores



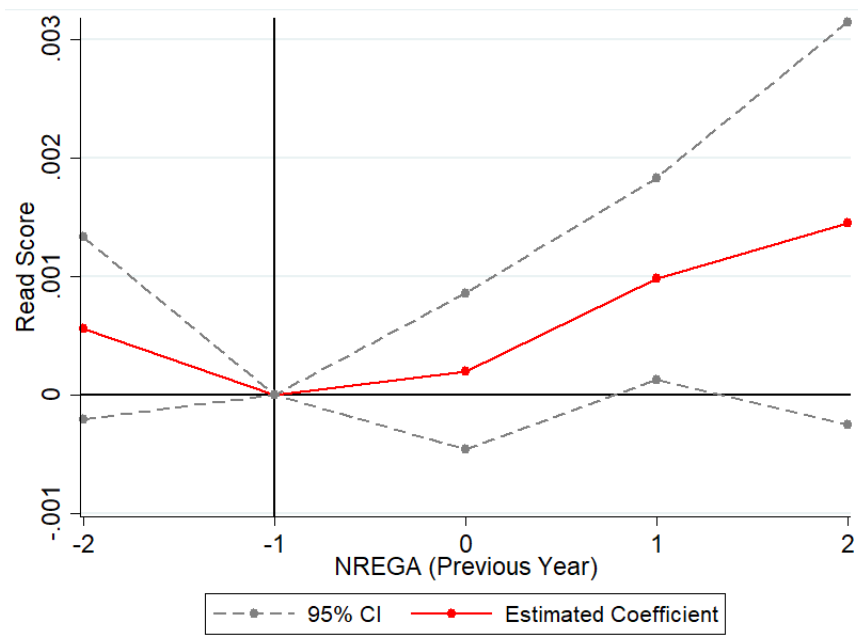
(b) Reading Scores

Notes: The figure shows the marginal effect of an additional hot day in the previous calendar year above 29°C relative to 15°C-17°C 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 13: Event Study: Long-Run Temperature, NREGA, and Test Scores



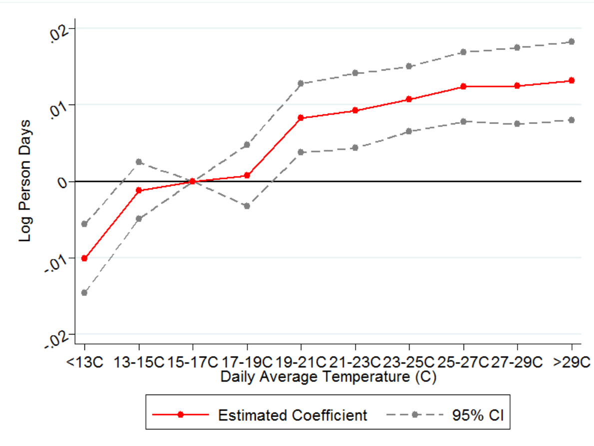
(a) Math Scores



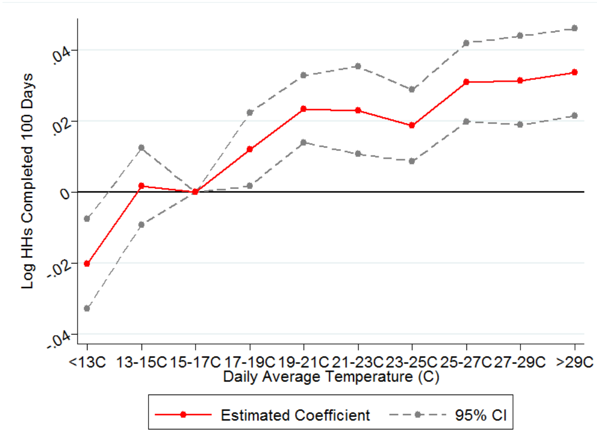
(b) Reading Scores

Notes: The figure shows the marginal effect of an additional hot day in the previous calendar year above 29°C relative to 15°C-17°C on math and reading performance in an event study around the introduction of NREGA. The omitted variable is the days above 29°C 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.

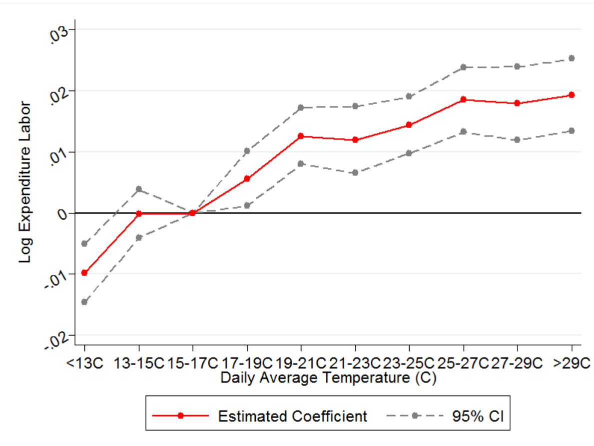
Figure 14: Effect of Temperature on NREGA Take-Up



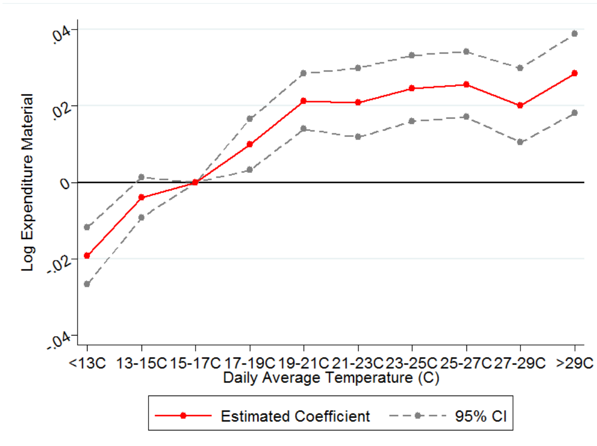
(a) Person Days



(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 15°C-17°C is normalized to zero and all other coefficients are interpreted relative to 15°C-17°C. 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: 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 and 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 aged 5-16. Standard errors are in parentheses, clustered by district.
*Significant at 10%.
**Significant at 5%.
***Significant at 1%.

Table 2: 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: Falsification Test: Temperature and 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 and 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 aged 5-16. Standard errors are in parentheses, clustered by district.
*Significant at 10%.
**Significant at 5%.
***Significant at 1%.

Table 4: 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 5: Growing v. Non-Growing Season: 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 and 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 aged 5-16. Standard errors are in parentheses, clustered by district.
*Significant at 10%.
**Significant at 5%.
***Significant at 1%.

Table 6: Heat-Resistant Crops: 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 and 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 aged 5-16. Standard errors are in parentheses, clustered by district.
*Significant at 10%.
**Significant at 5%.
***Significant at 1%.

Table 7: Event Study: Temperature, NREGA and Test Scores

	(1) Math Score (in SD) β / SE	(2) Read Score (in SD) β / SE
NREGA: T = -3	-0.0269	0.0068
	(0.0373)	(0.0338)
NREGA: T = -2	-0.0216	-0.0255
	(0.0342)	(0.0316)
NREGA: T = 0	-0.0841***	-0.0585**
	(0.0257)	(0.0239)
NREGA: T = 1	-0.1385***	-0.1187***
	(0.0342)	(0.0325)
NREGA: T = 2	-0.1278**	-0.1379**
	(0.0600)	(0.0553)
Days <13C	-0.0031**	-0.0014
	(0.0015)	(0.0013)
Days 13-15C	-0.0009	-0.0013
	(0.0017)	(0.0015)
Days 17-19C	0.0028*	0.0024
	(0.0016)	(0.0015)
Days 19-21C	0.0027**	0.0021*
	(0.0014)	(0.0013)
Days 21-23C	0.0020	0.0014
	(0.0014)	(0.0012)
Days 23-25C	0.0015	0.0012
	(0.0014)	(0.0012)
Days 25-27C	-0.0001	-0.0001
	(0.0015)	(0.0013)
Days 27-29C	-0.0002	-0.0001
	(0.0016)	(0.0014)
Days >29C	-0.0017	-0.0012
	(0.0017)	(0.0015)
NREGA: T = -3 * Days >29C	0.0009*	0.0003
	(0.0005)	(0.0005)
NREGA: T = -2 * Days >29C	0.0006	0.0006
	(0.0004)	(0.0004)
NREGA: T = 0 * Days >29C	0.0004	0.0002
	(0.0004)	(0.0003)
NREGA: T = 1 * Days >29C	0.0010**	0.0010**
	(0.0005)	(0.0004)
NREGA: T = 2 * Days >29C	0.0009	0.0014*
	(0.0009)	(0.0009)
Observations	1866623	1866623
R^2	0.177	0.168

Notes: This table tests if the impacts 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 29°C (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°C-17°C, 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 and 16 for 2006-2009. All specifications include district, year and age fixed effects. We control for precipitation terciles and relative humidity in all specifications. The sample includes children aged 5-16. Standard errors are in parentheses, clustered by district.
*Significant at 10%.
**Significant at 5%.
***Significant at 1%.

A Appendix (Online Only): Effects of Temperature on Day of Test

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.[35]

We perform our analysis on data from the Young Lives Survey, which provides the date of the cognitive test.[36] 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 use two specifications. First, we construct a binary indicator for average day-of-test temperature being above 23°C to estimate the following equation. We selected 23°C as the cutoff because it represents the 25th percentile of the average daily temperatures in the state of Andhra Pradesh.

$$Y_{ijdmt} = \beta(> 23°C)_{jdmt} + rain_{jdmt} + \alpha_i + \mu_{1d} + \mu_{2m} + \mu_{3t} + \epsilon_{ijdmt} \tag{A.6}$$

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 23°C relative to a day with average temperature below 23°C. 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 (A.6) imposes the key assumption that the marginal effect of the day-of-test temperature on performance is constant above and below 23°C. We relax this assumption and 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 23°C and 27°C representing the 25th and 75th percentiles of daily temperature

[35] 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 shown to diminish attention, memory, information retention and processing, and the performance of psycho-perceptual tasks (Hyde et al., 1997; Vasmatzidis, Schlegel and Hancock, 2002).

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

distribution with equally spaced bins in between.

$$Y_{ijdmt} = \beta_2(23°C - 25)_{jdmt} + \beta_3(25°C - 27°C)_{jdmt} + \beta_4(> 27°C)_{jdmt} + rain_{jdmt} + \alpha_i + \mu_{1d} + \mu_{2m} + \mu_{3t} + \epsilon_{ijdmt} \tag{A.7}$$

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

A.1 Results

We report the effects of day-of-test temperature on test scores in table A.1 and illustrate the results graphically in figure A.1. Columns (1) and (2) report the effect of temperature on math scores for equations (A.6) and (A.7) 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 a physiological channel connecting temperatures to test scores in the short run (Bowler and Tirri, 1974; Schiff and Somjen, 1985; Hocking et al., 2001). Specifically, we find that a 1°C increase in average day-of-test temperature above 23°C reduces within-cohort math test performance by 0.17 standard deviations. The magnitudes of our estimates 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 21°C, and Park (2017) finds a marginal effect of 0.1 standard deviations for every degree centigrade above 23°C. To allow for non-linearity in the marginal effects of temperature, we estimate our preferred specification is equation (A.7), as illustrated in figure 2(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. These results are described below.

Math v. Reading Performance

Different portions of the brain perform different cognitive functions. For instance, the prefrontal cortex, which is responsible for providing the “working memory” needed for performing mathematical problems, is more temperature sensitive than the 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) and (4), table A.1, figure 2(b)). Our results are consistent with 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.2).[37]

Persistence

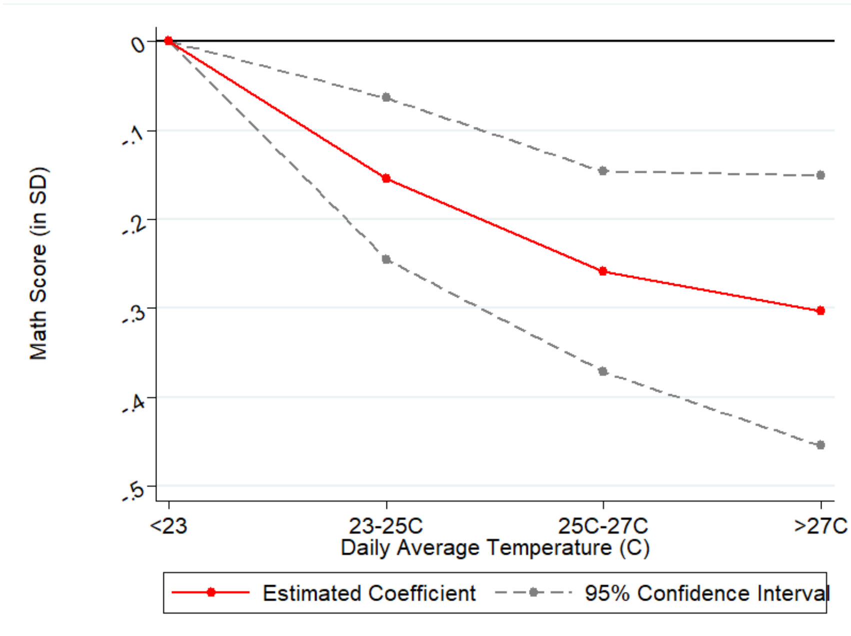
We test whether temperature can have persistent impacts; a hot day today could continue to affect performance in the future if the human body is unable to internally self-regulate to higher ambient temperatures.[38] We directly examine this possibility by testing for lags on the effects of short-run 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 A.2). This pattern largely holds for at least up to four weeks of leads and lags (figure A.3). The large day-of-test effect and the null week-of-test effect are consistent with a model of internal self-regulation in which the human body self-regulates higher temperatures, making the direct effects of temperature on cognitive performance temporary (Taylor, 2006).

[37]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 27°C, students spend marginally more time on tests (two minutes on math and one minute on reading tests respectively) than on days below 23°C (table A.3). 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 in which heat-driven changes in test takers' effort or behavior are driving the relationship between short-run temperature and performance.

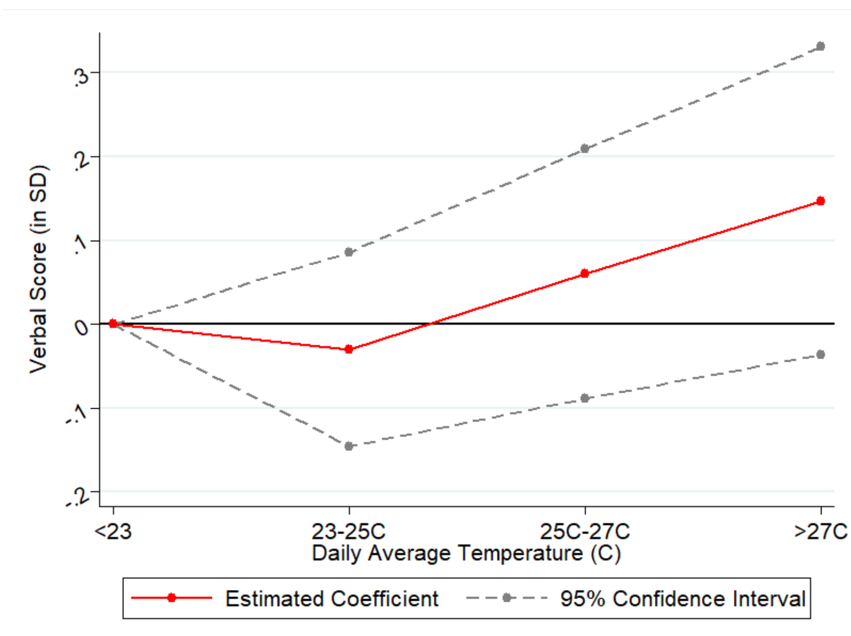
[38]Temperature on day-of-test can affect performance on high-stakes exams and translate into lower human capital production due to the structure of the education system, typically in the form of arbitrary cutoffs for passing or placing into high-achievement programs (Park, 2017). In our study, however, 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 4.1.

Figures

Figure A.1: Day-of-Test Temperature and Test Scores (YLS)



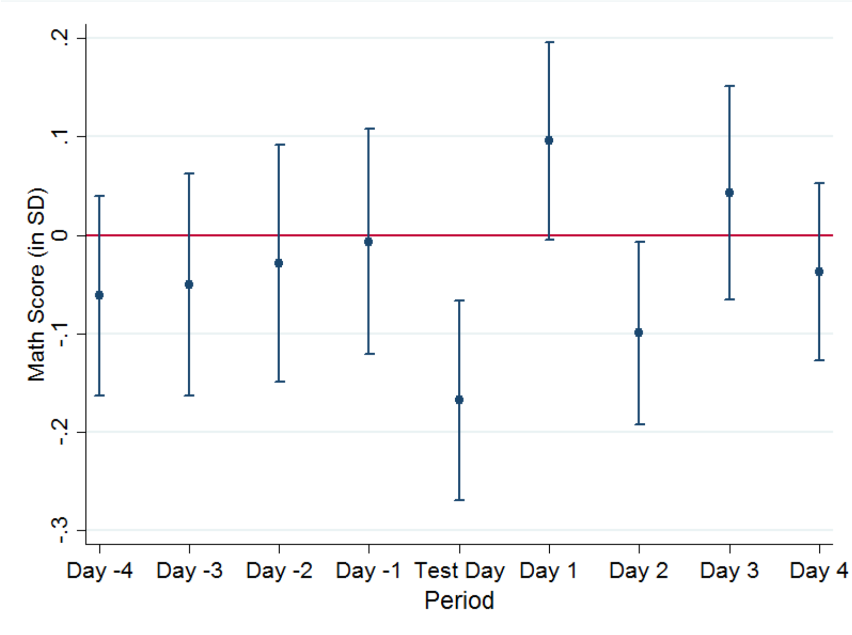
(a) Math Scores



(b) Reading Scores

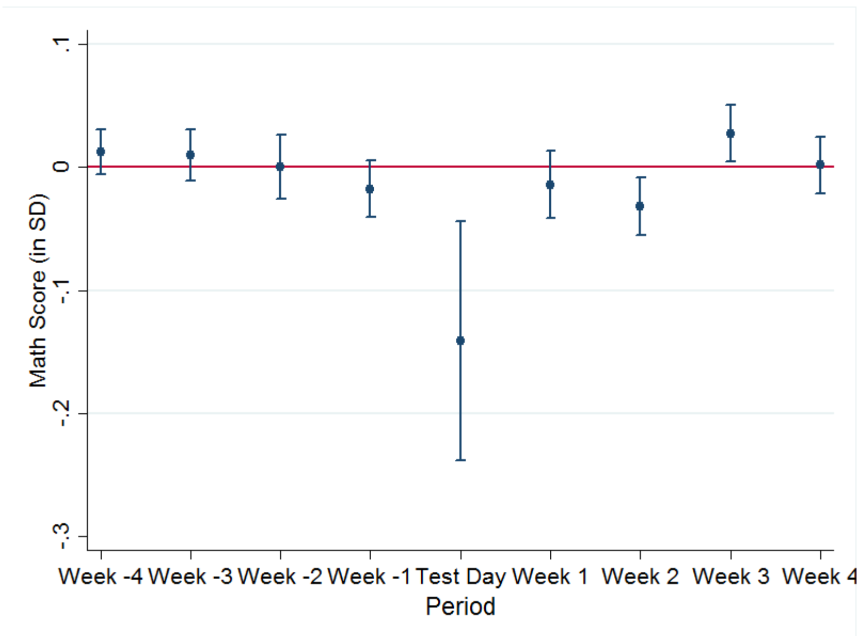
Notes: The figure shows the effect of day-of-test temperature on math and reading performance. The effect of temperature below 23°C is normalized to zero and all other coefficients are interpreted relative to below 23°C. The regressions include day of individual, week, month, and survey round fixed effects. 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 A.2: Leads and Lags in Days: Day-of-Test Temperature and Math Scores



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

Figure A.3: Leads and Lags in Weeks: Day-of-Test Temperature and Math Scores



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

Tables

Table A.1: Day-of-Test 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 A.2: Day-of-Test 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.3: Day-of-Test 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%.

B Appendix (Online Only): Additional Results

B.1 Robustness Checks for Effects of Longer-Run Temperature

B.1.1 Short- and Longer-Run Temperature and Test Scores

Table B.1: 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		-0.096**		-0.005
		(0.044)		(0.056)
Day 25-27C		-0.175***		0.139*
		(0.056)		(0.075)
Day >27C		-0.161**		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	0.069	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%.

B.1.2 ASER Results: On-Track Students Only

Table B.2: On-Track Children: 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 and 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 aged 5-16. Standard errors are in parentheses, clustered by district.
*Significant at 10%.
**Significant at 5%.
***Significant at 1%.

B.1.3 ASER Results - Degree Days

Table B.3: 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 and 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 aged 5-16. Standard errors are in parentheses, clustered by district.
*Significant at 10%.
**Significant at 5%.
***Significant at 1%.

Table B.4: 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 and 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 aged 5-16. Standard errors are in parentheses, clustered by district.
*Significant at 10%.
**Significant at 5%.
***Significant at 1%.

B.1.4 ASER Results: Adding Lags

Table B.5: Temperature and Test Scores (ASER): Adding Lags

	(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	-0.0025***		-0.0021***	
	(0.0007)		(0.0006)	
PY Days >21C	-0.0022***		-0.0014***	
	(0.0006)		(0.0005)	
PY Days <13C		-0.0031***		-0.0030***
		(0.0010)		(0.0008)
PY Days 13-15C		-0.0027***		-0.0020**
		(0.0010)		(0.0009)
PY Days 17-19C		-0.0025***		-0.0018**
		(0.0010)		(0.0009)
PY Days 19-21C		-0.0002		-0.0002
		(0.0010)		(0.0009)
PY Days 21-23C		-0.0027***		-0.0016*
		(0.0010)		(0.0009)
PY Days 23-25C		-0.0033***		-0.0024***
		(0.0010)		(0.0008)
PY Days 25-27C		-0.0032***		-0.0024***
		(0.0010)		(0.0009)
PY Days 27-29C		-0.0034***		-0.0023**
		(0.0011)		(0.0009)
PY Days >29C		-0.0035***		-0.0029***
		(0.0010)		(0.0009)
L.2-L.5 Controls	Yes	Yes	Yes	Yes
Observations	4581616	4581616	4581616	4581616
R^2	0.085	0.086	0.069	0.070

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 and 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%.

B.1.5 ASER Results: Adding State-Specific Time Trends

Table B.6: 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***		-0.0026***	
	(0.0006)		(0.0005)	
PY Days >21C	-0.0025***		-0.0013***	
	(0.0004)		(0.0004)	
PY Days <13C		-0.0036***		-0.0029***
		(0.0008)		(0.0007)
PY Days 13-15C		-0.0023***		-0.0018***
		(0.0008)		(0.0007)
PY Days 17-19C		0.0003		0.0001
		(0.0008)		(0.0008)
PY Days 19-21C		0.0001		0.0004
		(0.0007)		(0.0006)
PY Days 21-23C		-0.0018**		-0.0008
		(0.0007)		(0.0007)
PY Days 23-25C		-0.0024***		-0.0010
		(0.0008)		(0.0007)
PY Days 25-27C		-0.0031***		-0.0017**
		(0.0008)		(0.0007)
PY Days 27-29C		-0.0030***		-0.0014*
		(0.0009)		(0.0008)
PY Days >29C		-0.0032***		-0.0019**
		(0.0009)		(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 and 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%.

B.1.6 ASER Results: Adding State-Year FE

Table B.7: Temperature and Test Scores (ASER): Adding State-Year FE

	(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	-0.0015**		-0.0010	
	(0.0007)		(0.0007)	
Days >21C	-0.0021***		-0.0014**	
	(0.0006)		(0.0006)	
PY Days <13C		-0.0027***		-0.0021**
		(0.0010)		(0.0009)
PY Days 13-15C		-0.0013		-0.0009
		(0.0008)		(0.0007)
PY Days 17-19C		-0.0008		-0.0009
		(0.0009)		(0.0008)
PY Days 19-21C		-0.0008		-0.0010
		(0.0009)		(0.0008)
PY Days 21-23C		-0.0028***		-0.0022**
		(0.0010)		(0.0009)
PY Days 23-25C		-0.0031***		-0.0025***
		(0.0011)		(0.0009)
PY Days 25-27C		-0.0032***		-0.0026**
		(0.0011)		(0.0010)
PY Days 27-29C		-0.0029**		-0.0023**
		(0.0013)		(0.0011)
PY Days >29C		-0.0031**		-0.0026**
		(0.0014)		(0.0012)
Observations	4581616	4581616	4581616	4581616
R^2	0.102	0.102	0.079	0.079

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 and 16 for 2006-2014. All specifications include district, state-by-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%.

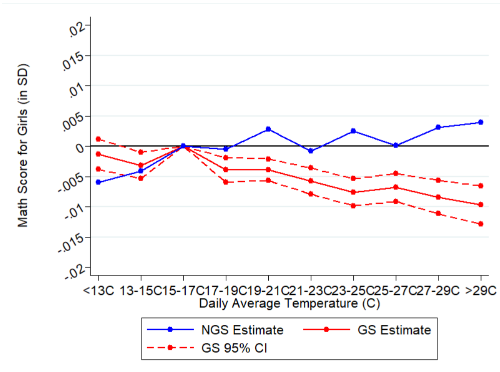
B.2 Robustness Checks: Agricultural Income Mechanism

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

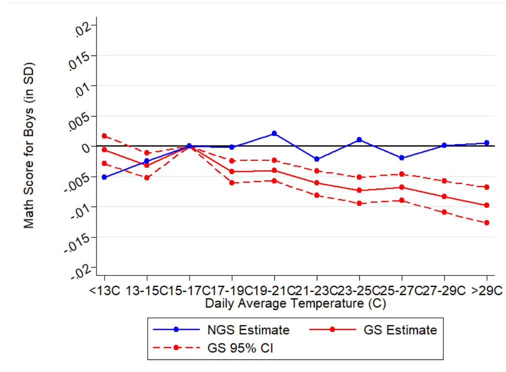
	(1) Log Yield: Top 6 Crops β / SE	(2) Log Yield: Top 5 Monsoon Crops β / SE
GS Days <13C	-0.0018**	-0.0023**
	(0.0008)	(0.0011)
GS Days 13-15C	0.0004	0.0029***
	(0.0007)	(0.0010)
GS Days 17-19C	-0.0013**	-0.0026**
	(0.0006)	(0.0011)
GS Days 19-21C	-0.0032***	-0.0033***
	(0.0007)	(0.0009)
GS Days 21-23C	-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%.

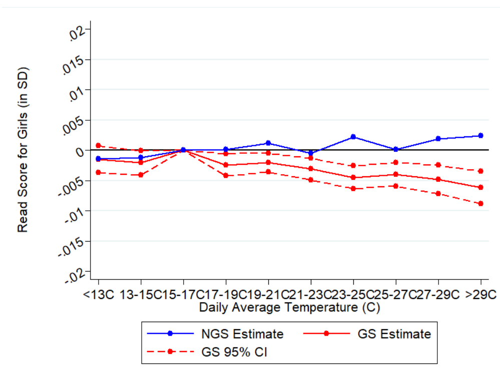
B.2.1 Heterogeneity — Gender



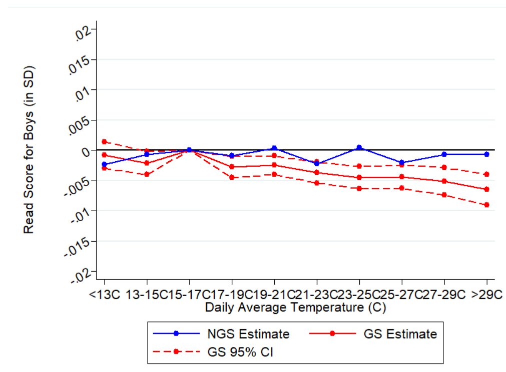
(a)
Girls(Math)



(b)
Boys(Math)



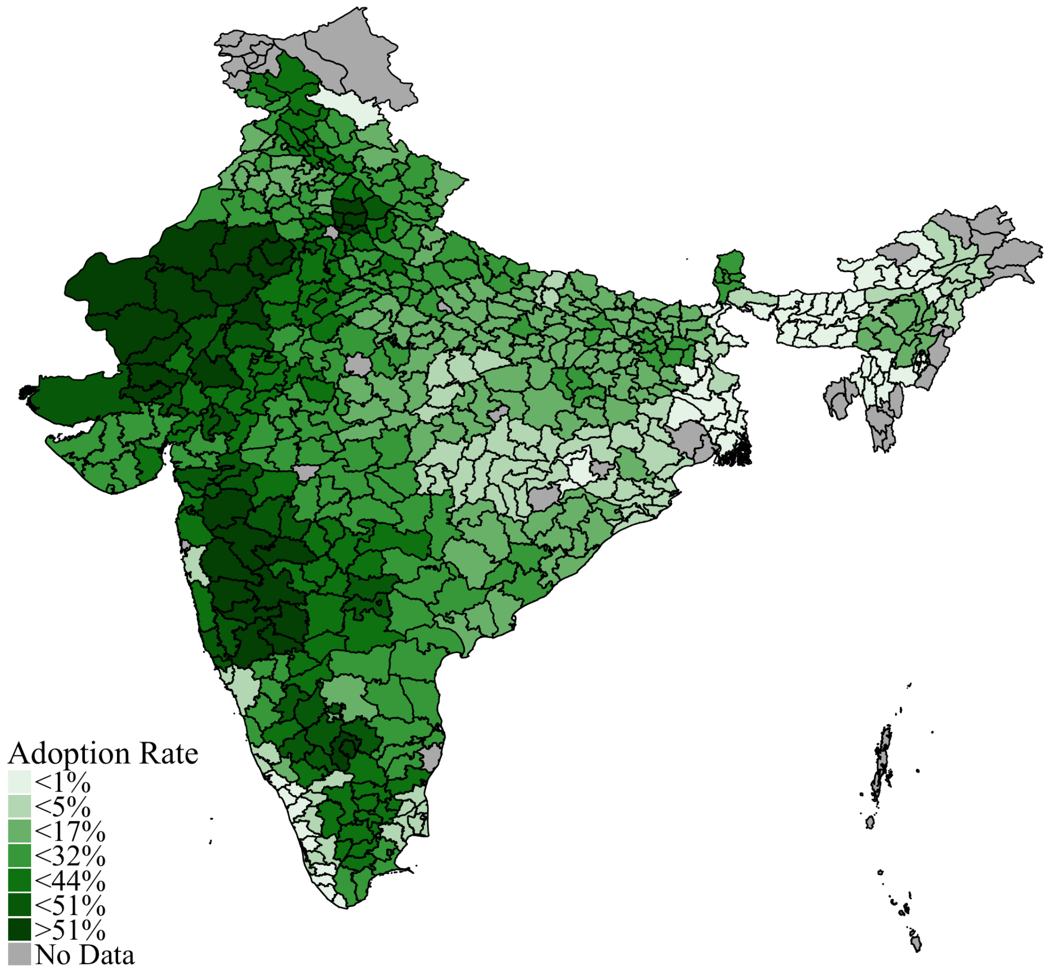
(c)
Girls(Read)



(d)
Boys(Read)

Figure B.1: Temperature and Test Scores (ASER): By Gender

Figure B.2: Average Take-Up of Heat Resistant Crops by District



B.2.2 Geographic Take-Up of Heat-Resistant Crops

B.2.3 Temperature Variation by Climate Deciles

Table B.9: Temperature Variation by Climate Deciles

	Removed District and Year FE % HHs
Decile 1: GS Days >21C below/above 5	0.24
Decile 2: GS Days >21C below/above 5	0.10
Decile 3: GS Days >21C below/above 5	0.21
Decile 4: GS Days >21C below/above 5	0.18
Decile 5: GS Days >21C below/above 5	0.19
Decile 6: GS Days >21C below/above 5	0.15
Decile 7: GS Days >21C below/above 5	0.31
Decile 8: GS Days >21C below/above 5	0.36
Decile 9: GS Days >21C below/above 5	0.38
Decile 10: GS Days >21C below/above 5	0.27

Notes: This table shows the proportion of observations in each climate decile with deviations larger than five days, over 21°C, after removing district and year fixed effects.

B.3 Alternative Explanations

B.3.1 Teacher Attendance

Table B.10: 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%.

B.3.2 Long-Run Temperature and Dropouts, Grade Progression

Table B.11: 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 and 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%.

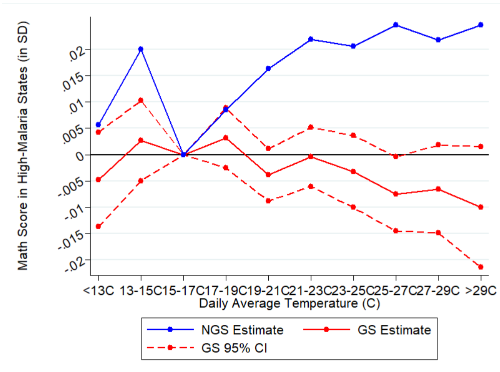
B.3.3 Temperature, Rainfall, and Test Scores

Table B.12: Temperature, Rainfall, and Test Scores

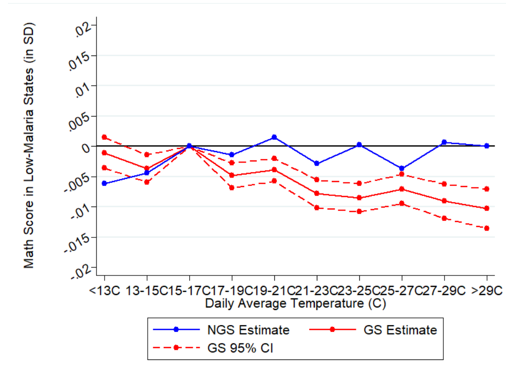
	(1) Math Score (in SD) β / SE	(2) Math Score (in SD) β / SE	(3) Read Score (in SD) β / SE	(4) Read Score (in SD) β / SE
PY Days <15C	-0.0020***	-0.0015*	-0.0017***	-0.0010
	(0.0006)	(0.0007)	(0.0006)	(0.0007)
PY Days >21C	-0.0021***	-0.0021***	-0.0011**	-0.0014**
	(0.0005)	(0.0006)	(0.0004)	(0.0006)
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 and 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 aged 5-16. Standard errors are in parentheses, clustered by district.
*Significant at 10%.
**Significant at 5%.
***Significant at 1%.

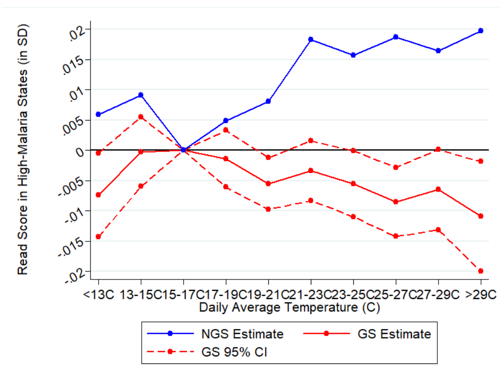
B.3.4 ASER Results: Results by Malaria-Prone States



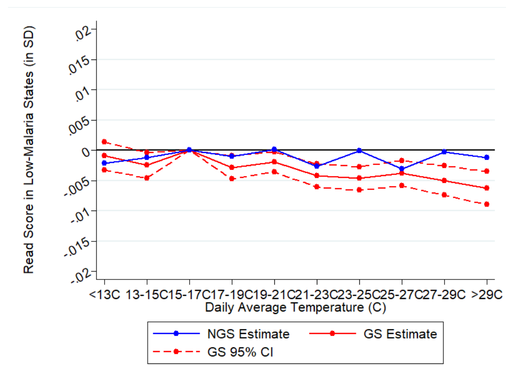
(a) Malaria-Prone States



(b) Other States



(c) Malaria Prone States



(d) Other States

Figure B.3: Temperature and Test Scores (ASER) By Malaria-Prone States

Table B.13: 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 and 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%.

C Appendix (Online Only): Why Does Income Matter?

Having found evidence that longer-run temperature affects test scores through heat-induced agricultural income losses, we present some suggestive evidence on the potential channels through which income losses might affect human capital production. In theory, there are at least two possible channels. First, temperature affects yields and consequently nutritional intake amongst households.[39] 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. We find some evidence for both these channels.

C.1 Additional Data Set

For this appendix, in addition to the data sets 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 obtained 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 both children and adults.

C.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, leading to increased sickness and, consequently, absence from school. We report three important findings. First, a hot day above 27°C in the year of test reduces consumption (measured in value, not quantity) of own-grown crops and own animal products by 1.6% and 0.5% respectively (table C.2, columns 4-6). Consequently, each additional hot day reduces value of household overall (home and market) consumption of grains by 0.6% (table C.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 27°C in the previous year reduces BMI by 0.04 age-specific standard deviations, which is comparable to the effect of temperature on test scores for both math and reading.

Third, we do find hot days increase school absence modestly, and much of this is driven by increased sickness (table C.4). However, these effects are not a result of the direct physiological exposure to heat. We find that, consistent with the agricultural income channel,

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

only temperature during the growing season of the previous year affects student absence in the current year (C.3).

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

Time-Use

We find modest evidence to support the time-use hypothesis. We find that households adjust their time use in response to higher temperatures (tables C.5, C.6). We find that an extra hot day above 23°C increases time spent by children in caring for infants by 5% (table C.5, column 2) and a 7% increase in household chores (table C.5, column 3). Simultaneously, we observe a corresponding drop in self-study time by 4% (table C.6, column 2). Importantly, however, we don't see any reduction in time spent in school (table C.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 B.11).

Table C.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 C.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%.

C.3 ASER: School Attendance

Table C.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 C.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%.

C.4 Time Use

Table C.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 C.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%.

C.5 IHDS

Table C.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 of 8 and 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 C.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 of 8 and 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 C.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 of 8 and 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%.

D Appendix (Online Only): NREGA

D.1 Triple Differences

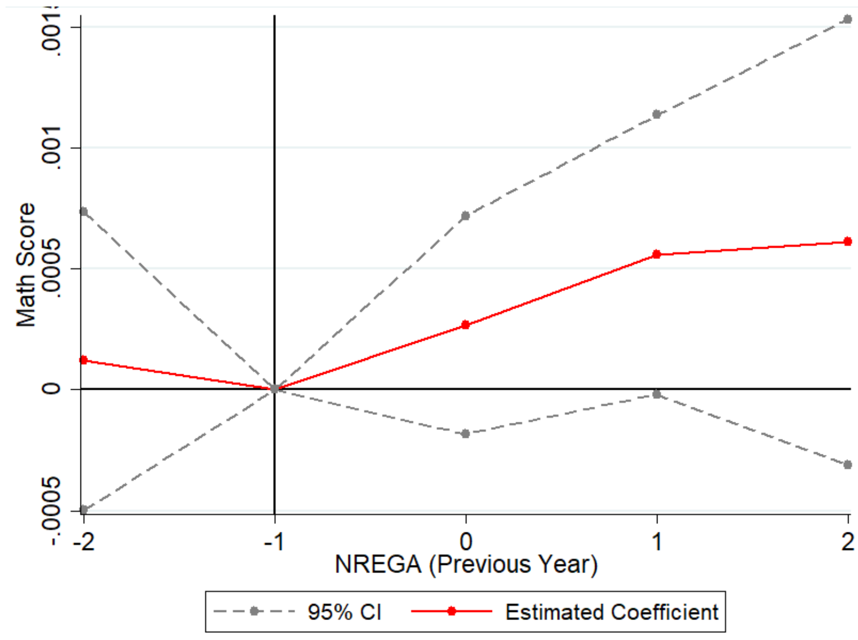
Table D.1: Triple Differences: Long-Run Temperature, NREGA ,and Test Scores

	(1) Math Score (in SD) β / SE	(2) Read Score (in SD) β / SE
Days >21C	-0.0009	-0.0006
	(0.0009)	(0.0007)
NREGA PY	-0.2001***	-0.1391**
	(0.0614)	(0.0580)
NREGA PY*Days >21C	0.0005***	0.0004**
	(0.0002)	(0.0002)
Observations	1866623	1866623
R^2	0.177	0.167

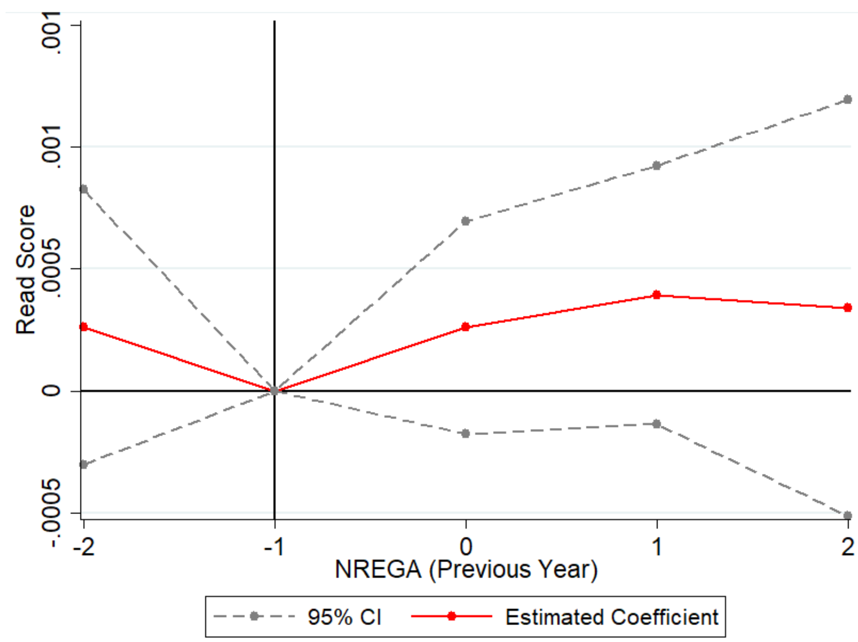
Notes: This table tests if the impacts of last year's temperature were attenuated by NREGA roll-out in that year. All specifications include district, year and age fixed effects. We control for precipitation in all specifications. The sample includes children between the ages of 5 and 16. Standard errors are in parentheses, clustered by district.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

D.2 Temperature, NREGA, and Test Scores: Parsimonious Model

Figure D.1: 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 21°C relative to 15°C-21°C on math and reading performance in an event study around the introduction of NREGA. The omitted variable is the days above 21°C 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.

Table D.2: Event Study: Temperature, NREGA, and Test Scores

	(1) Math Score (in SD) β / SE	(2) Read Score (in SD) β / SE
NREGA: T = -3	0.3636***	0.2357**
	(0.0940)	(0.0950)
NREGA: T = -2	-0.0369	-0.0771
	(0.0955)	(0.0882)
NREGA: T = 0	-0.1192*	-0.1044
	(0.0688)	(0.0669)
NREGA: T = 1	-0.1948**	-0.1390*
	(0.0884)	(0.0817)
NREGA: T = 2	-0.1680	-0.0966
	(0.1343)	(0.1269)
Days <15C	-0.0051***	-0.0041***
	(0.0012)	(0.0012)
Days >21C	-0.0011	-0.0008
	(0.0009)	(0.0008)
NREGA: T = -3 * Days >21C	-0.0012***	-0.0008**
	(0.0003)	(0.0003)
NREGA: T = -2 * Days >21C	0.0001	0.0003
	(0.0003)	(0.0003)
NREGA: T = 0 * Days >21C	0.0003	0.0003
	(0.0002)	(0.0002)
NREGA: T = 1 * Days >21C	0.0006*	0.0004
	(0.0003)	(0.0003)
NREGA: T = 2 * Days >21C	0.0006	0.0003
	(0.0005)	(0.0004)
Observations	1866623	1866623
R^2	0.098	0.081

Notes: This table tests if the impacts 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 21°C 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 15-21°C, 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 and 16 for 2006-2009. All specifications include district, year, and age fixed effects. We control for precipitation terciles and relative humidity in all specifications. The sample includes children aged 5-16. Standard errors are in parentheses, clustered by district.
*Significant at 10%.
**Significant at 5%.
***Significant at 1%.

D.3 Robustness: On-Track Only

Table D.3: 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
NREGA: T = -3	-0.0269	0.0068
	(0.0373)	(0.0338)
NREGA: T = -2	-0.0216	-0.0255
	(0.0342)	(0.0316)
NREGA: T = 0	-0.0841***	-0.0585**
	(0.0257)	(0.0239)
NREGA: T = 1	-0.1385***	-0.1187***
	(0.0342)	(0.0325)
NREGA: T = 2	-0.1278**	-0.1379**
	(0.0600)	(0.0553)
Days <13C	-0.0031**	-0.0014
	(0.0015)	(0.0013)
Days 13-15C	-0.0009	-0.0013
	(0.0017)	(0.0015)
Days 17-19C	0.0028*	0.0024
	(0.0016)	(0.0015)
Days 19-21C	0.0027**	0.0021*
	(0.0014)	(0.0013)
Days 21-23C	0.0020	0.0014
	(0.0014)	(0.0012)
Days 23-25C	0.0015	0.0012
	(0.0014)	(0.0012)
Days 25-27C	-0.0001	-0.0001
	(0.0015)	(0.0013)
Days 27-29C	-0.0002	-0.0001
	(0.0016)	(0.0014)
Days >29C	-0.0017	-0.0012
	(0.0017)	(0.0015)
NREGA: T = -3 * Days >29C	0.0009*	0.0003
	(0.0005)	(0.0005)
NREGA: T = -2 * Days >29C	0.0006	0.0006
	(0.0004)	(0.0004)
NREGA: T = 0 * Days >29C	0.0004	0.0002
	(0.0004)	(0.0003)
NREGA: T = 1 * Days >29C	0.0010**	0.0010**
	(0.0005)	(0.0004)
NREGA: T = 2 * Days >29C	0.0009	0.0014*
	(0.0009)	(0.0009)
Observations	1866623	1866623
R^2	0.177	0.168

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 29°C 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°C-17°C, 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 and 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 aged 5-16. Standard errors are in parentheses, clustered by district. *Significant at 10%. **Significant at 5%. ***Significant at 1%.

Figure D.2: Event Study—On-Track Children: Long-Run Temperature, NREGA, and Math Scores

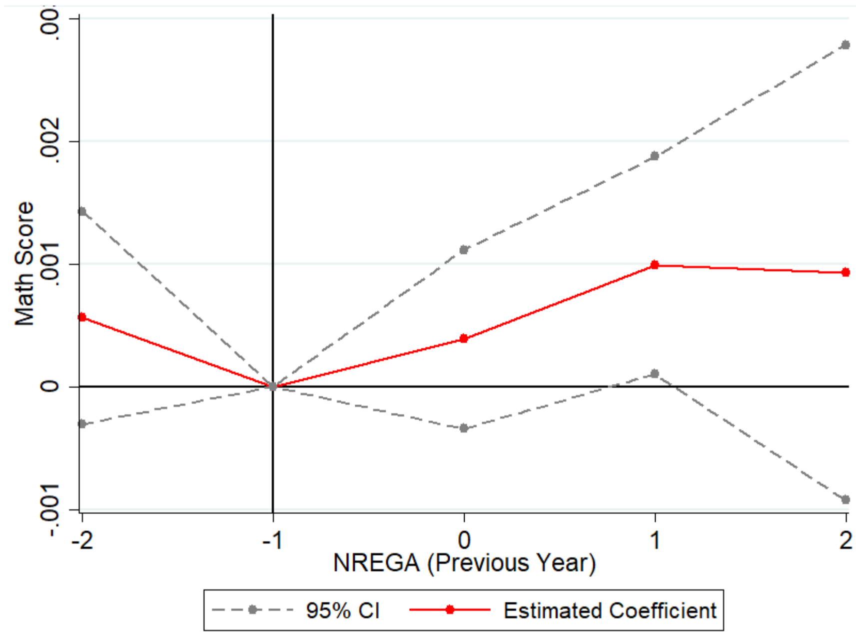


Figure D.3: Event Study—On-Track Children: Long-Run Temperature, NREGA, and Reading Scores

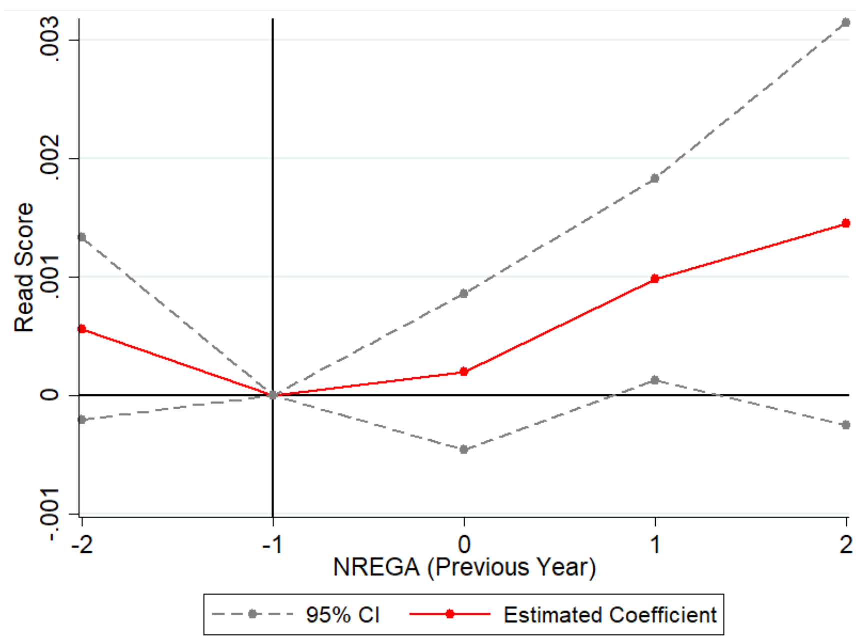


Table D.4: Event Study—On-Track Children: Long Run Temperature, NREGA, and Test Scores

	(1) Math Score (in SD) β / SE	(2) Read Score (in SD) β / SE
NREGA: T = -3	0.3797***	0.2525***
	(0.0915)	(0.0902)
NREGA: T = -2	0.0052	-0.0331
	(0.0996)	(0.0914)
NREGA: T = 0	-0.1073	-0.0920
	(0.0676)	(0.0654)
NREGA: T = 1	-0.2285***	-0.1742**
	(0.0834)	(0.0768)
NREGA: T = 2	-0.2840**	-0.2178*
	(0.1266)	(0.1190)
Days <15C	-0.0047***	-0.0037***
	(0.0011)	(0.0010)
Days >21C	-0.0011	-0.0008
	(0.0008)	(0.0007)
NREGA: T = -3 * Days >21C	-0.0013***	-0.0008***
	(0.0003)	(0.0003)
NREGA: T = -2 * Days >21C	-0.0000	0.0001
	(0.0003)	(0.0003)
NREGA: T = 0 * Days >21C	0.0002	0.0002
	(0.0002)	(0.0002)
NREGA: T = 1 * Days >21C	0.0006**	0.0005*
	(0.0003)	(0.0003)
NREGA: T = 2 * Days >21C	0.0009**	0.0007
	(0.0004)	(0.0004)
Observations	1866623	1866623
R^2	0.177	0.167

Notes: This table tests if the impacts 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 21°C 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 15-21°C, 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 and 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 aged 5-16. Standard errors are in parentheses, clustered by district. *Significant at 10%. **Significant at 5%. ***Significant at 1%.

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

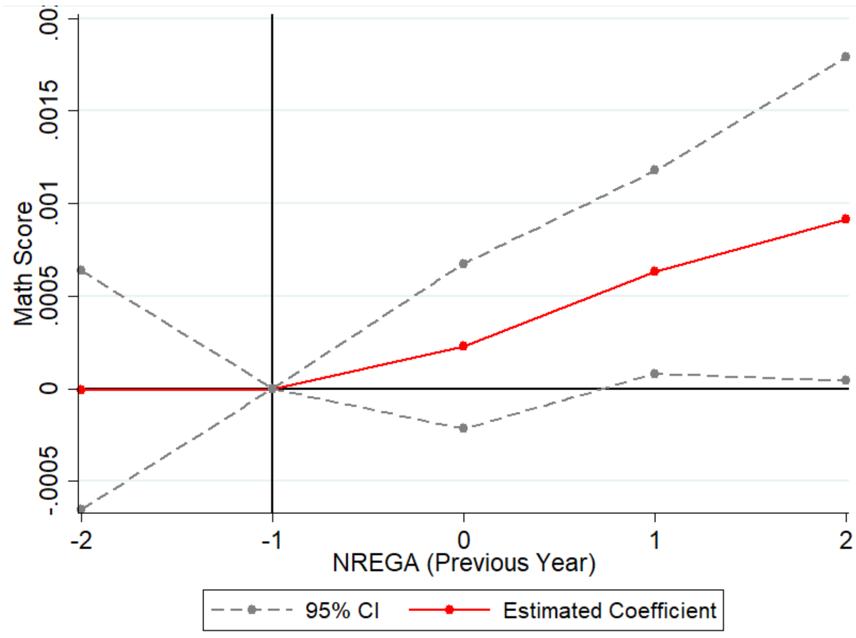


Figure D.5: Event Study—On-Track Children: Long-Run Temperature, NREGA, and Reading Scores

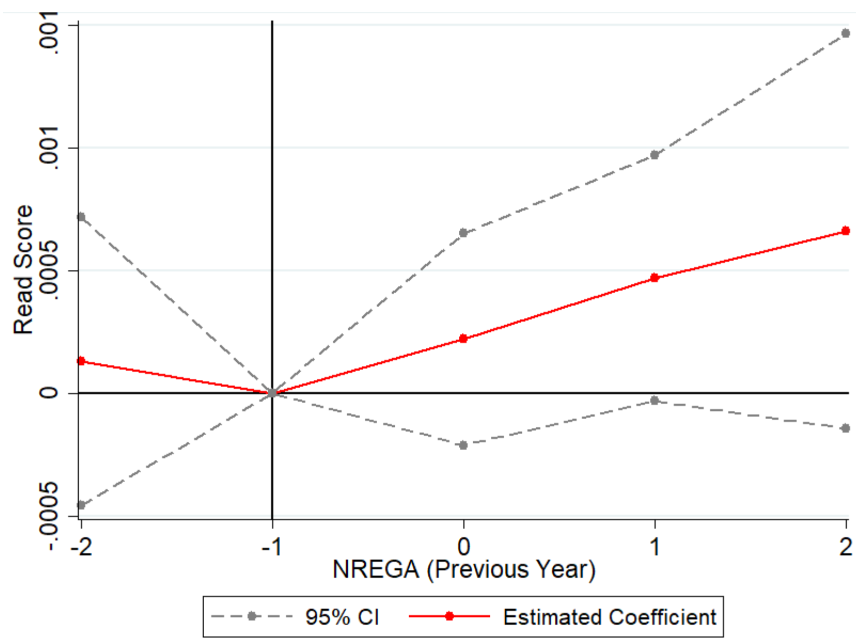


Table D.5: Difference in Difference—On-Track Children: Long-Run Temperature, NREGA, and Test Scores

	(1) Math Score (in SD) β / SE	(2) Read Score (in SD) β / SE
Days >21C	-0.0010	-0.0006
	(0.0008)	(0.0007)
NREGA PY	-0.2066***	-0.1502***
	(0.0526)	(0.0494)
NREGA PY*Days >21C	0.0005***	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 ages of 5 and 16. Standard errors are in parentheses, clustered by district.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

D.4 Temperature and take-up of NREGA

Table D.6: 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%.

E Appendix (Online Only): Data

E.1 ASER Math and Reading Scores

Table E.1: Summary Statistics: Mean Math and Reading Scores 2006-2009

	All	2006	2007	2008	2009
Read	2.66	2.70	2.74	2.73	2.76
	(1.44)	(1.44)	(1.38)	(1.41)	(1.37)
Math	2.37	1.84	2.59	2.54	2.61
	(1.33)	(1.13)	(1.33)	(1.35)	(1.33)
Observations	4581616	601342	594552	587080	550228

Notes: Standard deviations are in parentheses. In 2006, three math questions were asked, not four as in all other rounds.

Table E.2: Summary Statistics: Mean Math and Reading Scores 2010-2014

	2010	2011	2012	2013	2014
Read	2.74	2.64	2.53	2.52	2.51
	(1.39)	(1.44)	(1.50)	(1.51)	(1.54)
Math	2.57	2.40	2.27	2.24	2.22
	(1.34)	(1.34)	(1.34)	(1.33)	(1.33)
Observations	516238	488503	435948	408790	398935

Notes: Standard deviations are in parentheses.

E.2 Weather Data

Table E.3: Summary Statistics: Yearly Temperature Bins 2006-2010 (Mean no. of days)

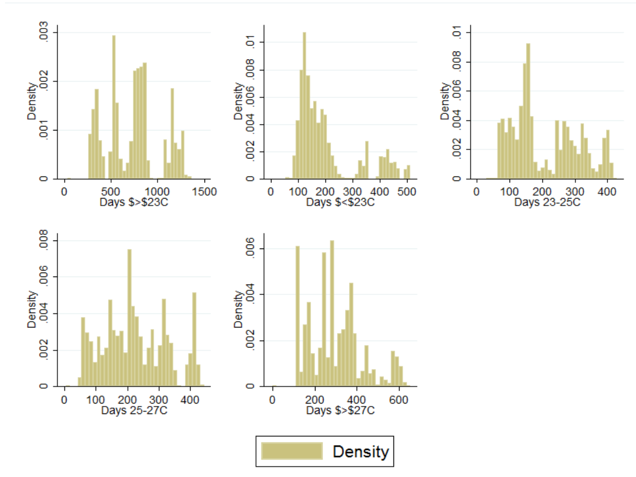
	All	2006	2007	2008	2009
PY Days >21C	250.49	249.75	257.84	245.86	247.68
	(87.46)	(83.67)	(88.98)	(89.34)	(91.98)
PY Days <13C	32.40	30.47	27.98	34.53	33.28
	(66.61)	(66.87)	(68.11)	(68.12)	(70.30)
PY Days 13-15C	16.48	18.39	15.12	16.94	17.29
	(15.14)	(15.81)	(15.37)	(15.65)	(15.73)
PY Days 15-17C	19.30	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.

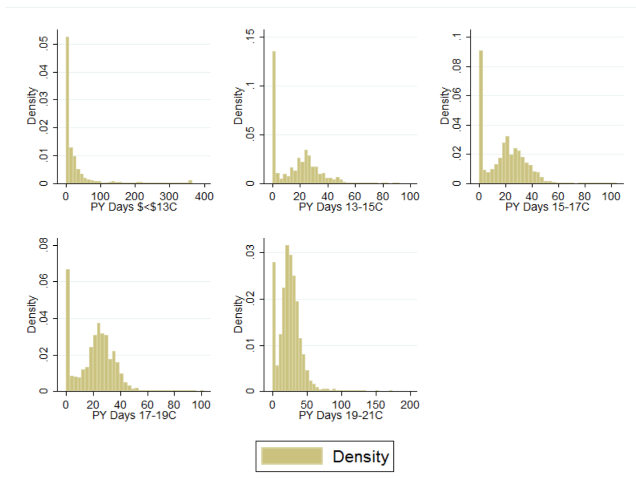
Table E.4: Summary Statistics: Yearly Temperature Bins 2011-2014 (Mean no. of days)

	2010	2011	2012	2013	2014
PY 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)

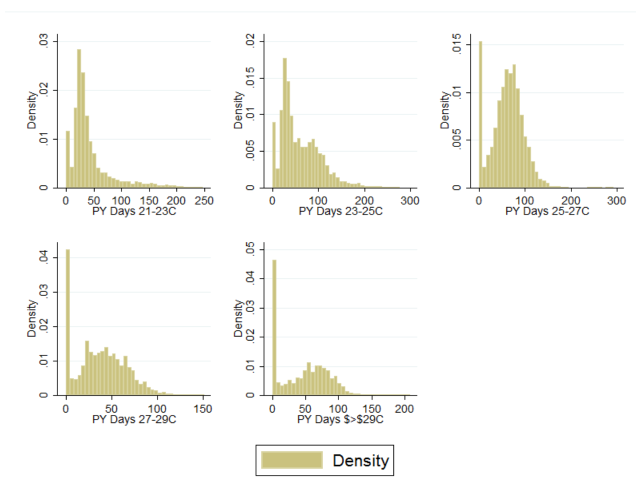
Notes: Standard deviations are in parentheses.



(a) Andhra Pradesh



(b) All India



(c) All India (continued)

Figure E.1: Long-Run Temperature Variation

E.3 NREGA Take-Up and Expenditure

Table E.5: Summary Statistics: Mean NREGA Take-Up and Expenditure 2006-2009

	All	2006	2007	2008	2009
HHs 100 Days	9031.10	15123.10	14760.87	13549.61	12368.24
	(18909.74)	(29223.31)	(26968.78)	(28657.80)	(21613.68)
Person Days	1801790.61	116557.60	113062.26	80121.31	90172.27
	(3431231.29)	(87513.16)	(82931.66)	(75922.57)	(79773.20)
Exp. Labor	4008.01	3347.02	3694.70	3485.44	4447.65
	(4338.61)	(2628.18)	(3245.35)	(4423.44)	(4861.09)
Exp. Material	1636.23	1453.60	1516.93	1502.36	1997.71
	(1716.39)	(1254.00)	(1560.48)	(2033.38)	(2064.93)

Notes: Standard deviations are in parentheses.

Table E.6: Summary Statistics: Mean NREGA Take-Up and Expenditure 2010-2014

	2010	2011	2012	2013	2014
HHs 100 Days	7778.25	6584.39	7984.97	7570.24	4004.05
	(12528.15)	(12402.45)	(17201.92)	(15052.13)	(8122.02)
Person Days	88952.69	3468616.01	3543158.49	3476210.45	2647656.55
	(83611.26)	(3838386.60)	(4669091.27)	(4495789.94)	(3428936.26)
Exp. Labor	4130.66	3953.48	4224.49	4211.79	3881.26
	(3844.14)	(3966.64)	(4867.16)	(4757.21)	(4296.47)
Exp. Material	1941.27	1774.65	1570.54	1410.36	1381.73
	(1889.50)	(1630.99)	(1499.61)	(1451.68)	(1479.16)

Notes: Standard deviations are in parentheses.