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Temperature and Human Capital in India

Teevrat Garg
University of California - San Diego

Maulik Jagnani
University of Colorado, Denver

Vis Taraz
Smith College, vtaraz@smith.edu

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By Teevrat Garg, Maulik Jagnani, and Vis Taraz*

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Abstract

We estimate the effects of temperature on human capital production in India. We show that high temperatures reduce math and reading test scores among school-age children. Agricultural income is one mechanism driving this relationship—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, higher temperatures will have large negative impacts on human capital production of poor populations in agrarian economies.

JEL Codes: Q54, O13, H53
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*Garg: School of Global Policy and Strategy, University of California at San Diego, La Jolla, CA 92103 (email: teevrat@ucsd.edu); Jagnani: Department of Economics, University of Colorado Denver, Denver, CO 80204 (email: maulik.jagnani@ucdenver.edu); Taraz: Department of Economics, Smith College, Northampton, MA 01063 (email: vtaraz@smith.edu). We thank Clément Imbert, Karthik Muralidharan, Nishith Prakash, and Wilima Wadhwa for sharing data. We thank Chris Barrett, Geoff Barrows, Marc Bellemare, Prashant Bharadwaj, Francois Cohen, Mitch Downey, Eyal Frank, Josh Graff Zivin, Gordon Hanson, Kelsey Jack, Gordon McCord, Doug Miller, Craig McIntosh, Karthik Muralidharan, Matthew Neidell, Manisha Shah, Jeff Shrader, Jeremy Tobacman, and Russell Toth for valuable feedback on earlier versions of this paper. Antony Colleti, William Honaker, Giang Thai, and Emily Zhou provided excellent research assistance. We are grateful for feedback from seminar participants at Duke/NCSU/RTI TREE Series, UC Berkeley, UC Santa Cruz, UC San Diego, Colorado School of Mines, Queen Mary University of London, RAND, World Bank, Cornell University, Fordham University, UMass Amherst, Oberlin College, Williams College, and University of Notre Dame as well as conference participants at the 2018 CSAE Conference, 2018 AEA Annual Meetings, 2017 NBER Summer Institute EEE, 2017 AAEA Annual Meetings, 2017 AERE Conference, 2017 PACDEV, 2017 MWIEDC, 2017 PAA Annual Meetings, 2017 NAREA Meetings, and 2016 ISI Delhi Conference. Garg gratefully acknowledges generous funding from the Center for Global Transformation at the School of Global Policy & Strategy at the University of California, San Diego. All errors are our own.

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 (Burke, Hsiang and Miguel, 2015*a*; Dell, Jones and Olken, 2012, 2014; Mendelsohn, Nordhaus and Shaw, 1994). Because human capital is an important driver of economic growth (Barro, 2000; Nelson and Phelps, 1966; Romer, 1986), 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.

We use math and reading test scores for more than 4.5 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. We identify one 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, 2018; Park, 2017). However, in poor countries, human capital production may also be affected by agricultural productivity (Maccini and Yang, 2009), and to the extent that agricultural productivity is temperature sensitive (Schlenker and Lobell, 2010; Schlenker and Roberts, 2009), higher temperatures may affect performance through such an agricultural income mechanism.[1]

First, using test scores from an India-wide repeated cross-section between 2006 and 2014, we show that over a longer-run horizon, measured as the number of hot days in the calendar year prior to the year of the test, high temperatures affect both math and reading scores; 10 extra days 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 (SD) respectively. These are economically meaningful effects. Using projections from the Community Climate Systems Model version 4 (CCSM v4), we estimate that by the end of the century higher temperatures would reduce math and reading test scores by 0.04 and 0.03 standard deviations respectively each year, which, accrued over the course a student's education, is equivalent to a loss of roughly 2 years of schooling.[2] We corroborate these findings using a rich longitudinal study from a large state in Southern India, Andhra Pradesh, where we also find evidence of a day-of-test, physiological effect

[1]While not the focus of our paper, hot weather can also affect human capital through harmful effects of early childhood exposure to extreme temperature on health (Isen, Rossin-Slater and Walker, 2017).

[2]We provide these calculations in Appendix A.2. See McEwan (2015) for a review of educational interventions in developing countries. The underlying assumption here is, *ceteris paribus*, that the only thing that changes is the underlying temperature distribution with no changes to underlying trends in adaptation along policy, technology, or other margins.

of heat stress.

Second, we find persuasive evidence that one underlying mechanism for our longer-run results is the harmful effect of higher temperatures on agricultural yields and incomes: (a) high temperatures have large negative effects on both agricultural yields, (b) 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, and (c) the effects of high temperatures are concentrated in warmer regions that grow below-median levels of heat-resistant crops. Other channels could, in theory, mediate the relationship between longer-run temperature and test scores, such as heat stress affecting learning in schools, school closures and teacher absenteeism driven by excessive heat, and incidence of diseases that thrive in hot and wet conditions. While we fail to find strong evidence for these mechanisms, we do not rule them out completely.

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), which guarantees 100 days of paid work each year to every rural household in India. We find that access to NREGA in the previous year attenuates the marginal effect of extra hot days in the calendar year prior to the test, on both math and reading test scores by 38%. We also show that hotter days in the previous year increase participation in NREGA contemporaneously. 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 (Cho, 2017; Graff-Zivin, Hsiang and Neidell, 2018; Park, 2017).[3] These studies have been set in developed countries, limiting them to a singular channel: the physiological effect of day-of-test temperature on math, but not reading performance (Graff-Zivin, Hsiang and Neidell, 2018; Park, 2017). However, they fail to find evidence for the effects of temperature on test scores over a time horizon longer than the day of the test. Cho (2017) does find that longer-run exposure to heat stress during the summer months affects both math and reading scores in South Korea, but the study is ambivalent about the underlying mechanism. In this paper, we provide the first evidence for the day-of-test physiological effects of heat stress, and more importantly, the effects of longer-run temperature on human capital, in a developing country context. Furthermore, in contrast to previous work, we find evidence that one mechanism underlying the effects of longer-run temperature on test scores is agricultural income. Our work highlights

[3] A rich literature considers the impacts of higher temperatures on a variety of economic outcomes including output (Burke and Emerick, 2016; Burke, Hsiang and Miguel, 2015*a*; Somanathan et al., 2015), mortality (Barreca et al., 2016; Burgess et al., 2017; Deschênes and Moretti, 2009), morbidity (White, 2017), and violence (Burke, Hsiang and Miguel, 2015*b*; Garg, McCord and Montfort, 2019).

the fact that a shared environmental issue—high temperatures—may have vastly different mechanisms and impacts depending on the country context, emphasizing the importance of examining environmental issues in developing countries (Barrows, Garg and Jha, 2019; Greenstone and Jack, 2015).

Second, we contribute to a new but growing literature on the role of public programs in helping households and individuals cope with environmental shocks. Relevant work in this literature includes Deryugina (2017), who explores the role of social safety net transfers in providing insurance to US hurricane victims; Gunnsteinsson et al. (2016), who find that a randomized public health intervention (vitamin A supplementation) in Bangladesh protected infants from negative tornado impacts; and, Adhvaryu et al. (2018), who find that conditional cash transfers in Mexico mitigate the negative impacts of early-life rainfall shocks on child human capital attainment. Our paper is the first to provide evidence on the role of public programs in helping households in poor countries to cope contemporaneously with extreme temperatures. 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).[4] 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.

The rest of the paper is organized as follows. In Section 2, we provide a conceptual framework for the varying channels through which temperature could affect human capital production and in Section 3 we describe the numerous datasets used in this paper. In Section 4 we cover the main empirical specifications and the corresponding results. In Section 5.1 we provide evidence that the underlying mechanism is agricultural income and in Section 5.2 we explore other candidate mechanisms. In Section 6 we demonstrate the role of social protection programs for adaptation and in Section 7 we provide concluding remarks.

2 Background

There are several mechanisms by which high temperatures could affect human capital accumulation. The two foremost mechanisms are an agricultural channel and a physiological channel. We provide more background on each of these channels below.

Agriculture is the primary occupation for a significant proportion of low-income households in developing countries, whether through subsistence agriculture or as hired labor. Agricultural incomes, however, can be low and erratic in the face of adverse weather conditions, as agricultural productivity in low-income countries is sensitive to both rainfall and temperature. Furthermore, markets in these agrarian economies are incomplete or imperfect. Thus, agricultural households

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

in low-income countries are often unable to smooth consumption over states of nature and across time. In such a context, investments in children may be influenced by household consumption needs instead of the rates of return. That is, if households cannot borrow, lend or store, negative income shocks could reduce human capital investment. For instance, Jacoby and Skoufias (1997) argue that time devoted to schooling is influenced by family resources by showing that income fluctuations among households in India lead to variability in school attendance. Similarly, Jensen (2000) shows that children living in regions that experienced adverse rainfall shocks had lower investments in education and health. Since time and income are important inputs into human capital, increased volatility in agricultural incomes due to weather conditions can have significant implications for children's educational outcomes in developing countries.

India is a hot country and currently experiences close to 50 days with average temperature over 29°C (84°F), compared to seven days over 29°C in the United States. Furthermore, more than 60% of the Indian population lives in rural areas and depends on agriculture for their livelihood. Therefore, if agricultural yields and the demand for agricultural labor is affected by the physical relationship between heat stress and crop growth (Schlenker and Lobell, 2010; Schlenker and Roberts, 2009), and if agricultural households are liquidity constrained,[5] higher temperatures could lead to a reduction in children's human capital investment for many households, through reductions in time and resources devoted to schooling or health investments in children (Jacoby and Skoufias, 1997; Jensen, 2000; Maccini and Yang, 2009). Thus, higher than normal temperatures in the previous period can have negative impacts on children's current human capital outcomes through reductions in the previous- and current-period resources available to the household. Conversely, it is possible that higher temperatures during the previous year could affect human capital via a farm labor productivity mechanism. For example, if children perform agricultural labor, their marginal product of on-farm labor will likely be higher during years with fewer hot days. As a result, parents may decide to keep children home from school more during those years. Conversely, during a year with many hot days, it may be more valuable for children to develop their human capital at school. Under this mechanism, higher than normal temperatures in the previous period would have positive impacts on children's current human capital outcomes.[6]

High temperatures could also affect children's human capital production through a physiological mechanism. Ambient temperature affects brain temperature. The brain's chemistry, electrical properties, and function are all temperature sensitive (Bowler and Tirri, 1974; Deboer, 1998; Hocking et al., 2001; Schiff and Somjen, 1985; Yablonskiy, Ackerman and Raichle, 2000), and both warm environmental temperatures and cognitive demands can elevate brain temperature. 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

[5]See for example, Burgess et al., 2017; Cole et al., 2013; Deaton, 1997; Dercon, 2005; Dercon and Krishnan, 2000; Paxson, 1993; Rosenzweig and Wolpin, 1993; Rosenzweig and Stark, 1989; Townsend, 1994.

[6]Shah and Steinberg (2017) find evidence of this effect in India, but looking at low rainfall, rather than hot days.

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, 2018). 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). Note that cold temperatures have also been shown to have an adverse effect on learning and cognitive function (Lieberman, Castellani and Young, 2009; Mäkinen et al., 2006; Muller et al., 2012; Sharma and Panwar, 1987; Taylor et al., 2016). However, India experiences few very cold days in a year, and the number of hot days are projected to increase disproportionately in the future. Hence, the focus of this paper is on hot, rather than cold, days.

Exposure to high temperatures can manifest in insults to children's human capital through the physiological mechanism in two ways: i) a hot day could continue to affect future learning if the human body is unable to internally self-regulate to higher ambient temperatures, and ii) repeated exposure to heat stress at school can affect learning repeatedly. Graff-Zivin, Hsiang and Neidell (2018), Park (2017) and Cho (2017) show that day-of-test temperatures affect test scores through a physiological relationship between heat stress and cognition. However, these studies either found no evidence for the effects of longer-run temperature on cognition (Graff-Zivin, Hsiang and Neidell, 2018; Park, 2017), or are ambivalent about the underlying mechanism (Cho, 2017).

In Section 5.1 we present compelling evidence for agricultural income as one mechanism underlying the longer-run temperature-test score relationship. Subsequently, in Section 5.2 we examine the influence of the physiological mechanism, and although we fail to find strong evidence for such a mediating channel, we do not rule it out completely. Other mechanisms through which high temperatures might affect children's human capital in India include incidence of diseases that thrive in hot and wet conditions, and school closures or teacher absenteeism driven by excessive heat. We also explore these channels in Appendix A.3.

3 Data

In this section, we describe the data sets that we use to explore the relationship between temperature and test scores. We use multiple data sets on test performance as well as detailed daily gridded weather data that include temperature, rainfall, and humidity. We obtain agricultural data from the International Crops Research Institute for Semi-Arid Tropics (ICRISAT).

3.1 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.

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. The sample is a nationally representative repeated cross-section at the district level. The ASER surveyors ask each child aged from 5 to 16, up to 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 questions are asked in the child's native language,

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 to 2014, ASER conducted more than 4.5 million tests across every rural district in India.[7] Given the considerable spatial variation in weather in India, the national coverage of ASER allows us to study the impacts of temperatures on test scores over a large support. Importantly, it is administered each year on 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. Note that ASER samples households, not children. All children in the 3-16 age group who are resident in the samples households are included in the survey, while learning assessment are done with all children age 5-16.

The ASER has two limitations. First, its repeated cross-sectional nature doesn't allow us to account for the role of prior human capital accumulation. Second, the ASER test instrument is relatively simple and is designed to capture the left-tail of the distribution, e.g., to test for basic competence.[8] Note that we address these limitations by complementing our ASER analysis with an analysis of the YLS test data (described below), which is a much broader test that effectively captures variation across the ability spectrum (Singh, 2015).

Young Lives Survey

The Young Lives Survey is an international study of childhood poverty coordinated by a team based at the University of Oxford.[9] The YLS study in India collects data from a single state, Andhra Pradesh, which is the fourth-largest state in India by area and had a population of more than 84 million in 2011. In this study, we use YLS data from 2002 to 2011. The study has collected

[7]While the ASER originated in 2005, the 2005 wave is not publicly available.

[8]However, the left-tail of the distribution or low-performing students are more likely to come from households with marginal livelihoods, especially considering the scope of the ASER data: *rural* districts in India. Thus, the ASER data set is ideal for investigating the hypothesized income channel underlying the temperature-test score relationship.

[9]Young Lives is funded by UK aid from the Department for International Development (DFID). The views expressed here are those of the author(s). They are not necessarily those of Young Lives, the University of Oxford, DFID, or other funders.

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. Data were 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 terms of 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 each child's age and current 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. Furthermore, YLS has additional information about the socio-economic background of the children's households and health data. We restrict our sampling frame to children who were in enrolled in school (Singh, 2015), and were tested at least thrice in both math and verbal.

3.2 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 poor. 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. 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 (Auffhammer et al., 2013; Schlenker and Lobell, 2010). 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 1 shows the spatial distribution of temperature in India during the study period and Figure 2 shows the distribution of daily temperatures for India and the state of Andhra Pradesh.

3.3 Other Data Sources

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 from 1979 to 2014 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 yearly 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 (Planning Commission, 2003). The backwardness index was based on three outcomes—agricultural wages, agricultural productivity, and the fraction of low-caste individuals in each district—based on data from the mid-1990's. 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 the period from 2006 to 2016 from the Management Information Systems (MIS). In particular, we focus on the number of rural households enrolled in NREGA in a particular district in a given year.

4 Do Longer-Run Temperatures Affect Test Scores?

To examine the effect of temperature on test scores, we rely primarily on the ASER data set. 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. To verify the robustness of our results, we also analyze the YLS data set, which provides an individual level panel but with coverage limited to a single state. With each data set we estimate both flexible and parsimonious models.

4.1 Empirical Strategy

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:

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

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 in year $t-1$. 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 to 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.

For rainfall, we include dummy variables that represent whether total annual rainfall for a certain district in a certain year was in the top, or bottom, tercile, relative to the long-run historical distribution of rainfall in that district.[10] To account for humidity, we include dummy variables for whether average annual humidity for a certain district in a certain year was in the top, or bottom, tercile.[11] We control for age fixed effects (χ_i), district fixed effects (α_j) and year fixed effects (μ_t). We cluster standard errors at the district level to account for serial correlation within a 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 an upper threshold of 21°C and a lower threshold of 15°C. Our choice of 15°C and 21°C for the parsimonious model is based on the kink points that were revealed by our estimation of the nonparametric analysis (Equation (1)).

[10] Our results are robust to alternative specifications of rainfall, including linear and quadratic terms for total annual rainfall.

[11] Our results are robust to excluding indicators for rainfall and humidity (Roberts, Schlenker and Eyer, 2013). As we note in Appendix A.1, in forecasting impacts under climate change, it may be important to consider the changes in weather variables (temperature, rainfall, and humidity) jointly over future climate scenarios.

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

An important limitation of the ASER data is that it does not provide the exact date of the test. Therefore, we can't control for day-of-test temperature. However, the omission of temperature on the day of the test would only confound our estimates if the day-of-test temperature is correlated with more hot days in the previous year. We believe that such a systematic correlation is unlikely because the day-of-test temperature is plausibly random.[12]

4.2 Results

We estimate Equation (1) and find that, relative to a day with average daily temperature between 15°C and 17°C, one extra day in the previous year with average daily temperature above 29°C reduces math and reading performance by 0.003 and 0.002 SD in the current year, respectively (Table 1). Using our binned approach, we find that test performance decreases for temperatures above 17°C. The results are similar to those estimated with our parsimonious approach: one extra day above 21°C reduces math and reading performances by 0.002 and 0.001 SD, respectively (Table 2).[13]

In addition to our analysis of standardized test scores, we also estimate the effects of previous year temperature using raw scores (Appendix Figure A.2). We find that a 10-day increase in the number of hot days above 29°C in the previous year decreases math scores by 0.03 points and reading scores by 0.02 points.[14] Both point estimates are statistically significant at the 5% level. Furthermore, to understand how higher temperatures impacted specific skills, we present effects on competencies covered on both math and reading tests. The effects of heat are driven by the harder questions on both math and reading tests. We find large negative effects on paragraph- and story-reading skills, but statistically insignificant effects on word- or letter-reading skills (Appendix Figure A.3). Ten extra days in the previous year with average daily temperature above 29°C (84°F) relative to 15°C-17°C (59°F-63°F) reduce story-reading ability by almost 1 percentage point. In 2006, almost 45% children in the ASER data set could read a story, so 1 percentage point decrease translates into a reduction of 2% in story reading skills. Similarly, we find negative effects

[12]In fact, we test this assumption explicitly using the YLS data where we have information on the day of the test.

[13]In addition to the significant negative effects of high temperatures, there are two other features to note about Table 1: first, there are also negative impacts of very low temperatures and, second, the gradient of the temperature impacts is relatively flat. The low temperature impacts are not the focus of our study, because there are fewer days in these bins and, furthermore, the number of days in these bins will decrease as climate change accelerates. However, as noted in Section 5.2, these cold-temperature impacts may be due to a physiological channel. Second, the flat gradient of the graph stands in contrast to other work on temperature impacts that often finds sharp threshold effects, such as Schlenker and Roberts (2009). However, as explored further in Section 5, this flat gradient may arise because the annual specification captures the combined effects of many channels (e.g. agricultural, physiological, and other), across many parts of the year (e.g. growing season versus non-growing season), which may vary in magnitudes.

[14]The average scores for both math and reading tests are approximately 2.5 points out of the maximum possible score of 4.

on division and subtraction skills, but statistically insignificant effects on single- or double-digit number recognition (Appendix Figure A.4). Ten extra days in the previous year with average daily temperature above 29°C (84°F) relative to 15°C-17°C (59°F-63°F) reduce division-solving ability by more than 1 percentage point, or 3%.

Robustness Checks: We demonstrate that our results are insensitive to numerous robustness checks, supporting the validity of our baseline model. 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 2). 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 Table A.1). Third, the addition of lags does not affect our point estimates (Appendix Table A.2). Fourth, our results remain unchanged with the inclusion of state-specific linear and quadratic trends (Appendix Table A.3). Fifth, our results remain unchanged with the inclusion of state-by-year fixed effects, which control for all time-varying unobservables at the state-level that may be correlated with children's test scores (Appendix Table A.4). Sixth, our results remain largely unchanged when we use nearest weather grid points or daily maximum temperature (Appendix Table A.5). Finally, we also control for a proxy of the same-day temperature—the number of hot days during the weekends of the testing month—and find that controlling for this does not change the coefficients appreciably (Appendix Table A.6).[15]

4.3 Individual Panel Analysis

Next, we use a longitudinal panel data set—the YLS—in which we have information on the exact date of the test, allowing us to control for temperature on the day of the test, as well as time-invariant child level attributes (e.g., ability), and estimate the effect of hot days between successive tests (covering at least one full agricultural cycle) on test scores.

Empirical Strategy We first estimate the following flexible model of the effects of temperature on test scores:

$$\begin{aligned} Y_{ijdmt} = {} & \gamma_2 T(23°C - 25°C)_{j,t-1} + \gamma_3 T(25°C - 27°C)_{j,t-1} + \gamma_4 T(> 27°C)_{j,t-1} \\ & + \beta_2(23°C - 25°C)_{jdmt} + \beta_3(25°C - 27°C)_{jdmt} + \beta_4(> 27°C)_{jdmt} \\ & + f\left(rain_{j,t-1}\right) + rain_{jdmt} + \alpha_i + \mu_{1d} + \mu_{2m} + \mu_{3t} + \epsilon_{ijdmt} \end{aligned} \tag{3}$$

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. Our coefficients of interest are $T(\cdot)$, counts of the number of the days since the previous test with average daily temperature within the specified

[15]Recall that we have to use such a proxy since the exact day of the ASER test is unavailable. We do, however, know that these tests take place during the weekends.

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. 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}). Inclusion of child fixed effects controls for unobservable child level attributes that do not vary over time (e.g., ability). Furthermore, we control for day-of-test temperature by including dummies indicating temperature was between 23°C and 25°C, 25°C and 27°C, or above 27°C, respectively. This also allows us to capture the effects of temperature on the day of the test. For instance, β_4 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. $rain_{jdmt}$ controls for rainfall on the day of the test.

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 0, 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:

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

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. Following the common practice in the literature on climate economics, we chose the threshold of 23°C because our estimation of the nonparametric specification (Equation (3)) revealed a kink at that level (Hsiang, 2016).

Results: 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 3).[16,17]

Furthermore, 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; Hocking et al., 2001; Schiff and Somjen, 1985). 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, but find no discernible or meaningful relationship between higher temperatures and reading comprehension. Different portions of the brain perform different cognitive functions. For instance, the pre-frontal 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). These day-of-test estimates are similar with those in prior work in developed countries (Cho, 2017; Graff-Zivin, Hsiang and Neidell, 2018; Park, 2017). Crucially for our analysis, controlling for day-of-test temperature does not affect the relationship between longer-run temperature and test scores (Appendix Table A.9).

Recall that the ASER test instrument primarily captures variation in the left-tail of the ability spectrum, whereas YLS is a more comprehensive test that captures variation over the entire distribution of ability. The fact that our results are consistent across the two data sets indicates that temperature shocks over the previous year have impacts on both low-performing students and students on other levels of the ability spectrum. From a policy point of view, we care about both groups of students: low-performing students may be coming from particularly disadvantaged households or vulnerable livelihoods; but conversely to understand economy-wide impacts, it is important to understand impacts that span the entire ability distribution.

5 Mechanisms

In this section we examine two primary mechanisms that may mediate the longer-run temperature-test score relationship: i) agricultural income and ii) direct physiological impacts on learning. Other plausible mechanisms such as the incidence of diseases that thrive in hot and wet conditions and school closures or teacher absenteeism driven by excessive heat are explored in Appendix A.3.

5.1 Is Agriculture a Mechanism Underlying the Relationship Between Longer-Run Temperatures and Test Scores?

If agricultural yields and the demand for agricultural labor are affected by the physical relationship between heat stress and crop growth, and if agricultural households are liquidity constrained, then

[16] While our YLS analysis includes only the younger sample to maintain comparability with the ASER results, the results are similar to when we consider the combined sample as well (Appendix Table A.7).

[17] We also cluster-bootstrap our standard errors at the district level (7 clusters) following Cameron, Gelbach and Miller (2008). Our estimates remain precisely estimated (Appendix Table A.8).

higher temperatures could lead to a reduction in children's human capital investment. For instance, we find that previous year temperature reduces current year school attendance (Appendix Table A.10) and children's body mass index (Appendix Table A.11), which suggests decreases in time and resources devoted to schooling (Jacoby and Skoufias, 1997) and health investments (Jensen, 2000) in children. Thus, if higher temperatures have large, negative effects on agricultural income in the previous year, it is possible that these effects have consequences for children's human capital production in the 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 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, and (b) comparing effects of heat on test scores across the geographic dispersion of heat-resistant crops.

5.1.1 Temperature and Agricultural Yields

To demonstrate that temperature affects human capital production by affecting the livelihoods of the rural poor, we first demonstrate that temperature affects agricultural yields. We find that agricultural yields, like test scores, are highly responsive to higher temperatures in the growing season, with comparatively modest effects of non-growing season temperatures. We use two different price-weighted agricultural yield indices: (a) the six major crops (rice, wheat, sugarcane, groundnut, sorghum, and maize), and (b) the five major monsoon crops (excludes wheat).

5.1.2 Growing Season versus Non-Growing Season

To further demonstrate evidence of an agricultural mechanism, we disaggregate our results by the growing season versus the non-growing season. India's main agricultural season (*kharif*) runs from June through November and the secondary growing season (*rabi*) runs October through February. We know that the ASER test is conducted in a given district on a single weekend between the end of September and the end of November. If hot days affect test scores by affecting household income that relies on agricultural output, these effects must be predominantly driven by growing season temperatures in the previous year. Thus, 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. We define the growing season as June through December and the non-growing season as March through May, broadly following the approach in Burgess et al. (2017). We exclude January and February from the growing season because very few hot days occur during these months. We focus on the growing season of the previous year (rather than the current year), because the previous year's output has been fully harvested, whereas the current year's harvest may be still in progress, at the time of the ASER test.

We find that the effect of temperature on test scores is primarily driven through higher temperatures in the previous years' agricultural growing seasons: an extra hot day above 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 reduce math scores by 0.1 standard deviations and reading scores by 0.06 standard deviations, compared to negligible effects in the non-growing season (Figure 4). These are large effects: 10 extra hot days in the previous year growing season could effectively wipe out gains made from a median educational intervention (McEwan, 2015). Furthermore, the difference between the effect of an extra hot day above 29°C in the growing season versus the non-growing season is statistically different at the 1% level. 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.

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% (Figure 4), with no effect of temperature on yields in the non-growing season. Our estimates are comparable to those found elsewhere in the literature (Burgess et al., 2017; Carleton, 2017; Taraz, 2018). Consistent with our finding of extremely cold days reducing performance, cold days also reduce agricultural yields, though to a lesser extent than hot days.[18,19] 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.

Our test score results are robust to several specification variation. Our baseline specification uses dry bulb temperatures, rather than wet bulb globe temperature (WBGT), because we believe that agricultural income is the primary channel that is driving the temperature-test score relationship. However, our results are qualitatively and quantitatively similar to using WBGT instead of dry air temperatures (Appendix Figure A.5). Separately, our baseline specifications are clustered at the district level. However, to address concerns over spatial correlation, we also run a specification with standard errors clustered at the state-level. The coefficients for previous year's growing season temperature bins remain precisely estimated (Appendix Figure A.6). Finally, we also show as a falsification test that future temperatures don't affect prior agricultural yields (Appendix Table A.12)

[18]In addition to analyzing aggregate, price-weighted yields, we have estimated temperature bin regressions for the raw yields (tons/hectare) of the six major crops. The results demonstrate that high temperatures negatively affect raw yields (Appendix Figure A.8).

[19]We also find that rural wages respond linearly to higher temperatures. An extra day above 29°C (relative to a day between 15°C and 17°C) decreases rural wages by 0.4% (Appendix Figure A.7). However, because our wage data is annual, we are not able to disaggregate this result by the growing versus the non-growing season.

5.1.3 Heat-Resistant Crops

To further explore the impact of temperature on agricultural yields and test scores, we analyze the role of heat-resistant crops. Following Hu and Li (2016), we separate crops into C4 crops and C3 crops. C4 crops extract carbon from carbon dioxide more efficiently than C3 crops, and are more resistant to high temperatures. In our data, the C4 crops are maize, sorghum, pearl millet, sugar cane, finger millet, and fodder, and all remaining crops are C3. 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 proportion of C4 crops is above the median, which is 23%. Appendix Figure A.9 shows the geographic distribution of the take-up 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. 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 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 lower math scores by 0.022 standard deviations, compared with a near-null effect in districts that grow above-median levels of heat-resistant crops (Appendix Table A.13).

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 historical average temperatures plant a larger fraction of their total cultivated area with heat-resistant crops (Figure 6(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 6(b)) and reading scores (Figure 6(c)). 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. 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, 2018). As an important robustness check, we show that future temperature shocks are not correlated with baseline levels of heat resistant crop adoption (Appendix Table A.14).

5.2 Can the Physiological Effects of Heat Stress Explain the Relationship Between Longer-Run Temperatures and Test Scores?

In this section, we consider human physiology as a potential underlying mechanism behind the longer-run temperature-test score relationship. Exposure to high temperatures harm children's human capital through the physiological mechanism in two ways: (i) a hot day could continue to affect future learning if the human body is unable to internally self-regulate to higher ambient temperatures, and (ii) repeated exposure to heat stress at school could affect learning repeatedly.[20]

5.2.1 Persistent Effects of a Hot Day

First, we test whether high temperatures can have persistent impacts: a hot day today could continue to affect performance in the future if the human body is unable to internally self-regulate to higher ambient temperatures. We examine this hypothesis by estimating the lagged effects of short-run temperature using the YLS data set. 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 (Appendix Figure A.10). This pattern largely holds for at least up to four weeks of leads and lags (Appendix Figure A.11). 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).

5.2.2 Repeated Exposure to Heat Stress

Yet, if children are repeatedly exposed to heat stress at school or on the field, then the cumulative effect of that heat stress can still 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 2). 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 3, 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 4). To

[20]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.

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.[21] 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 months have similar effects on performance (Appendix Figure 12), 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.

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 (Garg, Gibson and Sun, 2019; Masuda et al., 2019). 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, as mentioned earlier, heat stress during the concurrent year as the test has no effect on test scores (Table 2). India's main agricultural season lasts from June through November. Since ASER tests are conducted from late September to late 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.

Finally, another test for the physiological versus agricultural income channel is to draw a distinction between math and reading scores. Prior studies in both economics and neuroscience posit that the physiological effects of heat are experienced primarily in the part of the brain responsible for mathematical function (Graff-Zivin, Hsiang and Neidell, 2018; Hocking et al., 2001; Park, 2017). The effects of short-run (day-of-test) temperature, for example, are seen on math performance but not on reading performance. Our estimates for day-of-test temperatures are consistent with such a hypothesis. However, effects of longer-run (previous calendar year) temperature are observed in both math and reading scores. Furthermore, the magnitude of the effect on both math and reading performance is similar. Together, these results suggest that the longer-run temperature-test score relationship for high temperatures is not driven solely by a physiological mechanism.[22]

[21]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.

[22]In fact, the existence of significant negative effects of cold days may indicate that a physiological mechanism does exist. Our baseline specification finds statistically significant negative impacts from low temperatures in the previous year on current-year test scores. However, our growing vs. non-growing season estimates fail to find strong evidence for existence of an agricultural mechanism for cold days. Thus, it is plausible that cold stress affects learning due to physiological channels (Lieberman, Castellani and Young, 2009; Mäkinen et al., 2006; Muller et al., 2012; Sharma and Panwar, 1987; Taylor et al., 2016). Importantly, agricultural income and physiology are not mutually exclusive mechanisms.

6 Can Social Protection Programs Mitigate the Relationship Between Longer-Run Temperatures and Test Scores?

If income is indeed one mechanism of impact, can social protection programs play a role in shielding the poor from higher temperatures and facilitating adaptation to climate change? To investigate this question, we consider the largest workfare program in the world—the National Rural Employment Guarantee Act of 2005—which guarantees every person in rural India 100 days of paid employment on rural infrastructure projects, making NREGA a self-targeting conditional cash transfer program that has an income-stabilizing effect in the face of low and erratic agricultural incomes.

6.1 Empirical Strategy

If high temperatures reduce crop yields and the demand for agricultural labor in the previous year, it is plausible that rural households use NREGA in the previous year to help smooth consumption, and compensate (at least partially) for heat induced agricultural income losses. Thus, hotter days in the previous year might increase NREGA take-up in that year, attenuating the relationship between previous year temperature and current year test scores.[23] We exploit the staggered district-level roll-out of NREGA and test this hypothesis in an event study framework since the variation in treatment timing could result in biased difference-in-difference estimates (Goodman-Bacon, 2018). To do so, we estimate the marginal effect of an extra hot day above 21°C (relative to between 15°C and 21°C) for the same district before and after the introduction of NREGA. We estimate the following equation:

$$
\begin{aligned}
Y_{iajqt} = {} & \gamma_1 TMEAN(>21^{\circ}C)_{jq,t-1} + \gamma_2 TMEAN(<15^{\circ}C)_{jq,t-1} \\
& + \sum_{\tau=-3,\tau\neq-1}^{\tau=2} \beta_\tau NREGA(t-T_j^* = \tau)_{jq,t-\tau} \\
& + \sum_{\tau=-3,\tau\neq-1}^{\tau=2} \theta_\tau NREGA(t-T_j^* = \tau)_{jq,t-\tau} * TMEAN(<15^{\circ}C)_{jq,t-1} \\
& + \sum_{\tau=-3,\tau\neq-1}^{\tau=2} \theta_\tau NREGA(t-T_j^* = \tau)_{jq,t-\tau} * TMEAN(>21^{\circ}C)_{jq,t-1} + \chi_a \\
& + f(rain_{jq,t-1}) + g(humidity_{jq,t-1}) + \alpha_j + \mu_t + \epsilon_{iajqt}
\end{aligned} \tag{5}
$$

[23] NREGA has been shown to have impacts on a multitude of economic and social outcomes, as reviewed in Sukhtankar (2017). Outcomes affected include the demand for labor-intensive technologies (Bhargava, 2014) and agricultural yields, as laborers may switch from agricultural to NREGA participation (Taraz, 2019). We abstract away from these details and focus on the net effect of NREGA on the temperature-test score relationship.

The equation is identical to Equation (1) with an additional term, $NREGA(t-T_j^* = \tau)_{jq,t-\tau} * TMEAN_{jq,t-1}^{10}$, which captures the interaction of the number of days in the hot temperature bin in the previous year with NREGA event time dummies that take values 0 or 1. Specifically, we estimate separate coefficients on the $TMEAN(> 21°C)$ temperature bin for the periods before and after the introduction of NREGA in district j in state q. For instance, event time $T = 0$ takes the value 1 if NREGA was available in any district j in the previous year, 0 otherwise. So, if a district j got NREGA in 2009, $NREGA : T = 0 * Days > 21°C$ captures the interaction of number of days in the previous year where the temperature is over 21°C in 2009 with the dummy variable $T = 0$, to estimate the protective effects of NREGA on children's test scores in 2010. Similarly, the interaction of $T = 1$ with number of days in the previous year where the temperature is over 21°C would capture the compensatory effects of NREGA one year after it was made available to a district j in the previous year. The omitted event time $T = -1$ is the year before the previous year 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. We also control for age-for-grade status considering the level effects of NREGA on grade progression (Shah and Steinberg, 2015). Our specification compares the effect of a hot day on test scores before and after a district received NREGA in the previous year, relative to the effect of that hot day in other districts that didn't receive NREGA in that same year. To address any potential incidental correlation between NREGA and weather shocks, we explicitly test whether future weather shocks predict the rollout of NREGA. In Appendix Table A.15 we show that NREGA rollout is not predicted by future temperature shocks.

6.2 Results

The main coefficient of interest is the interaction between NREGA event time dummy variables and the number of days above 21°C in the previous year. Consistent with an income mechanism, we find that NREGA attenuates the effect of an extra hot day above 21°C in the prior calendar year on math and reading scores by more than 50% (Table 5). Figure 6 presents the event study graphically and shows that the introduction of NREGA attenuates the effect of those extra 10 hot days above 21°C on test scores by 0.01 standard deviations on both math and reading one year after the introduction of NREGA.[24] We note that the effects of NREGA represent intent-to-treat (ITT) estimates, since not all households in a district will respond by taking up NREGA. Importantly, these effects persist for at least 7 years, the maximum time period we can study in our sample. 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 A.16).

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

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 to 2016 and show that hotter days in the current year drive NREGA take-up and expenditures (Figure 7). 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, 3.4% more households are likely to use all 100 days of eligibility in the program. For each extra day above 29°C, district NREGA expenditure increases by 2% on labor and nearly 3% on materials. These results suggest that households use NREGA to stabilize damage to agricultural income in hotter years.

The remarkable effect of NREGA in attenuating the relationship between temperature and test scores is of considerable importance. 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.[25]

7 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 temperature in the calendar year prior to the test, or "longer-run" temperature affects human capital production. Furthermore, we show that agricultural income is likely one mechanism driving this relationship. Importantly, these effects are separate from the physiological impacts of day-of-test "short-run" temperature on test performance documented in the literature this far. The separation of the pathways through which temperature affects human capital over different time horizons has important implications for both climate change research 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 (Burke and Emerick, 2016; Dell, Jones and Olken, 2012). 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

[25]These types of programs act as a powerful potential "public" adaptation to climate change, which may mitigate some of the most harmful damages from climate change. Importantly, they complement to private adaptations that households can undertake in response to heat, such as crop choice, irrigation, livelihood adjustments and asset purchases, such as fans. Due to the nature of our data, private adaptations fall outside of the scope of our work.

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 may 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. 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. 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. Consequently, governments and policy makers should expect the dependence on their social protection programs to increase in the face of climate change.

Developing countries will have to carefully allocate scarce resources between productive capital and adaptive capital (Millner and Dietz, 2015), and will have to make difficult decisions about which margins of climate change damages to adapt to. 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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Tables and Figures

Figures

Figure 1: Average Annual Temperature in India at the District Level

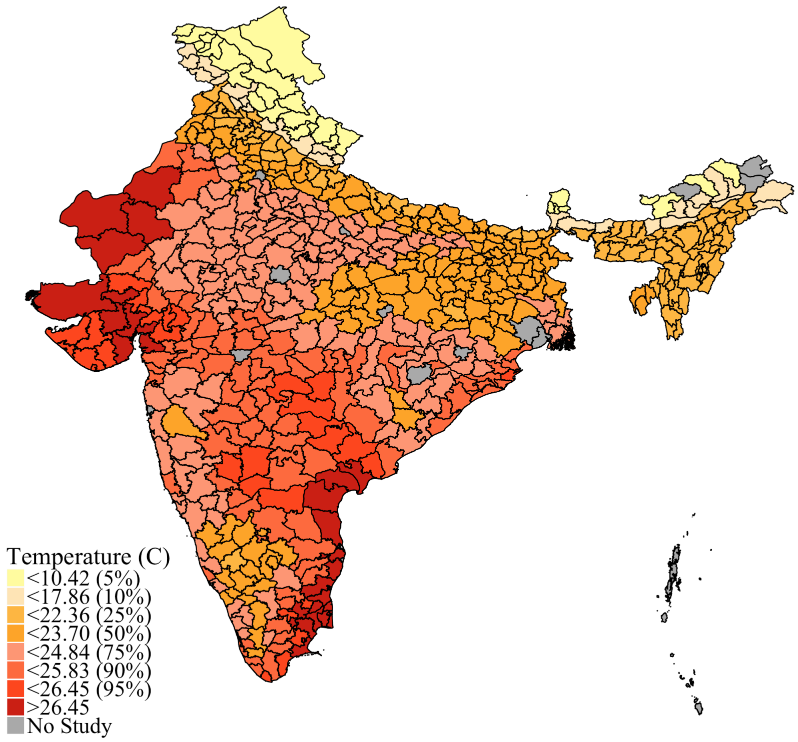


Figure 2: Distribution of Daily Average Temperatures for India and Andhra Pradesh

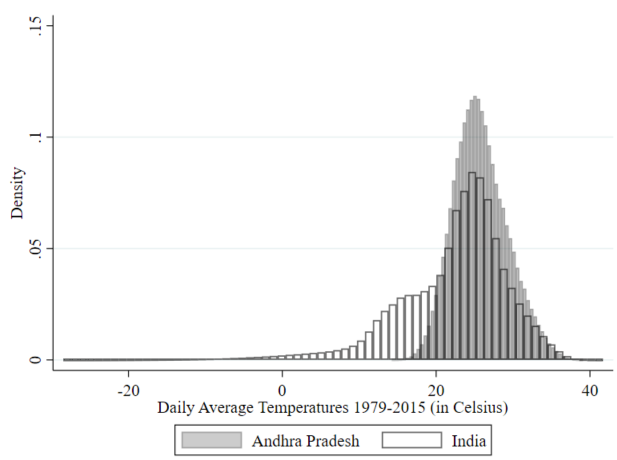
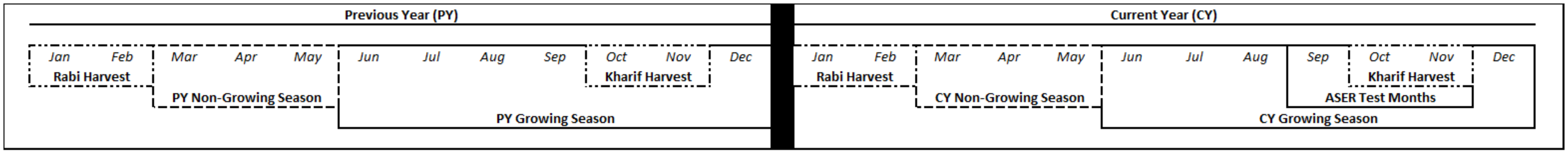
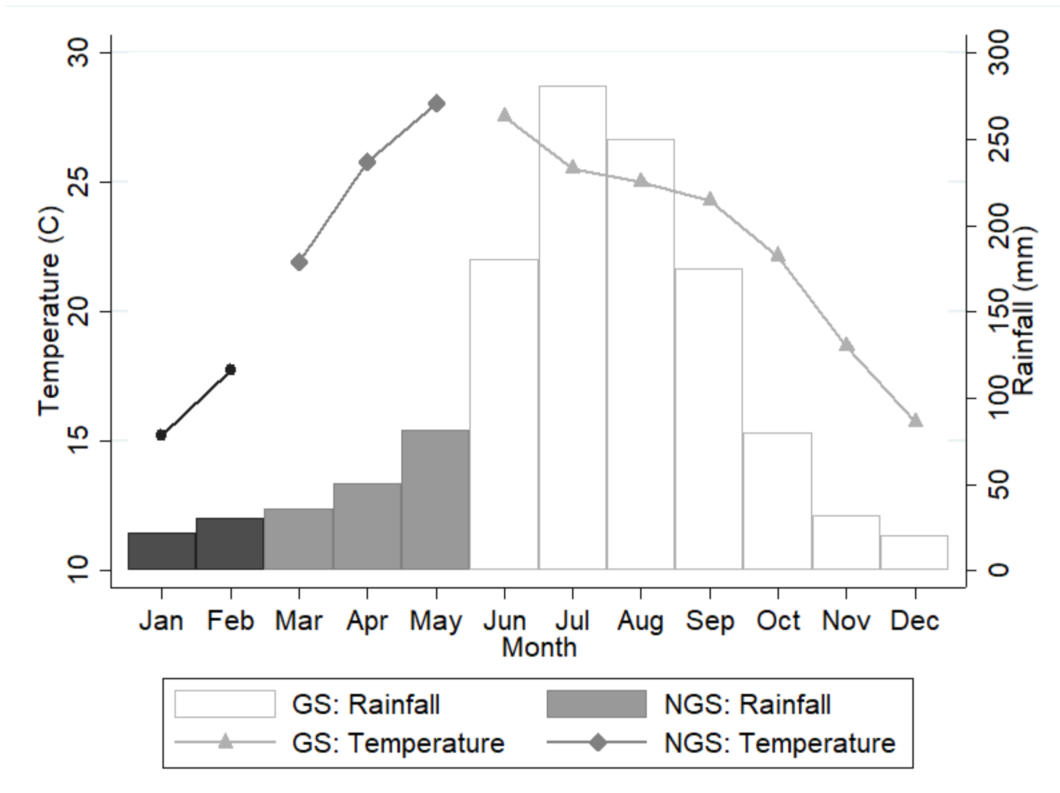


Figure 3: Timeline of Effects of Previous Year Temperature and Average Temperatures by Month and Season



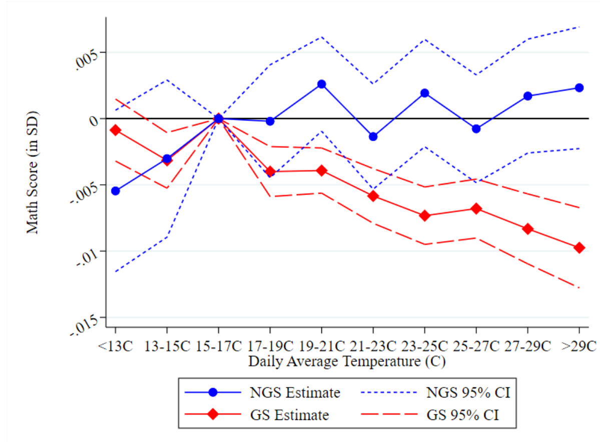
(a) Timeline of Effects of Longer-run Temperature



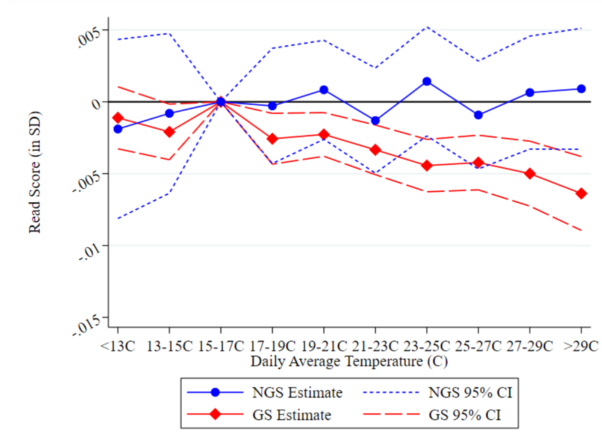
(b) Average Temperatures By Month and Season

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. GS: Growing Season; NGS: Non-Growing Season; PY: Previous Year; CY: Current Year.

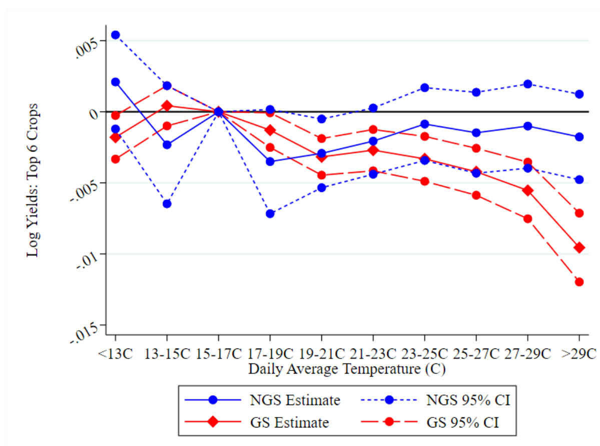
Figure 4: Growing Season v. Non-Growing Season: Previous Year Temperature, Test Scores (ASER), and Agricultural Yields



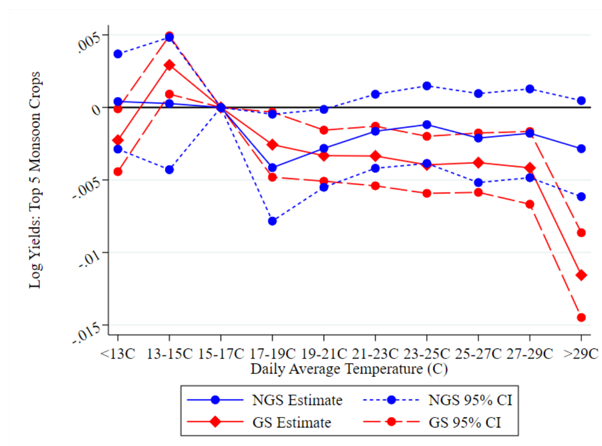
(a) Math Scores



(b) Reading Scores



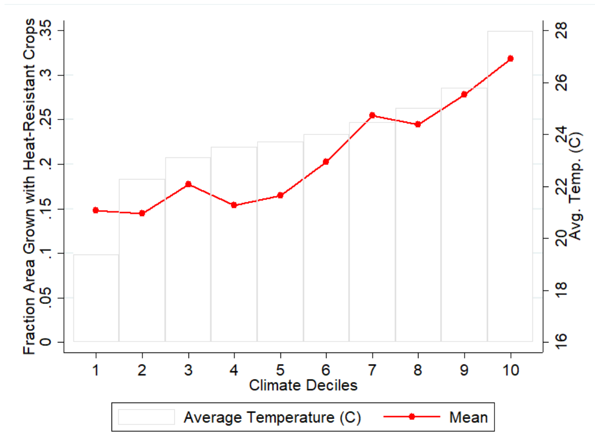
(c) Top 6 Crops



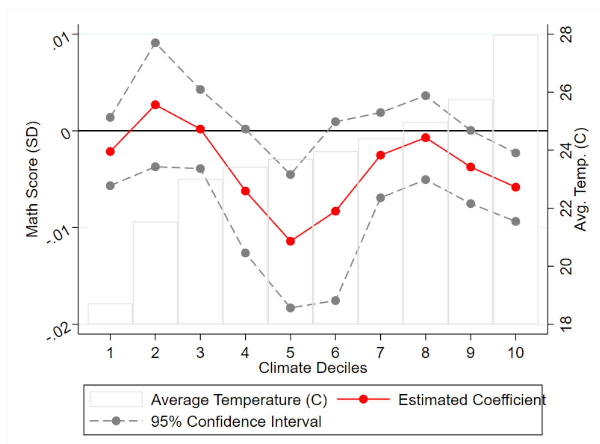
(d) Top 5 Monsoon Crops

Notes: Panel (a) and (b) show the effect of longer-run temperature (defined as number of days in the previous calendar year—see Figure 3) on current year math and reading performance divided amongst the growing season (June—Dec) and the non-growing season (March—May). In panel (c) and (d) the figure shows the effect of longer-run temperature (defined as number of days in the previous calendar year—see Figure 3) on previous year agricultural yields from 1979—2014 divided amongst the growing season (June—Dec) and the non-growing season (March—May). In all panels, 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. Panel (a) and (b) also include age fixed effects. We control flexibly for precipitation and humidity. Standard errors are clustered at district level. GS: Growing Season; NGS: Non-Growing Season.

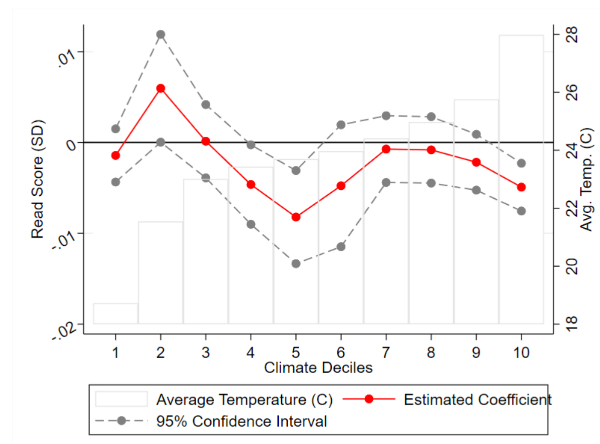
Figure 5: Heat-Resistant Crops and Effect of Previous Year Temperature on Test Scores (ASER) by Historical Temperature Deciles



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



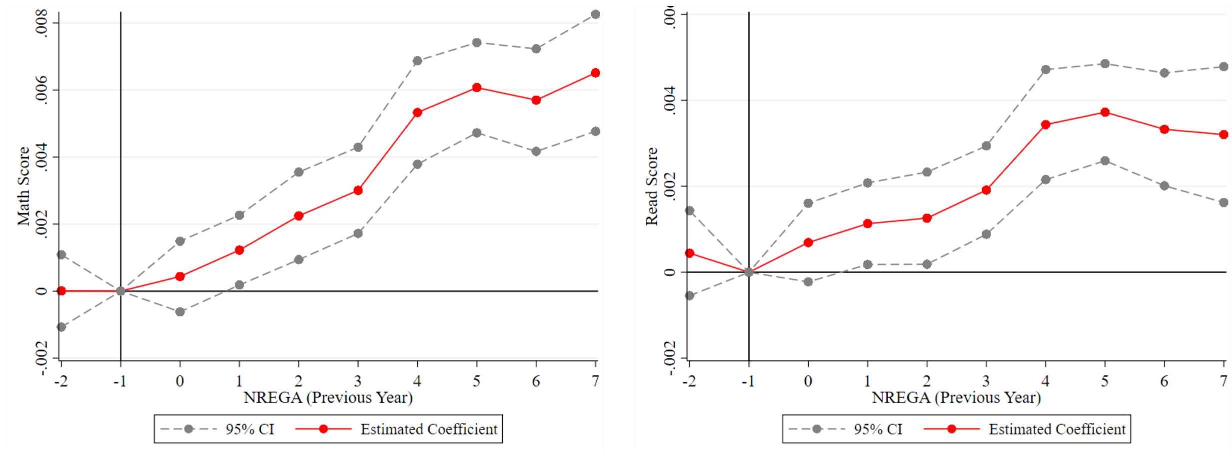
(b) Math Scores



(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 year (defined as number of days in the previous calendar year—see Figure 3) above 21°C on current year math and reading performance respectively by deciles of average long-term temperature, or the climate normal. The effect of days between 15°C-21°C is normalized to zero and coefficients are interpreted relative to 15°C-21°C. The regressions include district, year and age fixed effects. We control flexibly for precipitation and humidity. Standard errors are clustered at the district level.

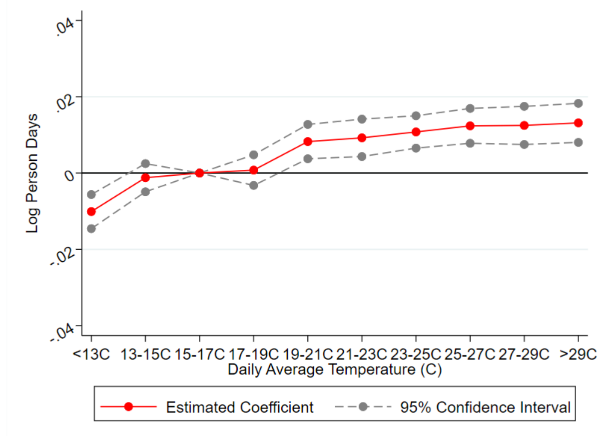
Figure 6: Event Study: Previous Year Temperature, NREGA, and Test Scores



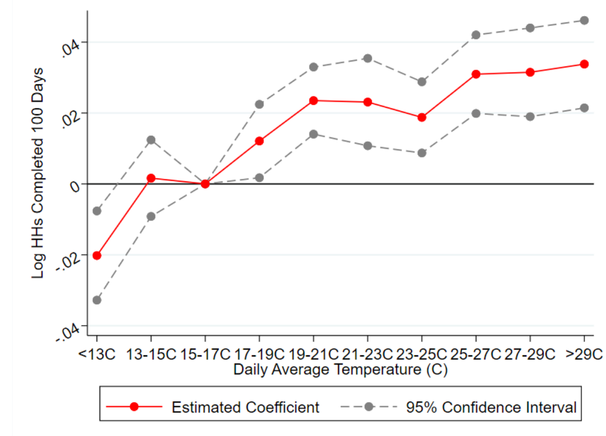
(a) Math Scores: $NREGA(T = \tau) * Days > 21°C$ (b) Reading Scores: $NREGA(T = \tau) * Days > 21°C$

Notes: The figure shows the influence of NREGA (in previous year) in attenuating the impact of longer-run temperature (defined as number of days in the previous calendar year—see Figure 3) on current year test performance in both math and reading. In Panel (a) and (b) the effect of days between 15°C-21°C is normalized to zero and all other coefficients are interpreted relative to 15°C-21°C. In Panel (a) and (b) the omitted variable is the days above 21°C in the year prior to the introduction of NREGA ($\tau = -1$). The regressions include district, year and age fixed effects, and control for age-for-grade status. We also control flexibly for precipitation and humidity. Standard errors are clustered at the district level.

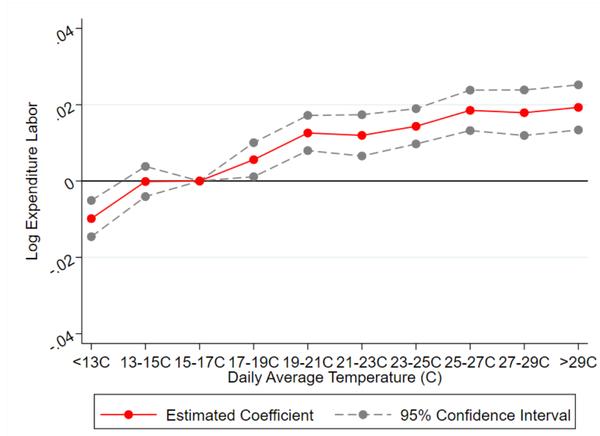
Figure 7: Effect of Previous Year Temperature on NREGA Take-Up



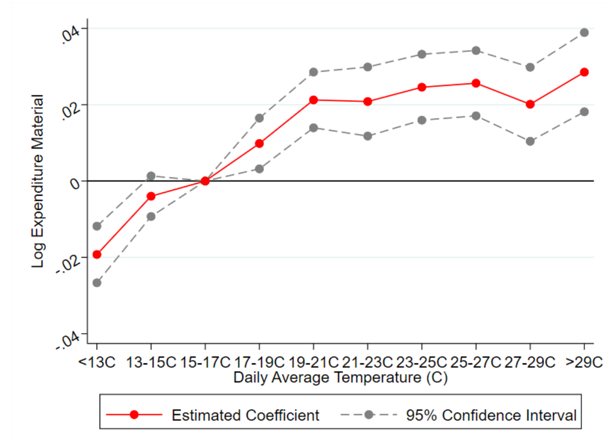
(a) Person Days



(b) HH's Completed All 100 Days



(c) Labor Expenditure



(d) Material Expenditure

Notes: The figure shows the effect of longer-run temperature (defined as number of days in the previous calendar year—see Figure 3) on previous year NREGA take-up, completion, and program expenditures. 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 clustered at the district level.

Tables

Table 1: Previous Year 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
PY Days <15C	-0.0024***		-0.0019***	
	(0.0006)		(0.0006)	
PY 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
		(0.0008)		(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 shows the effect of longer-run temperature (defined as number of days in the previous calendar year—see Figure 3) on current year math and reading performance using the ASER data set. In Columns (2) and (4) (Columns (1) and (3)), the effect of days between 15°C-17°C (15°C-21°C) is normalized to zero and all other coefficients are interpreted relative to 15°C-17°C (15°C-21°C). The regressions include district, year and age fixed effects. We control flexibly for precipitation and humidity. Standard errors are in parentheses, clustered at the district level. PY: Previous Year.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table 2: Previous Year, Current Year and Next Year 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 shows the effect of previous year (defined as number of days in the previous calendar year—see Figure 4(a)), current year, and next year temperature on current year math and reading performance using the ASER data set. The effect of days between 15°C-21°C is normalized to zero and all other coefficients are interpreted relative to 15°C-21°C. The regressions include district, year and age fixed effects. We control flexibly for precipitation and humidity. Standard errors are in parentheses, clustered at the district level. PY: Previous Year; CY: Current Year; NY: Next Year.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table 3: Longer-Run Temperature and Test Scores (YLS)

	(1) Math Score (in SD) β / SE	(2) Math Score (in SD) β / SE	(3) PPVT Score (in SD) β / SE	(4) PPVT Score (in SD) β / SE
Days Between Two Tests >23C	-0.004***		-0.005***	
	(0.001)		(0.001)	
Day-of-Test >23C	-0.112***		0.030	
	(0.042)		(0.058)	
Days Between Two Tests 23-25C		-0.007***		0.001
		(0.001)		(0.002)
Days Between Two Tests 25-27C		-0.002**		-0.007***
		(0.001)		(0.001)
Days Between Two Tests >27C		-0.007***		-0.009***
		(0.001)		(0.001)
Day-of-Test 23-25C		-0.096**		-0.005
		(0.044)		(0.056)
Day-of-Test 25-27C		-0.175***		0.139*
		(0.056)		(0.075)
Day-of-Test >27C		-0.161**		0.253***
		(0.073)		(0.097)
Observations	2604	2604	2541	2541
R^2	0.054	0.069	0.060	0.084

Notes: This table shows the effect of temperature (defined as number of days in a given bin between successive tests) on math and reading performance using the YLS data set. 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 (age) fixed effects. We control for day-of-test temperatures, and both cumulative and day-of-test precipitation as well as cumulative and day-of-test precipitation and humidity. Standard errors are in parentheses, clustered by district-week.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table 4: Heat-Resistant Crops (HRC): Previous Year Temperature and Test Scores (ASER)

	(1) Math Score (in SD) β / SE	(2) Read Score (in SD) β / SE
PY Days <15C	-0.0026***	-0.0020***
	(0.0007)	(0.0006)
PY Days >21C	-0.0031***	-0.0015***
	(0.0006)	(0.0005)
PY Days >21C * HRC	0.0021***	0.0009
	(0.0007)	(0.0006)
Observations	4403838	4403838
R^2	0.083	0.069

Notes: This table shows the effect of temperature (defined as number of days in the previous calendar year—see Figure 3) on current year math and reading performance by districts that grow heat-resistant using the ASER data set. In all specifications, the effect of days between 15°C-21°C is normalized to zero and all other coefficients are interpreted relative to 15°C-21°C. 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. PY: Previous Year.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table 5: Event Study: Previous Year Temperature, NREGA, and Test Scores (ASER)

	(1) Math Score (in SD) β / SE	(2) Read Score (in SD) β / SE
NREGA: T = -3	0.3477	-0.0445
	(0.2625)	(0.2441)
NREGA: T = -2	0.0028	-0.1408
	(0.1836)	(0.1678)
NREGA: T = 0	-0.1711	-0.2416
	(0.1779)	(0.1540)
NREGA: T = 1	-0.3999**	-0.3569**
	(0.1793)	(0.1618)
NREGA: T = 2	-0.6955***	-0.3838**
	(0.2277)	(0.1858)
NREGA: T = 3	-0.9605***	-0.6008***
	(0.2266)	(0.1805)
NREGA: T = 4	-1.7553***	-1.1235***
	(0.2655)	(0.2206)
NREGA: T = 5	-1.9902***	-1.2180***
	(0.2299)	(0.1925)
NREGA: T = 6	-1.8587***	-1.0772***
	(0.2545)	(0.2197)
NREGA: T = 7	-2.1085***	-1.0245***
	(0.2889)	(0.2608)
PY Days <15C	-0.0075***	-0.0054***
	(0.0011)	(0.0010)
PY Days >21C	-0.0045***	-0.0030***
	(0.0008)	(0.0006)
NREGA: T = -3 * PY Days >21C	-0.0012	-0.0000
	(0.0008)	(0.0007)
NREGA: T = -2 * PY Days >21C	0.0000	0.0004
	(0.0006)	(0.0005)
NREGA: T = 0 * PY Days >21C	0.0004	0.0007
	(0.0005)	(0.0005)
NREGA: T = 1 * PY Days >21C	0.0012**	0.0011**
	(0.0005)	(0.0005)
NREGA: T = 2 * PY Days >21C	0.0022***	0.0013**
	(0.0007)	(0.0005)
NREGA: T = 3 * PY Days >21C	0.0030***	0.0019***
	(0.0007)	(0.0005)
NREGA: T = 4 * PY Days >21C	0.0053***	0.0034***
	(0.0008)	(0.0007)
NREGA: T = 5 * PY Days >21C	0.0061***	0.0037***
	(0.0007)	(0.0006)
NREGA: T = 6 * PY Days >21C	0.0057***	0.0033***
	(0.0008)	(0.0007)
NREGA: T = 7 * PY Days >21C	0.0065***	0.0032***
	(0.0009)	(0.0008)
Observations	3653357	3653357
R^2	0.079	0.067

Notes: This table shows the influence of NREGA (in previous year) in attenuating the effects of longer-run temperature (defined as number of days in the previous calendar year—see Figure 3) on current year math and reading performance. The effect of days between 15°C-21°C is normalized to zero and all other coefficients are interpreted relative to 15°C-21°C. The omitted variable is the days above 21°C in the year prior to the introduction of NREGA ($\tau = -1$) The regressions include district, year and age fixed effects, and control for age-for-grade status. We also control flexibly for precipitation and humidity. Standard errors are clustered at the district level. PY: Previous Year. *Significant at 10%. **Significant at 5%. ***Significant at 1%.

A Appendix (Online Publication Only)

A.1 Climate Change Projections

To estimate the predicted impact of future climate change, we use climate projection data from a business-as-usual scenario from the National Center for Atmospheric Research's (NCAR) Community Climate System Model 4 (CCSM4) Global Circulation Model (NCAR, 2010). Details of the model are described in Gent et al. (2011).[26] An earlier version of this model was used in the fourth IPCC Assessment Report (IPCC, 2007).

CCSM4 model output predictions are available for several Representative Concentration Pathways (RCPs), each of which is a greenhouse gas concentration (not emissions) trajectory adopted by the IPCC for its fifth Assessment Report. We focus on RCP 8.5, which is a high-concentration pathway or "business-as-usual" scenario that is appropriate to consider when judging future impacts in the absence of policies to restrict greenhouse gas emissions.

We accessed daily average temperature predictions for grid points spanning India for the CCSM4 model for the years 2075-2099.[27] The model output is based on a single run of the model and is available for 1 degree by 1.25 degree latitude–longitude grid. To convert from the gridded projection data to our districts, we calculate the inverse-distance weighted average among all grid points within 100 km of each district centroid.

To compute the impact of projected climate change on future test scores, we calculated the average number of days in each temperature bin under the current climate for our sample (2004-2014) and compared that to the average number of days in each temperature bin under the projected climate for end of century (2075-2099).[28] Panel (a) of Figure A.1 shows these two bin distributions. We then calculated the change in number of days for each bin and multiplied that by the appropriate coefficient from our temperature–test score regression to estimate the impact of projected climate change on test scores. Panel (c) of Figure A.1 shows these impacts. As can be seen from the figure, for bins 6, 7, and 8 there will be small gains for test scores, as the coefficients for these bins are negative, and there will be reductions in the number of days in these bins under climate change. However, these is more than offset by the large increase in number of bin 10 days, which leads to an overall net decrease in scores.

Panel (e) presents the bin-by-bin impacts on test scores, but weights the calculations by the rural population in each district (instead of weighting each district equally). Panels (b), (d), and (f), present results analogous to panels (a), (c), and (e), but focus on growing season temperature bins. Focusing on panel (d), which gives growing season impacts with equally weighted districts, we find an he overall impact that we find on test scores is a reduction of 0.04 standard deviations for math and 0.03 standard deviations for reading, for each year that a child is in school.

A.2 Converting Test Score Gains into Schooling Years and Wages

In order to convert these reductions in test score standard deviations to more concrete measures, we follow the methodology and parameter estimates from Evans and Yuan (2019). These estimates are based on the World Bank's STEP Skills Measurement Program, which is a test designed to test proficiency in literacy with respect to word meaning, sentence processing and basic passage

[26] Information about the model and other related models can also be found at http://www.cesm.ucar.edu/experiments/.

[27] The CCSM4 output data can be accessed from https://www.earthsystemgrid.org.

[28] Please note it may be important to consider changes in weather variables (temperature, rainfall, and humidity) jointly over future climate scenarios while calculating the impacts of climate change.

comprehension, in the language of the resident country (World Bank, 2018).[29] Evans and Yuan (2019) find a one standard deviation gain in literacy skill is associated with between 4.7 and 6.8 additional years of schooling. In other words, it takes about 4.7 to 6.8 years of schooling to increase literacy skills by one standard deviation. Using this metric, our result that reading scores decrease by 0.06 standard deviations if a child experiences 10 hot days during the growing season in the previous year, means that this is equivalent to reducing the effective years of schooling the child has received by 0.35 years [5.75*0.06 SD] (using 5.75 years of equivalent schooling as the conversion factor, which is the midpoint of the range of the estimates of 4.7 to 6.8).

We can also convert this reduction of equivalent schooling into a wage loss, using the methodology and assumptions in Evans and Yuan (2019). Assume that students enter the labor market at age 20 and work for 40 years. Furthermore, use a social discount rate of 3%, as is common in the literature in public finance (Borsch-Supan, 2000; Hagist et al., 2005; Hanushek and Woessmann, 2010). Following Evans and Yuan (2019) and Aslam et al. (2011), we use the estimate that a one standard deviation increase in literacy skills is associated with a 51% increase in wages. Hence, 10 additional hot days will lead to a 3% decrease in wages [0.51*0.06 SD].

Turning to our CCSM projections, we can do some similar calculations. Here, we examine how the distribution of daily temperatures in the growing season will look in India by the end of the century (under a business-as-usual emissions scenario), and we estimate the impact that this will have on a child's test scores, assuming that the impacts will accrue over all 12 years of a child's schooling (ages 5 to 16). Using this approach, we find that the higher temperatures will lead to a reduction of the equivalent years of schooling of -2.07 years (-0.03 SD * 5.75 * 12).

In addition, we can use the methodology and assumptions in Evans and Yuan (2019), to convert this reduction of equivalent years of schooling into a wage impact and into a net present value. Using the estimates from Evans and Yuan (2019) and Aslam et al. (2011), we find that the reduction in schooling due to higher temperatures at the end of the century, accrued over a student's 12 years of schooling, will lead to a 18.36% decrease in wages [-0.03 SD *12*0.51]. We further convert this into a net present value; in 2015 the GNI per capita in India (2015 USD PPP) was $6,020, with a 0.29 labor share of income (World Bank, 2018), demonstrating that the average labor income of a worker was $1,769. Hence a 18.36% decrease in wages is worth $325/year. Over a 40-year work life, this fixed additional income has a present value of roughly $7,500, if discounted at 3 percent.

A.3 Other Alternative Explanations

A.3.1 School Closures and 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.[30] Furthermore, it is possible that schools are closed in response to very

[29] Like the World Bank's STEP Skills Measurement Program, the ASER reading test is designed to capture basic literacy skills (Banerji, Bhattacharjea and Wadhwa, 2013). Therefore, in this exercise, we focus only on the impacts of extra hot days on reading test scores. In addition, since our growing season specification is our preferred specification, we focus specifically on the impact of additional hot days during the growing season.

[30] 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.

hot days (Agüero and Beleche, 2013), thereby affecting learning and test performance. We find two pieces of evidence that are inconsistent with such a hypothesis. First, if heat-induced school closures or teacher absenteeism were driving our results, we would see the effects on performance of only hot days during the school year (Figure A.12). The near-identical effects of heat during the school and non-school parts of the year suggest that teacher attendance or school closures are not the sole mechanism driving our results. However, we cannot fully rule out the possibility that, in addition to agricultural mechanisms, teacher attendance and school closures might be contributing to part of the relationship that we find.

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 (Table A.12). Thus, we fail to find evidence that teacher attendance is the key factor linking hotter days to reduced test score performance. Again however, we cannot fully rule out this possibility.

A.3.2 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, 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.

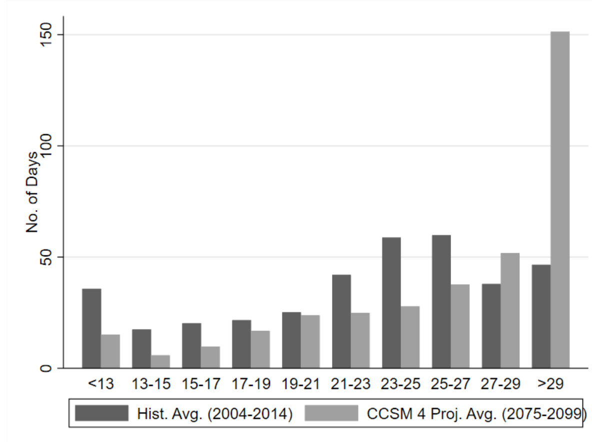
However, because of the life cycle of disease pathogens we would expect more recent higher temperatures to have a larger effect on health, and therefore performance, than similar days in the previous calendar year. Malaria, for example, is transferred through the *Anopheles* mosquito, which typically 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 2, we show that temperature in the current year has no effect on test score performance.[31] 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 A.13 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.[32]

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

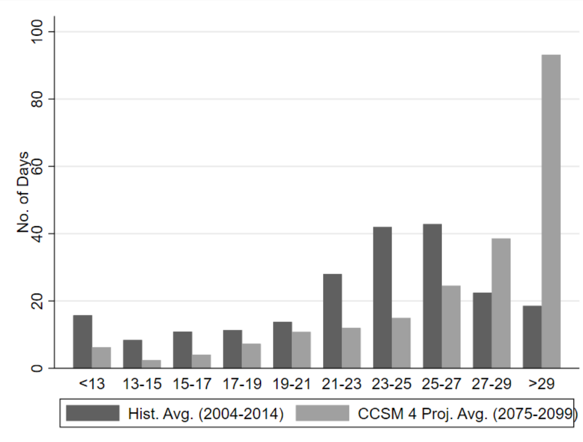
[32] The malaria-prone states are Chhattisgarh, Jharkhand, Orissa, Karnataka, and West Bengal.

Figures

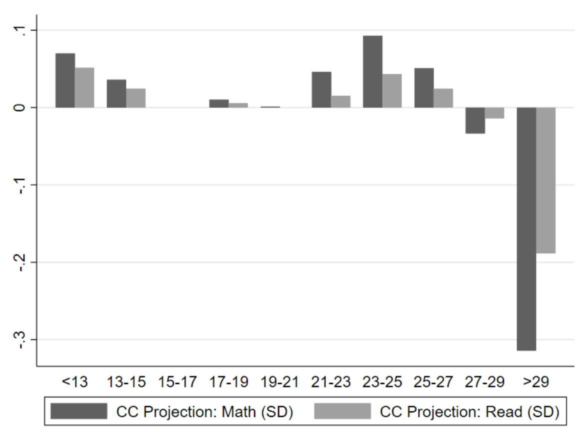
Figure A.1: CCSM Projections



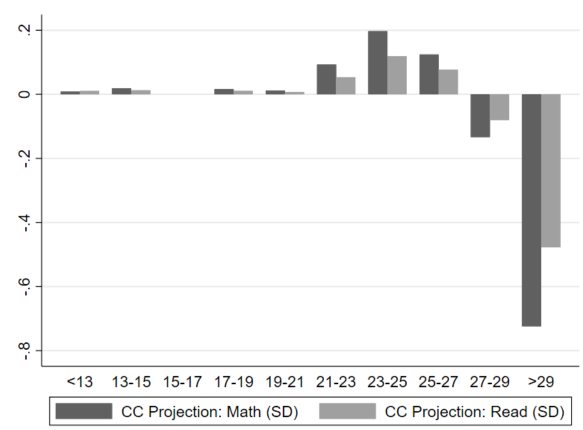
(a) Number of Hot Days



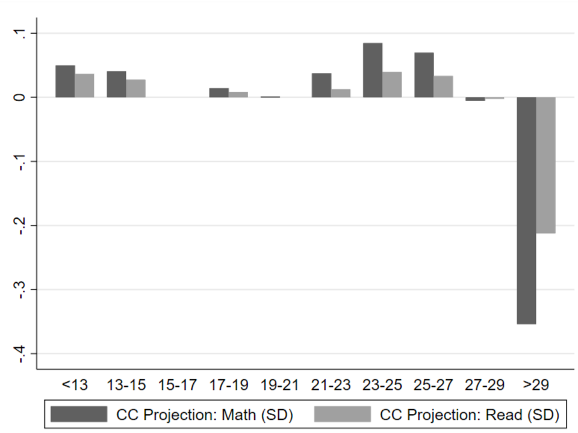
(b) Number of Hot Days in Growing Season



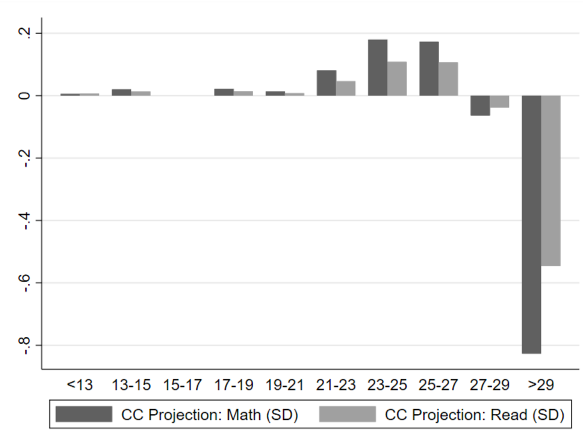
(c) Number of Hot Days*Effect of Hot Days



(d) Number of Hot Days in Growing Season*Effect of Hot Days

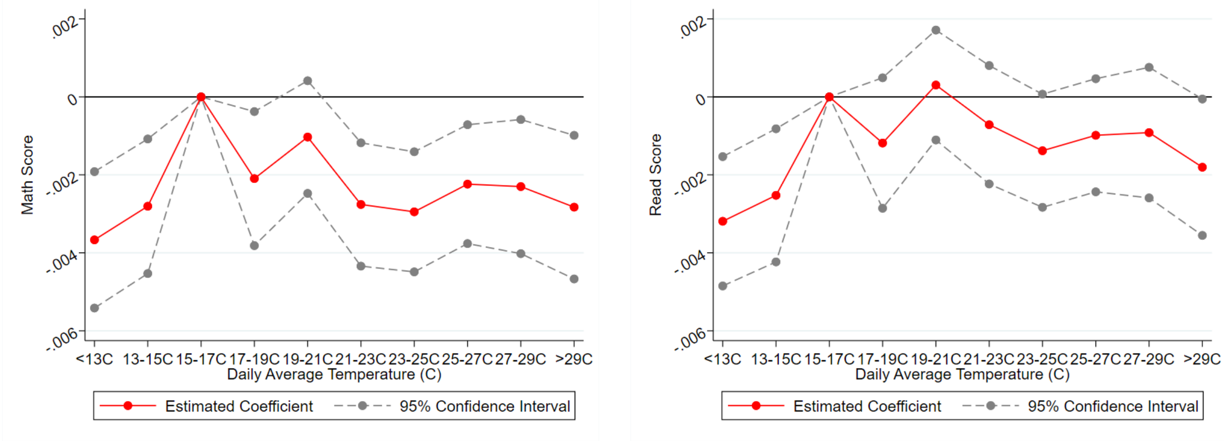


(e) Number of Hot Days*Effect of Hot Days (Weighted by Rural Population)



(f) Number of Hot Days in Growing Season*Effect of Hot Days (Weighted by Rural Population)

Figure A.2: Previous Year Temperature and Test Scores (ASER)

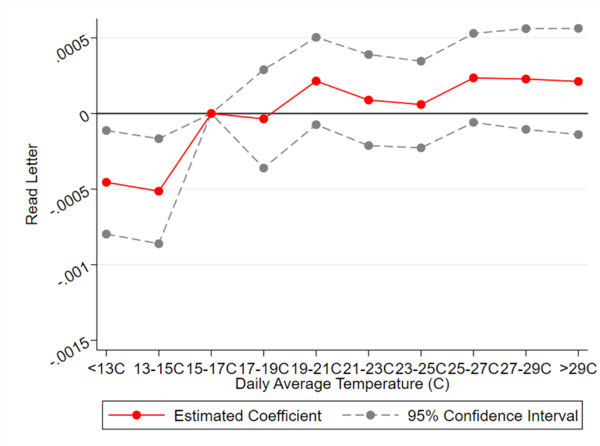


(a) Math Scores (ASER)

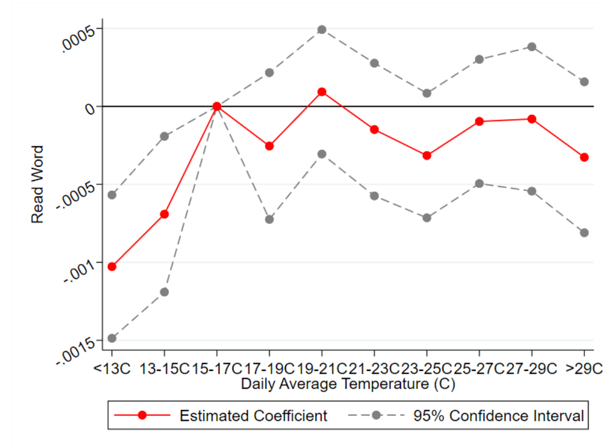
(b) Reading Scores (ASER)

Notes: Panels (a) and (b) show the effect of longer-run temperature (defined as number of days in the previous calendar year—see Figure 3) on current year raw math and reading scores using the ASER data set. 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, year and age fixed effects. We control flexibly for precipitation and humidity. Standard errors are clustered at the district level.

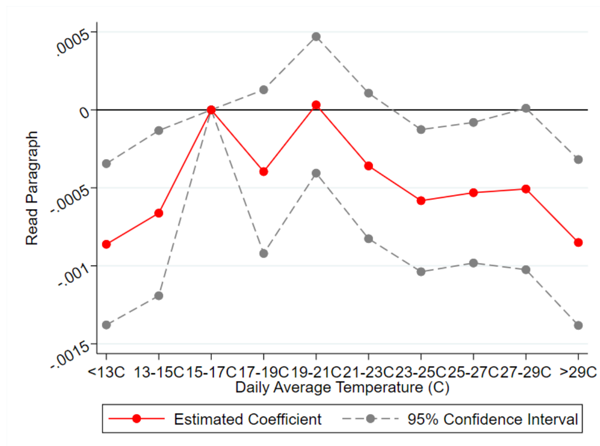
Figure A.3: Previous Year Temperature and Reading Ability (ASER)



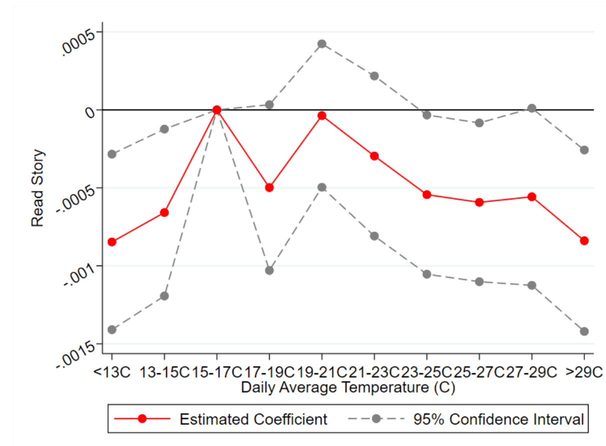
(a) Letter



(b) Word



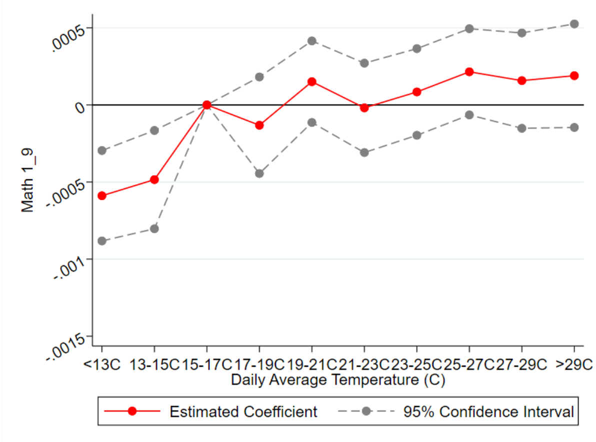
(c) Paragraph



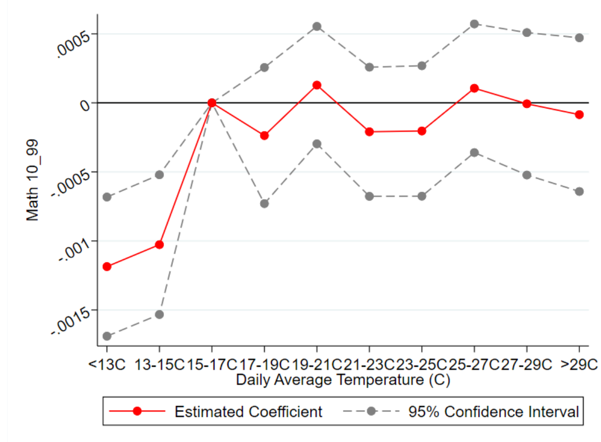
(d) Story

Notes: Panels (a), (b), (c) and (d) show the effect of longer-run temperature (defined as number of days in the previous calendar year—see Figure 3) on reading ability using the ASER data set. 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, year and age fixed effects. We control flexibly for precipitation and humidity. Standard errors are clustered at the district level.

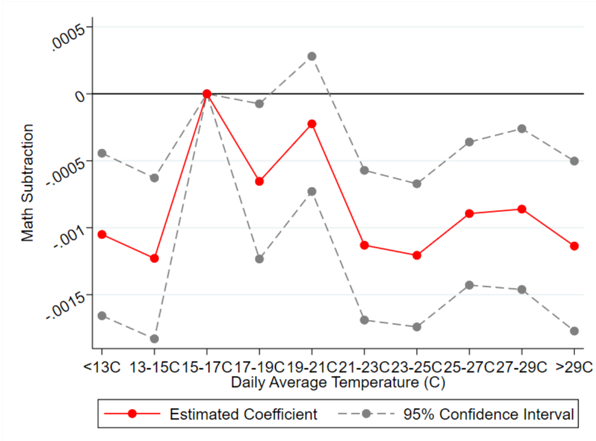
Figure A.4: Previous Year Temperature and Math Ability (ASER)



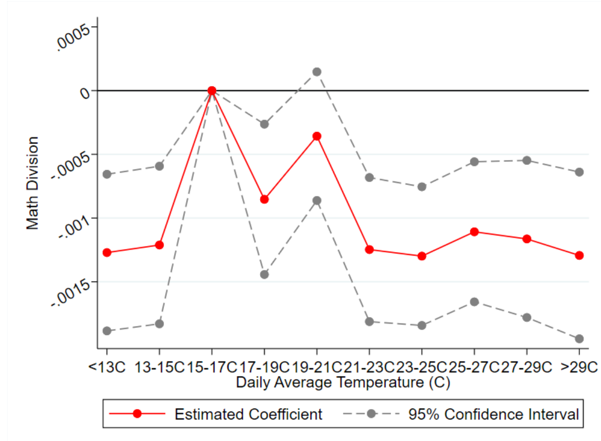
(a) Single Digit Number Recognition



(b) Double Digit Number Recognition



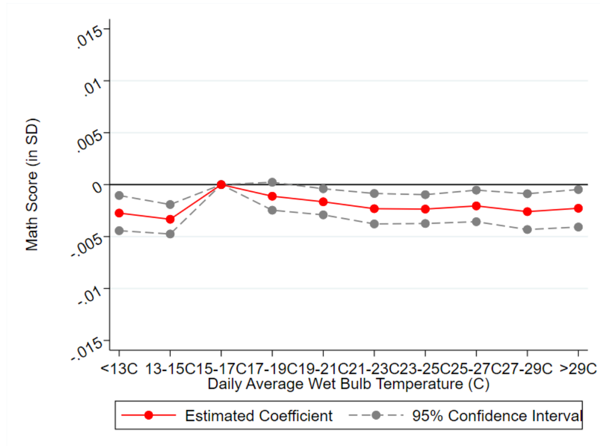
(c) Subtraction



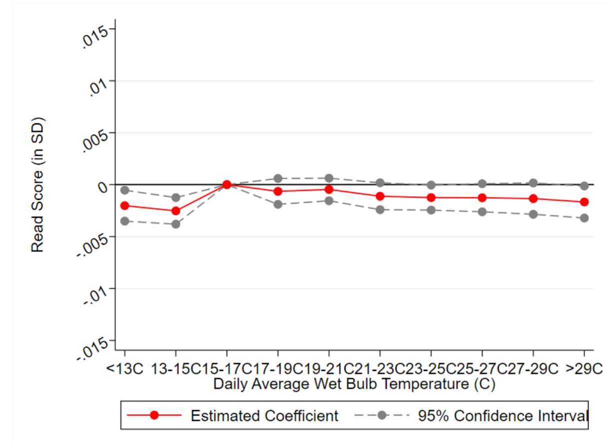
(d) Division

Notes: Panels (a), (b), (c) and (d) show the effect of longer-run temperature (defined as number of days in the previous calendar year—see Figure 3) on current year math ability using the ASER data set. 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, year and age fixed effects. We control flexibly for precipitation and humidity. Standard errors are clustered at the district level.

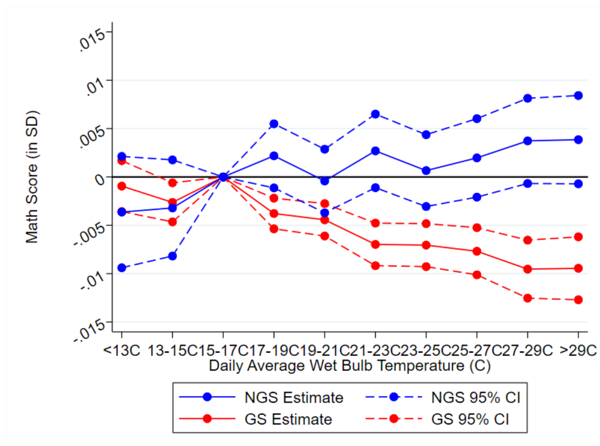
Figure A.5: Wet Bulb Global Temperatures (WBGT): Previous Year Temperature and Test Scores (ASER)



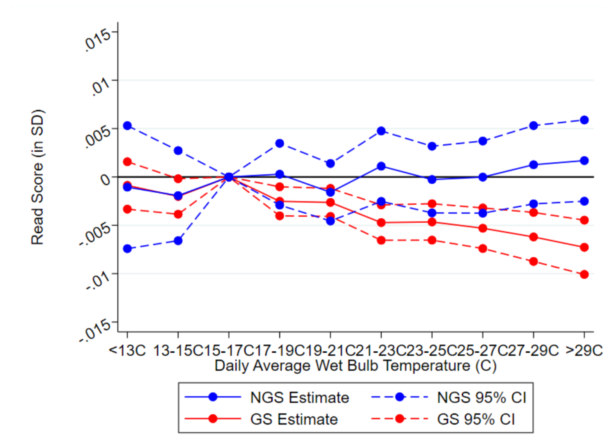
(a) Math Scores



(b) Reading Scores



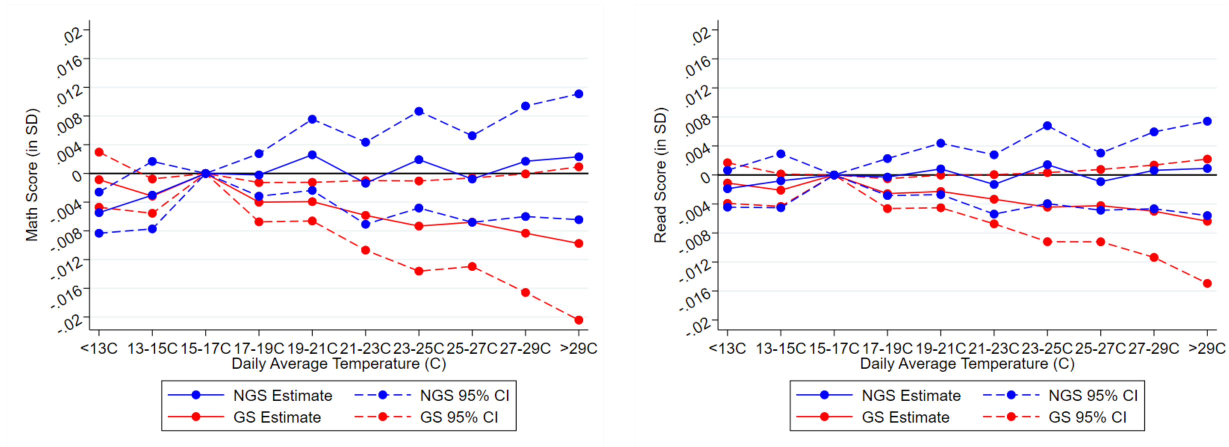
(c) Math Scores



(d) Reading Scores

Notes: Panel (a) and (b) show the effect of longer-run WBGT temperature (defined as number of days in the previous calendar year—see Figure 3) on current year math and reading performance. In panel (c) and (d) the figure shows the effect of longer-run WBGT temperature (defined as number of days in the previous calendar year—see Figure 3) on current year math and reading performance divided amongst the growing season (June—Dec) and the non-growing season (March—May). In all panels, 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, year and age fixed effects. We control flexibly for precipitation and humidity. Standard errors are clustered at district level. GS: Growing Season; NGS: Non-Growing Season.

Figure A.6: Standard Errors Clustered at the State Level: Previous Year Temperature and Test Scores (ASER)

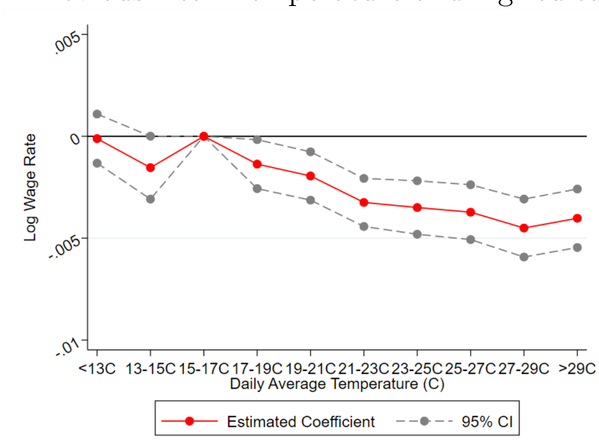


(a) Math Scores

(b) Reading Scores

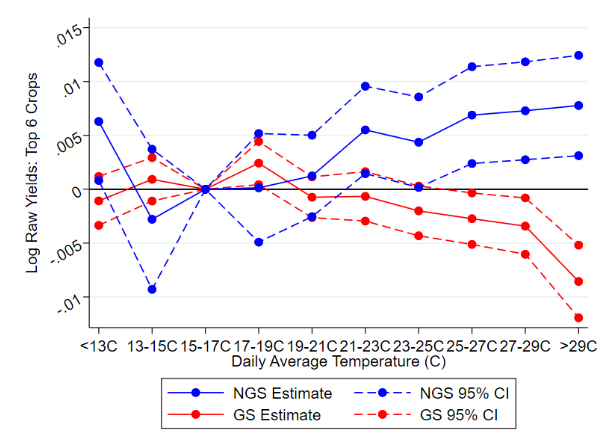
Notes: Panel (a) and (b) show the effect of longer-run temperature (defined as number of days in the previous calendar year—see Figure 3) on current year math and reading performance divided amongst the growing season (June—Dec) and the non-growing season (March—May). In all panels, the effect of days 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, year and age fixed effects. We control flexibly for precipitation and humidity. Standard errors are clustered at state level. GS: Growing Season; NGS: Non-Growing Season.

Figure A.7: Previous Year Temperature and Agricultural Wages

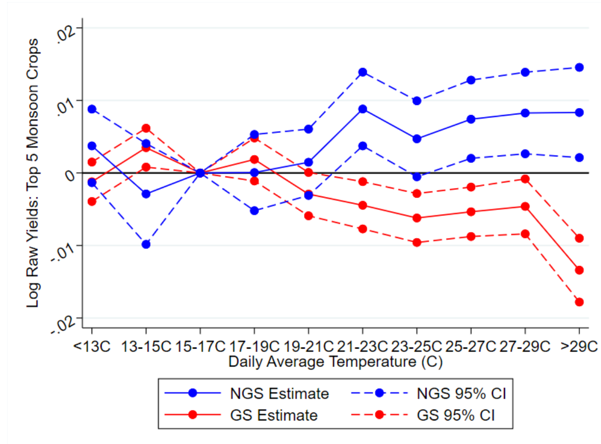


Notes: This figure shows the effect of longer-run temperature (defined as number of days in the previous calendar year—see Figure 3) on previous year agricultural wages from 1980—2014. In all panels, the effect of days between 15°C-17°C is normalized to zero and all other coefficients are interpreted relative to 15°C-17°C. The regressions include district and year fixed effects. We control flexibly for precipitation. Standard errors are clustered at district level.

Figure A.8: Growing Season v. Non-Growing Season: Previous Year Temperature and Raw Agricultural Yields



(a) Top 6 Crops



(b) Top 5 Monsoon Crops

Notes: Panel (a) and (b) show the effect of longer-run temperature (defined as number of days in the previous calendar year—see Figure 3) on previous year raw agricultural yields from 1979—2014 divided amongst the growing season (June—Dec) and the non-growing season (March—May). In all panels, 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. Standard errors are clustered at district level. GS: Growing Season; NGS: Non-Growing Season.

Figure A.9: Historical (Average) Take-Up of Heat Resistant Crops by District

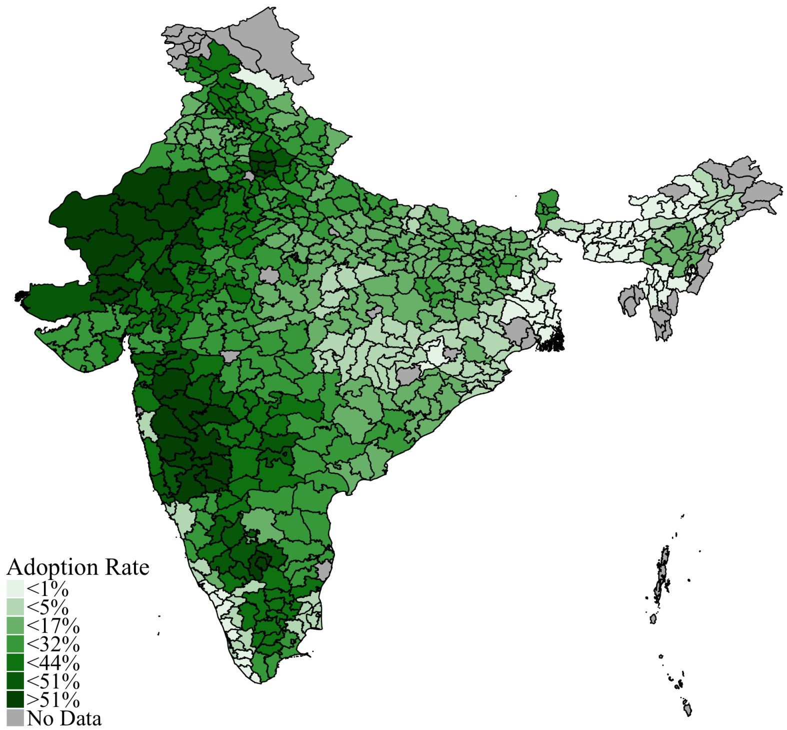
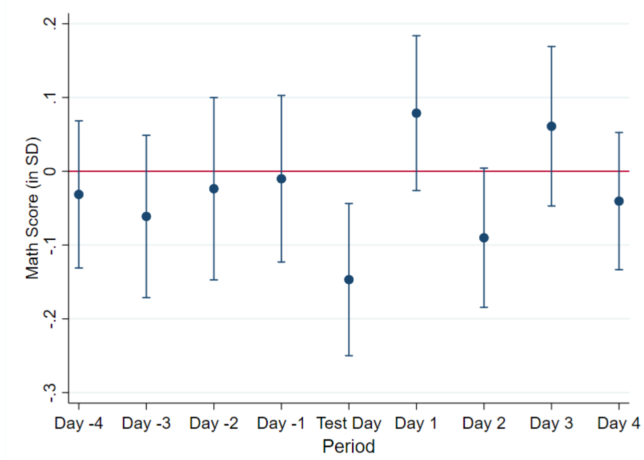
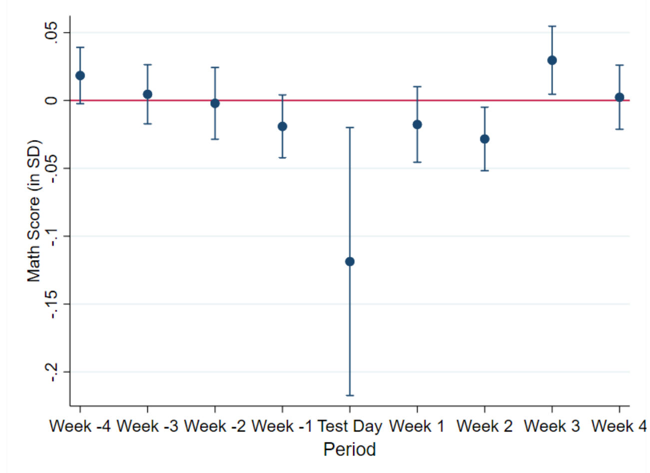


Figure A.10: Leads and Lags in Days: Day-of-Test Temperature and Math Scores



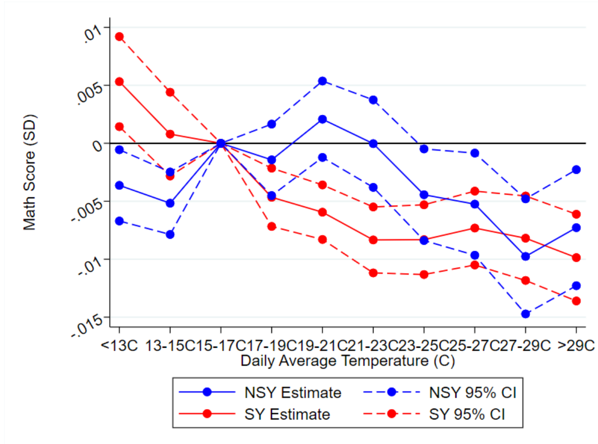
Notes: The figure presents the impact of short-run temperature from four weeks before test day to four weeks after the test. Temperature is captured as 1 if temperature is > 23 on the day of the test for "Test Day", 0 otherwise. Includes individual, day of week, month, and survey round fixed effects. We control for precipitation and humidity in all periods. Standard errors are clustered at the district-week level. 95% confidence intervals are presented in the figure.

Figure A.11: Leads and Lags in Weeks: Day-of-Test Temperature and Math Scores

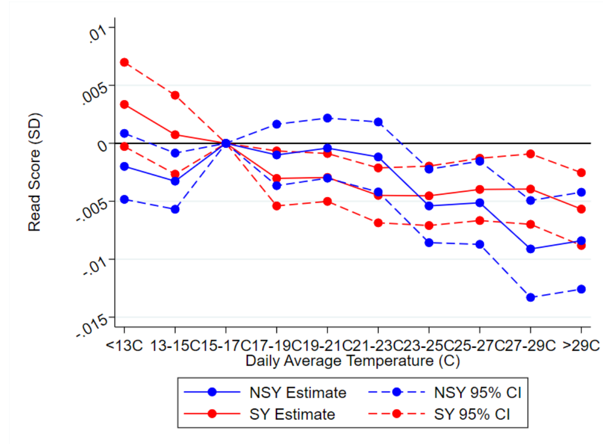


Notes: The figure presents the impact of short-run temperature from four weeks before test day to four weeks after the test. Temperature is captured as the number of days when the temperature is >23°C during a week for "*No.* Week", and if temperature is > 23 on the day of the test for "Test Day". Includes individual, day of week, month, and survey round fixed effects. We control for precipitation and humidity in all periods. Standard errors are clustered at the district-week level. 95% confidence intervals are presented in the figure.

Figure A.12: School Year v. Non-School Year: Previous Year Temperature and Test Scores (ASER)



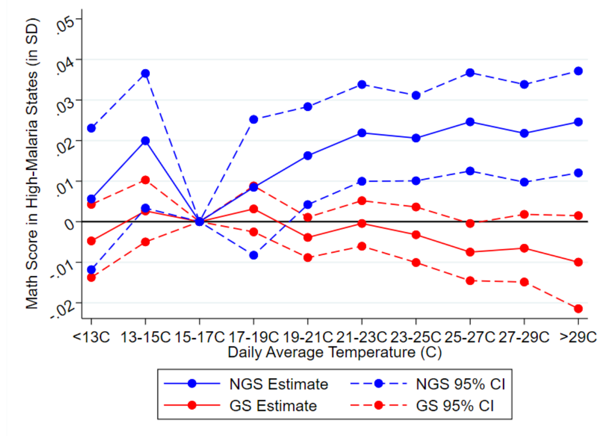
(a) Math Scores



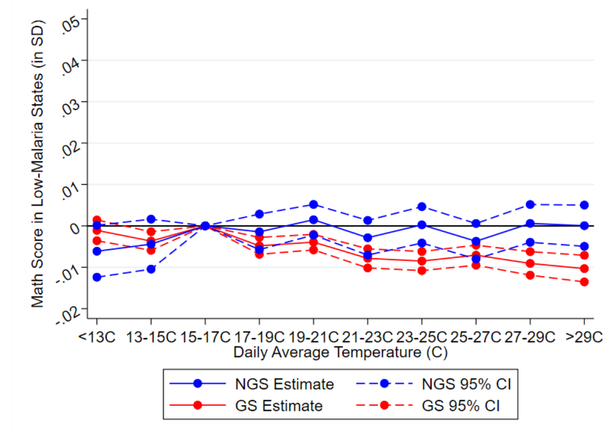
(b) Reading Scores

Notes: The figure shows the effect of longer-run temperature (defined as number of days in the previous calendar year—see figure 4(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, year and age fixed effects. We control flexibly for precipitation and humidity. Standard errors are clustered at the district level. SY: School year; NSY: Non-School Year.

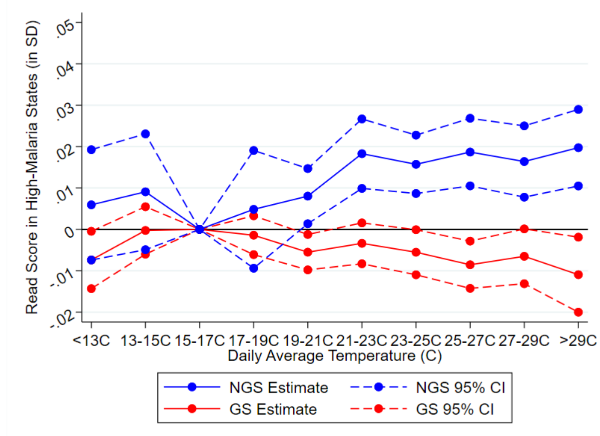
Figure A.13: Previous Year Temperature and Test Scores (ASER) by Malaria Prone States



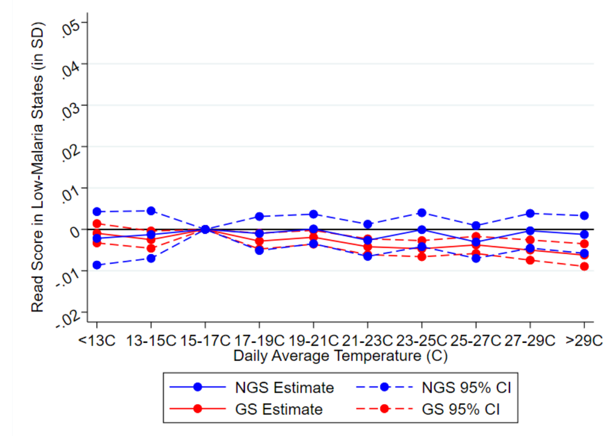
(a) Malaria-Prone States



(b) Other States



(c) Malaria-Prone States



(d) Other States

Notes: This figure shows the effect of longer-run temperature (defined as number of days in the previous calendar year—see Figure 4(a)) on current year math and reading performance by malaria prone states. The malaria prone states are Orissa, Chattisgarh, West Bengal, Jharkhand, and Karnataka. 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, year and age fixed effects. We control flexibly for precipitation and humidity. Standard errors are clustered at the district level. GS: Growing Season; NGS: Non-Growing Season.

Tables

Table A.1: On-Track Children: Previous Year 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
PY Days <15C	-0.0027***		-0.0021***	
	(0.0006)		(0.0005)	
PY 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	0.089	0.065	0.065

Notes: This table shows the effect of longer-run temperature (defined as number of days in the previous calendar year—see Figure 3) on current year math and reading performance for on-track students using the ASER data set. In Columns (2) and (4) (Columns (1) and (3)), the effect of days between 15°C-17°C (15°C-21°C) is normalized to zero and all other coefficients are interpreted relative to 15°C-17°C (15°C-21°C). The regressions include district, year and age fixed effects. We control flexibly for precipitation and humidity. Standard errors are in parentheses, clustered at the district level. PY: Previous Year

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

Table A.2: Adding Lags: Previous Year 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
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 shows the effect of longer-run temperature (defined as number of days in the previous calendar year—see Figure 3) on current year math and reading performance using the ASER data set. In Columns (2) and (4) (Columns (1) and (3)), the effect of days between 15°C-17°C (15°C-21°C) is normalized to zero and all other coefficients are interpreted relative to 15°C-17°C (15°C-21°C). The regressions include district, year and age fixed effects. We control flexibly for precipitation and humidity. We also control for lagged temperature, precipitation and humidity. Standard errors are in parentheses, clustered at the district level. PY: Previous Year.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table A.3: Adding State-Specific Time Trends: Previous Year 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
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 shows the effect of longer-run temperature (defined as number of days in the previous calendar year—see Figure 3) on current year math and reading performance using the ASER data set. In Columns (2) and (4) (Columns (1) and (3)), the effect of days between 15°C-17°C (15°C-21°C) is normalized to zero and all other coefficients are interpreted relative to 15°C-17°C (15°C-21°C). The regressions include district, year and age fixed effects, and state-specific linear and quadratic trends. We control flexibly for precipitation and humidity. Standard errors are in parentheses, clustered at the district level. PY: Previous Year.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table A.4: Adding State-Year FE: Longer-Run Temperature and Test Scores (ASER)

	(1) Math Score (in SD) β / SE	(2) Math Score (in SD) β / SE	(3) Read Score (in SD) β / SE	(4) Read Score (in SD) β / SE
PY Days <15C	-0.0015**		-0.0010	
	(0.0007)		(0.0007)	
PY 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***
		(0.0010)		(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 shows the effect of longer-run temperature (defined as number of days in the previous calendar year—see Figure 3) on current year math and reading performance using the ASER data set. In Columns (2) and (4) (Columns (1) and (3)), the effect of days between 15°C-17°C (15°C-21°C) is normalized to zero and all other coefficients are interpreted relative to 15°C-17°C (15°C-21°C). The regressions include district, age and state-by-year fixed effects. We control flexibly for precipitation and humidity. Standard errors are in parentheses, clustered at the district level. PY: Previous Year.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table A.5: Nearest (N) Weather Gridpoint and Maximum (M) Daily Temperature: 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
PY Days <13C N	-0.0023***		-0.0015**	
	(0.0009)		(0.0007)	
PY Days 13-15C N	-0.0027***		-0.0017**	
	(0.0009)		(0.0008)	
PY Days 17-19C N	-0.0008		-0.0003	
	(0.0009)		(0.0008)	
PY Days 19-21C N	-0.0006		0.0006	
	(0.0007)		(0.0006)	
PY Days 21-23C N	-0.0016*		-0.0002	
	(0.0008)		(0.0007)	
PY Days 23-25C N	-0.0023***		-0.0009	
	(0.0008)		(0.0007)	
PY Days 25-27C N	-0.0016**		-0.0007	
	(0.0008)		(0.0006)	
PY Days 27-29C N	-0.0015*		-0.0003	
	(0.0008)		(0.0007)	
PY Days >29C N	-0.0024***		-0.0014*	
	(0.0009)		(0.0008)	
PY Days <17C M		-0.0026***		-0.0016*
		(0.0009)		(0.0008)
PY Days 17-19C M		-0.0033***		-0.0025***
		(0.0009)		(0.0008)
PY Days 21-23C M		-0.0016**		-0.0005
		(0.0008)		(0.0007)
PY Days 23-25C M		-0.0019***		-0.0003
		(0.0007)		(0.0007)
PY Days 25-27C M		-0.0016*		-0.0004
		(0.0008)		(0.0007)
PY Days 27-29C M		-0.0012		0.0001
		(0.0008)		(0.0007)
PY Days 29-31C M		-0.0011		0.0002
		(0.0008)		(0.0007)
PY Days 31-33C M		-0.0017*		-0.0003
		(0.0009)		(0.0008)
PY Days >33C M		-0.0018**		-0.0009
		(0.0009)		(0.0008)
Observations	4581616	4581616	4581616	4581616
R^2	0.084	0.084	0.068	0.068

Notes: This table shows the effects of longer-run temperature (defined as number of days in the previous calendar year) on current year math and reading performance. The regressions include district, year and age fixed effects. We control flexibly for precipitation and humidity. Standard errors are in parentheses, clustered at the district level. PY: Previous Year.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table A.6: Controlling for ASER Weekend Test Month (WTM) Temperature and ASER Weekday Test Month (NWTM) Temperature

	(1) Math Score (in SD) β / SE	(2) Read Score (in SD) β / SE	(3) Math Score (in SD) β / SE	(4) Read Score (in SD) β / SE
PY Days <13C	-0.0035***	-0.0024***	-0.0023**	-0.0019**
	(0.0009)	(0.0008)	(0.0010)	(0.0009)
PY Days 13-15C	-0.0028***	-0.0019**	-0.0012	-0.0008
	(0.0009)	(0.0009)	(0.0008)	(0.0008)
PY Days 17-19C	-0.0032***	-0.0020**	-0.0011	-0.0009
	(0.0009)	(0.0008)	(0.0009)	(0.0009)
PY Days 19-21C	-0.0005	0.0000	-0.0005	-0.0008
	(0.0008)	(0.0007)	(0.0010)	(0.0009)
PY Days 21-23C	-0.0022***	-0.0008	-0.0022**	-0.0017*
	(0.0008)	(0.0008)	(0.0010)	(0.0009)
PY Days 23-25C	-0.0031***	-0.0018**	-0.0028**	-0.0021**
	(0.0008)	(0.0008)	(0.0011)	(0.0010)
PY Days 25-27C	-0.0022***	-0.0014*	-0.0029**	-0.0022**
	(0.0008)	(0.0008)	(0.0012)	(0.0010)
PY Days 27-29C	-0.0024**	-0.0014	-0.0025*	-0.0017
	(0.0009)	(0.0009)	(0.0013)	(0.0011)
PY Days >29C	-0.0033***	-0.0023***	-0.0027*	-0.0021*
	(0.0010)	(0.0009)	(0.0014)	(0.0012)
CY WTM Days <13C	-0.0076	-0.0042	-0.0196**	-0.0141
	(0.0095)	(0.0088)	(0.0097)	(0.0093)
CY WTM Days 13-15C	-0.0145**	-0.0097*	-0.0101*	-0.0081
	(0.0058)	(0.0052)	(0.0058)	(0.0055)
CY WTM Days 17-19C	-0.0198***	-0.0158***	-0.0052	-0.0077*
	(0.0046)	(0.0043)	(0.0048)	(0.0044)
CY WTM Days 19-21C	-0.0327***	-0.0252***	-0.0111*	-0.0124**
	(0.0059)	(0.0055)	(0.0065)	(0.0060)
CY WTM Days 21-23C	-0.0362***	-0.0272***	-0.0085	-0.0092
	(0.0067)	(0.0060)	(0.0067)	(0.0063)
CY WTM Days 23-25C	-0.0381***	-0.0294***	-0.0067	-0.0074
	(0.0073)	(0.0062)	(0.0073)	(0.0069)
CY WTM Days 25-27C	-0.0350***	-0.0274***	-0.0040	-0.0039
	(0.0077)	(0.0065)	(0.0078)	(0.0072)
CY WTM Days 27-29C	-0.0304***	-0.0254***	-0.0026	-0.0025
	(0.0084)	(0.0071)	(0.0086)	(0.0080)
CY WTM Days >29C	-0.0201	-0.0192*	-0.0009	0.0022
	(0.0136)	(0.0115)	(0.0137)	(0.0126)
CY NWTM Days <13C	-0.0008	-0.0013	0.0074*	0.0031
	(0.0046)	(0.0043)	(0.0044)	(0.0040)
CY NWTM Days 13-15C	-0.0055*	-0.0054**	-0.0003	-0.0012
	(0.0029)	(0.0027)	(0.0030)	(0.0027)
CY NWTM Days 17-19C	-0.0016	-0.0002	0.0011	0.0020
	(0.0023)	(0.0021)	(0.0024)	(0.0022)
CY NWTM Days 19-21C	0.0005	0.0045*	0.0038	0.0073***
	(0.0027)	(0.0024)	(0.0029)	(0.0027)
CY NWTM Days 21-23C	0.0053*	0.0074***	0.0013	0.0055*
	(0.0030)	(0.0026)	(0.0033)	(0.0031)
CY NWTM Days 23-25C	0.0064**	0.0074***	-0.0017	0.0036
	(0.0032)	(0.0027)	(0.0036)	(0.0033)
CY NWTM Days 25-27C	0.0071**	0.0070**	-0.0034	0.0019
	(0.0033)	(0.0028)	(0.0038)	(0.0035)
CY NWTM Days 27-29C	0.0039	0.0067**	-0.0027	0.0031
	(0.0037)	(0.0032)	(0.0045)	(0.0041)
CY NWTM Days >29C	-0.0027	0.0016	-0.0061	0.0007
	(0.0056)	(0.0048)	(0.0071)	(0.0063)
Age FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	No
State-by-Year FE	No	No	Yes	Yes
Observations	4581616	4581616	4581616	4581616
R^2	0.087	0.070	0.103	0.079

Notes: This table shows the effects of longer-run temperature (defined as number of days in the previous calendar year) on current year math and reading performance. The regressions include district, year and age fixed effects. We control flexibly for precipitation, humidity, and current year temperature in the months before the ASER test months (NTM: January-August). Standard errors are in parentheses, clustered at the district level. PY: Previous Year.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table A.7: Combined (Older and Younger Cohort) Sample: Longer-Run Temperature and Test Scores (YLS)

	(1) Math Score (in SD) β / SE	(2) Math Score (in SD) β / SE	(3) PPVT Score (in SD) β / SE	(4) PPVT Score (in SD) β / SE
Days Between Two Tests >23C	-0.002***		-0.003***	
	(0.001)		(0.001)	
Day-of-Test >23C	-0.070**		0.054	
	(0.030)		(0.040)	
Days Between Two Tests 23-25C		-0.002***		-0.003***
		(0.001)		(0.001)
Days Between Two Tests 25-27C		-0.002***		-0.004***
		(0.001)		(0.001)
Days Between Two Tests >27C		-0.005***		-0.003***
		(0.001)		(0.001)
Day-of-Test 23-25C		-0.061**		0.038
		(0.030)		(0.039)
Day-of-Test 25-27C		-0.110***		0.156***
		(0.036)		(0.056)
Day-of-Test >27C		-0.078		0.320***
		(0.052)		(0.071)
Observations	5869	5869	6257	6257
R^2	0.050	0.058	0.074	0.079

Notes: This table shows the effect of temperature (defined as number of days in a given bin between successive tests) on math and reading performance using the YLS data set. 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, cohort, and survey round (age) fixed effects. We control for day-of-test temperatures, and both cumulative and day-of-test precipitation as well as cumulative and day-of-test humidity. Standard errors are in parentheses, clustered by district-week.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table A.8: Cluster-Bootstrapped Standard Errors: Longer-Run Temperature and Test Scores (YLS)

	(1) Math Score (in SD) β / p-value	(2) Math Score (in SD) β / p-value	(3) PPVT Score (in SD) β / p-value	(4) PPVT Score (in SD) β / p-value
Days Between Two Tests >23C	-0.003		-0.004	
	(0.41)		(0.38)	
Days Between Two Tests 23-25C		-0.007		0.000
		(0.09)		(0.93)
Days Between Two Tests 25-27C		-0.002		-0.007
		(0.01)		(0.25)
Days Between Two Tests >27C		-0.008		-0.007
		(0.01)		(0.12)
Observations	2604	2604	2541	2541
R^2	0.766	0.770	0.542	0.547

Notes: This tables shows the effect of longer-run temperature (defined as number of days in a given bin between successive tests) on math and reading performance using the YLS data set. 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 (age) fixed effects. We control for day-of-test temperatures, and both cumulative and day-of-test precipitation as well as cumulative and day-of-test humidity. **P-values are in parentheses, obtained from cluster-bootstrapping our standard errors at the district level (200 iterations).**
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table A.9: Longer-Run Temperature and Test Scores (YLS)

	(1) Math Score (in SD) β / SE	(2) Math Score (in SD) β / SE	(3) PPVT Score (in SD) β / SE	(4) PPVT Score (in SD) β / SE
Days Between Two Tests >23C	-0.003***	-0.003***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Day-of-Test >23C		-0.114***		0.042
		(0.043)		(0.057)
Observations	2604	2604	2541	2541
R^2	0.052	0.058	0.073	0.077

Notes: This tables shows the effect of longer-run temperature (defined as number of days in a given bin between successive tests) on math and reading performance using the YLS data set. 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 (age) fixed effects. In Columns (1) and (2), we control for cumulative precipitation and humidity. In Columns (2) and (4), we control for day-of-test temperatures, and both cumulative and day-of-test precipitation as well as cumulative and day-of-test humidity. Standard errors are in parentheses, clustered by district-week.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table A.10: Previous and Current Year Temperature, and Student Attendance (ASER)

	(1) Student Attendance Proportion β / SE	(2) Student Attendance Proportion β / SE
PY NGS Days <15C	0.0001	-0.0000
	(0.0005)	(0.0005)
PY NGS Days >21C	0.0003	0.0003
	(0.0004)	(0.0004)
PY GS Days <15C	-0.0005**	-0.0005**
	(0.0002)	(0.0002)
PY GS Days >21C	-0.0005***	-0.0005***
	(0.0002)	(0.0002)
CY NGS Days <15C	-0.0000	-0.0001
	(0.0005)	(0.0006)
CY NGS Days >21C	0.0002	0.0002
	(0.0003)	(0.0003)
CY GS Days <15C	0.0000	-0.0000
	(0.0003)	(0.0003)
CY GS Days >21C	-0.0001	-0.0001
	(0.0002)	(0.0002)
Observations	93432	93432
R^2	0.429	

Notes: This table shows show the effect of previous and current year temperature (defined as number of days in the calendar year—see Figure 3) on current year student attendance in public schools divided amongst the growing season (June—Dec) and the non-growing season (March—May). The effect of days between 15°C-21°C is normalized to zero and all other coefficients are interpreted relative to 15°C-21°C. The regressions include district and year fixed effects. We control flexibly for precipitation and humidity. Column (1) presents results from an OLS regression, while Column (2) presents results from a tobit specification censored at 1 (100%). Standard errors are clustered at the district level. GS: Growing Season; NGS: Non-Growing Season; PY: Previous Year; CY: Current Year.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table A.11: Previous Year Temperature and Body Mass Index (BMI) (YLS)

	(1) BMI β / SE	(2) BMI-for-Age Z-Score β / SE
PY Days 23-25C	-0.015***	-0.009***
	(0.004)	(0.002)
PY Days 25-27C	-0.023***	-0.015***
	(0.004)	(0.003)
PY Days >27C	-0.025***	-0.018***
	(0.005)	(0.004)
Observations	3460	3460
R^2	0.342	0.080

Notes: This table shows the effect of longer-run temperature (defined as number of days in the previous calendar year) on BMI using the YLS data set. 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 (age) fixed effects. We control for cumulative precipitation and humidity. Sample only includes only a balanced panel of school-age children. Robust standard errors are in parentheses. PY: Previous Year.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table A.12: Previous and Current Year Temperature, and Teacher Attendance (ASER)

	(1) Teacher Attendance Proportion β / SE	(2) Teacher Attendance Proportion β / SE
PY Days <15C	0.0001	0.0003
	(0.0002)	(0.0005)
PY Days >21C	0.0001	0.0006
	(0.0001)	(0.0004)
CY Days <15C	0.0002	0.0005
	(0.0002)	(0.0005)
CY Days >21C	0.0000	0.0004
	(0.0001)	(0.0004)
Observations	75328	75328
R^2	0.052	

Notes: This tables shows the effect of previous and current year temperature (defined as number of days in a given bin between successive tests) on teacher attendance at public schools using the ASER data set. The effect of days between 15°C-21°C is normalized to zero and all other coefficients are interpreted relative to 15°C-21°C. The regressions include district and year fixed effects. We control flexibly for precipitation and humidity. Column (1) presents results from an OLS regression, while Column (2) presents results from a tobit specification censored at 1 (100%). Standard errors are clustered at the district level. PY: Previous Year.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table A.13: Falsification Test: Future Temperature Doesn't Negatively Impact Prior Yields

	(1) Top 6 Crops Log(Yield) β / SE	(2) Top 6 Crops Lag Log (Yield) β / SE	(3) Top 5 Monsoon Crops Log (Yield) β / SE	(4) Top 5 Monsoon Crops Lag Log (Yield) β / SE
GS Days <13C	-0.0018	-0.0000	-0.0023	0.0007
	(0.0014)	(0.0008)	(0.0019)	(0.0009)
GS Days 13-15C	0.0004	-0.0006	0.0029***	-0.0003
	(0.0009)	(0.0009)	(0.0009)	(0.0012)
GS Days 17-19C	-0.0013	0.0010	-0.0026	0.0029
	(0.0011)	(0.0007)	(0.0025)	(0.0020)
GS Days 19-21C	-0.0032***	0.0023	-0.0033**	0.0053
	(0.0010)	(0.0014)	(0.0015)	(0.0033)
GS Days 21-23C	-0.0027**	0.0031*	-0.0033*	0.0062
	(0.0011)	(0.0017)	(0.0016)	(0.0037)
GS Days 23-25C	-0.0033**	0.0035*	-0.0040**	0.0067*
	(0.0012)	(0.0018)	(0.0016)	(0.0035)
GS Days 25-27C	-0.0042***	0.0026*	-0.0038**	0.0054*
	(0.0012)	(0.0014)	(0.0013)	(0.0031)
GS Days 27-29C	-0.0055***	0.0023	-0.0042***	0.0053
	(0.0010)	(0.0016)	(0.0011)	(0.0032)
GS Days >29C	-0.0096***	0.0017	-0.0116***	0.0044
	(0.0023)	(0.0017)	(0.0035)	(0.0033)
NGS Days <13C	0.0021	0.0034	0.0004	-0.0006
	(0.0021)	(0.0020)	(0.0015)	(0.0013)
NGS Days 13-15C	-0.0023*	-0.0012	0.0003	-0.0058
	(0.0013)	(0.0026)	(0.0019)	(0.0039)
NGS Days 17-19C	-0.0035**	-0.0012	-0.0042	0.0004
	(0.0016)	(0.0011)	(0.0026)	(0.0020)
NGS Days 19-21C	-0.0029*	0.0002	-0.0028	-0.0008
	(0.0016)	(0.0015)	(0.0016)	(0.0021)
NGS Days 21-23C	-0.0021	-0.0009	-0.0016	-0.0014
	(0.0012)	(0.0014)	(0.0017)	(0.0019)
NGS Days 23-25C	-0.0009	-0.0030	-0.0012	-0.0037
	(0.0015)	(0.0017)	(0.0019)	(0.0023)
NGS Days 25-27C	-0.0015	-0.0025	-0.0021	-0.0029
	(0.0017)	(0.0021)	(0.0023)	(0.0026)
NGS Days 27-29C	-0.0010	-0.0005	-0.0018	-0.0006
	(0.0019)	(0.0022)	(0.0024)	(0.0028)
NGS Days >29C	-0.0018	-0.0030	-0.0028	-0.0030
	(0.0020)	(0.0022)	(0.0025)	(0.0028)
Observations	9479	9479	9475	9475
R^2	0.885	0.878	0.877	0.870

Notes: This table examines the effect of hot days on contemporaneous (columns (1) and (3)) and past (columns (2) and (4)) yields. 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, year and age fixed effects, and control for age-for-grade status. We also control flexibly for precipitation. Standard errors are in parentheses, clustered at the state level. GS: Growing Season, NGS: Non-Growing Season

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

Table A.14: Future Temperature Shocks Are Uncorrelated With Baseline Heat Resistant Crop Adoption

	(1) 2006 β / SE	(2) 2007 β / SE	(3) 2008 β / SE	(4) 2009 β / SE	(5) 2010 β / SE
PY Days <15C (Residualized)	0.0001	-0.0024	-0.0014	0.0030	0.0021
	(0.0022)	(0.0032)	(0.0035)	(0.0035)	(0.0021)
PY Days >21C (Residualized)	-0.0018	0.0027	0.0051**	-0.0062***	-0.0003
	(0.0021)	(0.0020)	(0.0024)	(0.0021)	(0.0027)
Observations	525	536	539	541	538
R^2	0.010	0.049	0.036	0.038	0.020

	(6) 2011 β / SE	(7) 2012 β / SE	(8) 2013 β / SE	(9) 2014 β / SE
PY Days <15C (Residualized)	-0.0083***	-0.0022	0.0019	0.0023
	(0.0030)	(0.0037)	(0.0024)	(0.0031)
PY Days >21C (Residualized)	0.0050**	0.0005	0.0018	-0.0011
	(0.0022)	(0.0025)	(0.0018)	(0.0030)
Observations	525	528	515	537
R^2	0.055	0.012	0.023	0.011

Notes: This table examines if residualized adoption of heat-resistant crops (binary indicator for above median adoption as used in main-analysis) co-varies with number of hot days in the previous year. 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, year and age fixed effects, and control for age-for-grade status. We also control flexibly for precipitation and humidity. Standard errors are in parentheses, clustered at the district level. PY: Previous Year.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table A.15: Does NREGA rollout co-vary with hot days in the previous year?

	(1) NREGA (0/1) β / SE
PY Days <13C	0.0005
	(0.0034)
PY Days 13-15C	-0.0029
	(0.0042)
PY Days 17-19C	-0.0022
	(0.0037)
PY Days 19-21C	-0.0059*
	(0.0032)
PY Days 21-23C	-0.0004
	(0.0032)
PY Days 23-25C	0.0003
	(0.0033)
PY Days 25-27C	0.0029
	(0.0035)
PY Days 27-29C	0.0061
	(0.0038)
PY Days >29C	0.0030
	(0.0039)
Observations	1306
R^2	0.698

Notes: This table examines if NREGA rollout co-varies with number of hot days in the previous year. Regression includes districts and year fixed effects. We control flexibly for precipitation and humidity. Standard errors are in parentheses, clustered at the district level.
*Significant at 10%.
**Significant at 5%.
***Significant at 1%.

Table A.16: Triple Difference: Previous Year Temperature, NREGA, and Test Scores

	(1) Math Score (in SD) β / SE	(2) Read Score (in SD) β / SE
PY Days >21C	-0.0044***	-0.0026***
	(0.0007)	(0.0006)
NREGA PY	-0.9384***	-0.5209***
	(0.1427)	(0.1227)
NREGA PY * PY Days >21C	0.0029***	0.0016***
	(0.0004)	(0.0004)
Observations	3653357	3653357
R^2	0.076	0.066

Notes: This table shows the influence of NREGA in attenuating the effects of longer-run temperature (defined as number of days in the previous calendar year—see Figure 3) on current year math and reading performance. The effect of days between 15°C-21°C is normalized to zero and all other coefficients are interpreted relative to 15°C-21°C. The regressions include district, year and age fixed effects, and control for age-for-grade status. We also control flexibly for precipitation and humidity. Standard errors are in parentheses, clustered at the district level. PY: Previous Year.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.