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

Teevrat Garg†
Maulik Jagnani ‡
Vis Taraz§

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Abstract

We present the first estimates of the effect of temperature on cognitive performance in a developing country with limited propagation of air-conditioning, and find that an additional 10 days in a year above 29C relative to 15C-17C reduces math test scores by 0.03 standard deviations. We find strong evidence for persistent income effects - hot days during the growing season reduce agricultural yields and test score performance with comparatively modest effects in the non-growing season. The rollout of a conditional cash transfer program, by providing a safety net for the poor, weakens the link between temperature and rural incomes, in turn moderating the impact of temperature on test scores. Our results suggest that climate change will have disproportionate and large negative impacts on human capital accumulation of poor populations in agrarian economies, increasing the persistence of poverty.

JEL Codes: H41, I0, Q5, Q54
Keywords: climate change, human capital, workfare, agriculture

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†School of Global Policy and Strategy, University of California, San Diego. E: teevrat@ucsd.edu; Address: 1303 Robinson Complex, 9500 Gilman Dr, La Jolla, CA 92093.

‡Charles H. Dyson School of Applied Economics and Management, Cornell University. E: mvj22@cornell.edu; Address: 362 Warren Hall, Ithaca, NY 14850

§Department of Economics, Smith College. E: vtaraz@smith.edu; Address: Pierce Hall 204, Northampton, MA 01063

1 Introduction

While the threat of climate change represents a challenge for policy makers and individuals across the world, the problem is most acute in poor countries where livelihoods are more climate-exposed and where individuals are financially constrained in coping with climate stressors. Considering the central role of human capital accumulation as a driver of economic growth (Nelson & Phelps, 1996; Romer, 1986) and as a pathway out of poverty (Barrett, Garg and McBride, 2016; Barro, 2000), we provide the first estimates of the potential impacts of climate change on human capital accumulation in a developing country context where the propagation of heat-avoiding technologies such as air-conditioning is extremely limited.

Using data from nearly 3.5 million test scores from 2006-2014 in India, we find three major results. First we find strong evidence for the negative effects of extreme temperatures on human capital accumulation; 10 extra days in a year with average *daily* temperature above 29C relative to 15-17C reduces math and reading test performance by 0.03 and 0.02 standard deviations respectively, equivalent to erasing one-fourth of the gains from smaller class sizes[1]. Second, we find strong evidence for an income mechanism. In particular we find that (a) hot days during the agricultural growing season have large effects on test score performance whereas hot days in the non-growing season have minimal effects, (b) the effects are concentrated in areas that don't grow heat resistant crops, and (c) hot days have large effects on agricultural yields. Third, we exploit the rollout of the world's largest workfare program, NREGA to examine the role of the safety net program in modulating the effect of temperature on test scores. Importantly, we find that NREGA attenuates the effect of hot

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

days on math and reading scores by 31-38%.

In our conceptual framework, which we elaborate on in section 2, we recognize that to the extent adaptation to effects of climate change on human-capital accumulation are possible within a year, the reduced-form year-of-test effects are the effects of extreme temperatures *net of adaptation.* While this reflects the incidence of extreme temperatures, adaptation or other forms of avoidance behavior including defensive investments are expensive and the failure to account for the cost of such behavior will understate the welfare costs of climate change (Deschenes, Greenstone and Shapiro, 2012; Bartik, 1988). To the extent that adaptation has a non-negative cost, the net effect represents the lower bound on the human capital related welfare costs of climate change.

We make contributions to several areas of economics. First, we build on the nascent literature on the impacts of weather and climate on human-capital accumulation. Prior work has focussed entirely in the US (Graff-Zivin, Hsiang and Neidell, 2015; Park, 2016); in sharp contrast, we focus on a developing country context with two important considerations: a) the propagation of defensive investments such as air conditioners is quite limited, and b) relatedly, occupations and incomes are much more climate exposed. As such the relationship between extreme temperatures and human capital accumulation is of particular interest for developing countries given the critical role of human capital in moving out of persistent poverty (Barrett, Garg and McBride, 2016).

Second, we are the first to provide evidence on the role of pro-social programs in helping households in poor countries to cope with extreme temperatures in the face of climate change. Despite consideration of technological mechanisms such as air conditioners playing a role in attenuating the impacts of extreme temperatures on households (particularly in developed countries; see Barreca et al. (2013); Rogot and Backlund (1992) for more details), they are unlikely to be part of the adaptation strategy amongst a large share of households in developing countries given cost considerations [2]. By contrast, pro-social programs are more likely to allow households to cope with extreme temperatures.

Third, prior work on avoidance behavior has relied on documenting specific channels of adaptation [3]. To the extent that avoidance behavior is costly and important to include in the estimation of welfare costs of climate change (Deschenes, Greenstone and Shapiro, 2012), the researcher would need to credibly identify all possible channels of avoidance behavior, requiring exogenous variation in each. By contrast, we use long-run weather variation and exogenous variation in contemporaneous income to respectively estimate likely lower- and upper-bounds on the human capital accumulation related welfare costs of extreme temperatures. More recently, researchers have used differences in panel and cross-sectional methods to estimate *ex-post* avoidance behavior (Burke and Emerick, 2016; Graff-Zivin, Hsiang and Neidell, 2015) and well as public forecasts (Shrader, 2016) to estimate total *ex-ante* avoidance behavior. However, because the researchers are unable to quantify the costs of such avoidance behavior (in part, due the numerous forms of avoidance behavior), these important papers fall short of estimating the welfare costs of extreme temperatures. We use exogenous "compensating" variation in income to quantify the likely upper bound on the total human capital accumulation related welfare costs of extreme temperatures.

The rest of the paper is organized as follows. Section 2 provides background informa-

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

[3] A non-exhaustive set of channels of adaptation include air conditioners (Barreca et al., 2013), nutritional supplements (Gunnsteinsson et al., 2014), crop switching behavior (Taraz, 2015), time use changes (Graff-Zivin and Neidell, 2014) etc. See Dell, Benjamin and Olken (2012) and Hsiang (2016) for a more exhaustive review.

tion on the relation between temperature and human cognition and outlines our conceptual framework for welfare calculations. Section 3 describes the data. In section 4 we outline the empirical strategy and our main results, including threats to identification. In section **??** we perform welfare calculations and conclude with section 5.

2 Background and Model

2.1 Background

Climate can affect human capital through various plausible mechanisms that relate ambient temperature to human capital production [4]. First, ambient temperature affects brain temperature. The brains chemistry, electrical properties, and function are all temperature sensitive (Bowler and Tirri, 1974; Schiff and Somjen, 1985; Hocking et al., 2001; Deboer, 1998; Yablonskiy, Ackerman and Raichle, 2000), and both warm environmental temperatures and cognitive demands can elevate brain temperature. There exists a vast body of empirical evidence linking cognitive impairment to high temperatures as a result of heat stress. For instance, military research has shown that soldiers executing complex tasks in hot environments make more errors than soldiers in cooler conditions (Fine and Kobrick, 1978; Froom et al., 1993). Further, LED lighting, which emits less heat than conventional bulbs, decreases indoor temperature, and has been shown to raise productivity of workers

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

in garment factories in India, particularly on hot days (Adhvaryu and Nyshadham, 2015). Exposure to heat has also been show to diminish attention, memory, information retention and processing, and the performance of psycho-perceptual tasks (e.g. Vasmatzidis, Schlegel and Hancock (2002) and Hyde et al. (1997)). Contextually closer to this paper, short-run changes in temperature have also been shown to cause decreases in cognitive performance on math (Graff-Zivin, Hsiang and Neidell, 2015).

Second, higher wages increase human capital investments (Jacoby (1997); Jensen (2000) and Maccini and Yang (2009)), and increased investment in human capital has been shown to increase test scores (Das et al. (2013)). Therefore, if extreme weather affects household income, such income effects could be another potential channel through which extreme temperatures affect human capital formation in the long-run [5]. Our detailed temperature and test score data that includes information on the day of the test, allows us to separately estimate the direct neurological short-run effect as distinct from long-run effects that may differ due to other channels and endogenous adaptation.

Quality of instruction has been a central component to virtually all proposals to raise school quality (Hanushek and Rivkin (2012)). Teaching quality has been linked to student test scores, as well as later-life outcomes (Chetty, Friedman and Rockoff (2014*a*) and Chetty, Friedman and Rockoff (2014*b*)). Through environments effect on brain temperature, short-run weather can also have an impact on the quality of instruction which in turn can have persistent human capital effects. Additionally, hot temperatures can increase the cost of effort required to attend school, and lead to both student and teacher absenteeism. Using

[5]Relatedly, recent research in India has documented a causal link between rainfall and agricultural incomes, as well as hot weather and agricultural incomes (Burgess and Greenstone (2014)). Moreover, Shah and Steinberg (2016), have translated these effects into long-term impacts on human capital.

unannounced visits to measure attendance, a nationally representative survey found that 24 percent of teachers in India were absent during school hours (Chaudhury et al. (2006)). Higher student absenteeism is associated with higher failure rates (Ehrenberg et al. (1991)), while a randomized control trial in India that incentivized teachers attendance, found that teacher absenteeism fell and test scores of children in the treatment group increased (Duflo, Hanna and Ryan (2012)). Thus, if hot climate encourages teacher or student absenteeism, it could have an impact of human capital accumulation.

2.2 Conceptual Model

In this section we present a simple model to motivate our empirical section as well as to provide intuition for our approach to estimating the upper and lower bounds on the welfare impacts of climate change. We assume that a typical agent in our setting derives utility from the consumption of a normal good (c) and cognitive performance (y). The cognitive performance of the agent is a function of prior human capital (k), weather realization (w) as well as choices made over investment in avoidance behaviors denoted by a. The agent chooses consumption level (c) and investments in avoidance behavior a subject to her budget I and prevailing price of avoidance $p > 0$. We treat the price of the consumption good as 1 for simplicity. From the agent's optimization problem, we follow Graff-Zivin, Hsiang and Neidell (2015) and denote cognitive performance (y) as:

$$y = f\left[k, (1 - a(w, I))w\right] \tag{1}$$

We denote our baseline case with weather w_1, budget I_1 and subsequent cognitive performance as y_1. Now consider the case where there is realization of a negative weather shock w_2. The resultant cognitive performance is denoted by y_2 at the same budget I_1 such that:

$$y_2 = f\left[k, (1 - a(w_2, I_1))w_2\right] < \left[k, (1 - a(w_1, I_1))w_1\right] = y_1 \tag{2}$$

Under fairly unrestrictive assumptions, there exists a budget level I_2 that under weather realization w_2 will yield cognitive performance y_1. That is there exists I_2 such that,

$$y_1 = f\left[k, (1 - a(w_2, I_2))w_2\right] = \left[k, (1 - a(w_1, I_1))w_1\right] \tag{3}$$

In effect $\Delta I = I_2 - I_1$ represents the transfer needed to erase the gross effects of weather realization w_2 relative to w_1 on cognitive performance. However, since the individual maximizes utility and not cognitive performance, under the benign assumption that consumption and cognitive performance are normal goods, ΔI represents the likely upper bound on the human capital accumulation related welfare costs of climate. The empirical challenge, of course, remains finding an exogenous source of income transfers that attenuates the relationship between temperatures and cognitive performance.

Following equation (1), we can also characterize the lower bound on the human capital accumulation related welfare costs of climate change.

$$\frac{\partial y}{\partial w} = (1 - a)\frac{\partial f}{\partial w} - w\frac{\partial f}{\partial a}\frac{\partial a}{\partial w} \tag{4}$$

The first term on the right hand side captures the neurological effect of exposure whereas the second term captures the ex-ante avoidance behavior. However, in a reduced form setting we can only observe $\frac{\partial y}{\partial w}$ which is net of avoidance behavior. To the extent that the avoidance behavior is costly, the reduced form effect provides a likely lower bound on the welfare costs of extreme temperature insofar as it doesn't include the costs of avoidance behavior.

3 Data

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

3.1 Annual Status of Education Report (ASER)

The Annual Status of Education Report (ASER) is a survey on educational achievement in primary school children in India and has been conducted by Pratham, an educational non-profit, every year starting in 2005. The sample is a representative repeated cross section at the district level. The ASER surveyors ask each child four potential questions in math and reading (in their native language). In each subject, they begin with the hardest of four questions. If a child is unable to answer that question, they move on to the next easiest question and so on and so forth.

The ASER is a valuable dataset for our analysis for multiple reasons. First, ASER provides national coverage and a large sample size; in our study period of 2006-2014, ASER conducted nearly 3.5 million tests across every rural district in India [6]. 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. Second, unlike schools-based data, ASER is not administered in schools and therefore covers children both in and out of school. This allows us to measure effects on test performance without confounding selection around school attendance, access to schools etc. ASER tests children ages 5-16, who are currently enrolled, dropped out, or have never enrolled in school.

3.2 Young Lives Survey (YLS)

While the ASER has the advantage of national coverage and large number of tests, its repeated cross-sectional nature (as opposed to an individual level panel) doesn't allow us to account for the role of prior human capital accumulation. Therefore, we also employ the Young Lives Survey, which is an international study of childhood poverty coordinated by a team based at the University of Oxford. In this study we use data from between 2002 and 2011 in the state of Andhra Pradesh (unlike ASER, YLS is conducted in a single state in India) [7]. The study has collected data on two cohorts of children: 1008 children born between January 1994 and June 1995, and 2011 children born between January 2001 and June 2002. Data was collected from children and their families using household visits in 2002, 2007 and 2009/10. Extensive test data were collected from children in the sample in all rounds of the survey. The tests differed in their focus on which dimension of cognitive

[6] The ASER originated in 2005, however the ASER 2005 is not in public domain and the organizing body is no longer making the 2005 data available.

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

achievement they attempted to capture and how closely they related to the formal school curriculum in Andhra Pradesh; often, different tests were administered to children across rounds in order to ensure that they were appropriate for the age and the stage of education that the children were in.

Further, YLS has particularly rich information about the socio-economic background of the children's households, parental expectations/aspirations for the children, and also detailed child-specific data on time-use. The study also collected extensive data through visits to the schools of a randomly selected sub-sample of the younger cohort across 247 schools in 2011. The school-level survey was conducted between December 2010 and March 2011, i.e. in the school year immediately after the third wave of household-level data collection. The survey also administered questionnaires to principals, and teachers in the school, and contains detailed information on school inputs, including teacher qualifications, attendance etc.

3.3 Weather Data

In an ideal research setting, we would employ observational data from ground stations in each location where the ASER and YLS data were collected. However, the spatial and temporal coverage of ground stations in India is several lacking, particularly in recent years. In the absence of consistent coverage from ground weather stations, we use temperature and precipitation reanalysis data from the ERA-Interim archive, which is constructed by researchers at the European Centre for Medium-Term Weather Forecasting (ECMWF). Such reanalysis data has been supported in the literature as generating a consistent best-estimate of weather in a grid-cell and has been used extensively in economics (Schlenker and Roberts, 2009; Schlenker and Lobell, 2010; Auffhammer et al., 2013) We use the ERA-Interim daily temperature and precipitation data on a 1 x 1 degree latitude-longitude grid, from 1979 to present day.[8] To construct weather variables for each district or village, we construct an inverse-distance weighted average of all the weather grid points within a 100km range of the village or district centroid. 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. Figure 3 shows the long-run variation in temperature in Andhra Pradesh (panel A) and all India (panel B, C).

3.4 Agricultural Data

We use agricultural data from the Village Dynamics in South Asia Meso data set (henceforth VDSA), which is compiled by researchers at the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT 2015). The data set provides district-level information on annual agricultural production, prices, acreage and yields, by crop.

4 Weather and Test Scores

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

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

we estimate the following equation:

$$
\begin{aligned}
Y_{ijq,t+1} =& \alpha + \gamma_1(<13C)_{ijqt} + \gamma_2(13-15C)_{jqt} + \gamma_4(17-19C)_{jqt} + \\
& \gamma_5(19-21C)_{jqt} + \gamma_6(21-23C)_{jqt} + \gamma_7(23-25C)_{jqt} + \\
& \gamma_8(25-27C)_{jqt} + \gamma_9(27-29C)_{jqt} + \gamma_{10}(>29C)_{jqt} + rain_{jqt} + \\
& \eta_j + \mu_{qt} + \epsilon_{ijqt}
\end{aligned}
\tag{5}
$$

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

The national coverage of the ASER data allows us to capture a wider temperature distribution when examining the effects of temperature on test scores but does not allow us to take into account past human capital accumulation. To account for the role of prior human capital accumulation, we use the individual level panel data in the YLS survey to estimate the following equation:

$$Y_{ijt} = \alpha + \gamma_2(23 - 25C)_{jt} + \gamma_3(25 - 27C)_{jt} + \gamma_4(> 27C)_{jt} + Rain_{jt} + \eta_j + \mu_t + \epsilon_{ijt} \quad (6)$$

Y_{ijt} is math or reading test scores for child i, in district j, in year t, standardized by round. The temperature bins follow a similar interpretation as above but since YLS covers a single state, the temperature distribution is narrower and the reference bin is $(< 23C)_{jt}$. In addition, to account for prior human-capital accumulation, the temperature bins record the number of days with average temperature in that bin since the last YLS test (instead of the calendar year, since in the YLS data we know the actual date of the test). We control for individual, month, day-of-week, year and survey-round fixed effects. Standard errors are clustered at the district-week level.

4.1 Temperature and Test Scores in the Long-Run

We estimate equation (5) and find that an extra 10 days in a year with average daily temperature above 29C relative to a day with average daily temperature between 15C and 17C reduces math performance 0.03 standard deviations and reading performance by 0.02 standard deviations (table 1) which would effectively erase XXXX intervention. In fact, using our binned approach, we find that test performance decreases linearly in temperatures above 17C (figures 4). Accounting for prior human capital, we estimate equation (6) using individual panel data from the YLS survey and find similar results. Considering the effects of temperature on human capital accumulation between successive tests conditional on prior test performance, we find that an extra 10 days between successive tests above 27C relative to below 23C, reduces test math and reading scores by 0.07 standard deviations each (table 2). Noticeably, the temperature range over which we find effects is smaller in YLS than in ASER given that the YLS was fielded in a single state in India limiting spatial variation in temperature. As in the case of ASER, the deleterious effects of temperature on test score performance are increasing with higher temperatures (figures 5).

4.2 Mechanisms

We find evidence for both an income and a physiological mechanism to explain the effect of temperature on test score performance, with the latter prevalent in the short-run and the former dominant in the long-run. In this section, we present evidence supporting both mechanisms.

4.2.1 Income Mechanism

India is primarily an agricultural country where most households in rural areas rely on agricultural incomes. Given that our data is focussed on rural areas (with ASER being collected exclusively in rural areas), we find strong evidence to support an income-based mechanism for the effect of temperature on test scores. Specifically, we present two pieces of evidence. First, the effect of temperature on test scores is primarily driven through higher temperatures in the agricultural growing seasons; an extra hot day above 21C in the growing season has three to four times larger effects on test scores than a corresponding extra hot day in the non-growing season days. Specifically, an extra 10 days above 21C in the growing season reduces math scores by 0.035 standard deviations and reading scores by 0.02 standard deviations compared to 0.013 and 0.005 for math and reading respectively in the non-growing season (table 3). The differences between the effects of temperature on test scores across growing v. non-growing seasons increase with higher temperatures for both math and reading scores (figures 6).An immediate concern could be that this effect is not driven by incomes but rather by increased exposure to higher temperatures from working on the field. Therefore we test the impact of temperature on agricultural yields in the 6 major crops as well as the 5 major monsoon crops[9]. Using district level yields data, we find that an extra day above 29C in the growing season test scores by an order of magnitude more than the same day in the non-growing season. In absolute terms, the magnitude is large; an extra 10 days above 29C relative to a day between 15C and 17C reduces yields by 10% (table A.1). The large impact of temperature on yields is consistent with a model where temperature affects test scores through declines in agricultural income.

Second, we find that the effects of temperature on test scores are pronounced in districts where the dominant crops are not heat-resistant with no economically meaningful effects of temperature on test scores in districts that grow heat resistant crops[10]. In fact, growing

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

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

heat resistant crops erases any effect of temperature on test scores in the long-run. An extra 10 hot days above 21C in districts that don't grow heat-resistant crops lowers math scores by 0.022 standard deviations compared with a near-null effect in districts that grow heat-resistant crops (table 4).

4.2.2 Physiological Mechanism

Consistent with the neuroscience literature on the impacts of temperature on cognitive performance we find strong evidence for the presence of physiological channel connecting temperatures to test scores in the short-run (Bowler and Tirri, 1974; Schiff and Somjen, 1985; Hocking et al., 2001). In line with earlier work by Graff-Zivin, Hsiang and Neidell (2015), we support the presence of a physiological effect in two ways. First, we exploit our knowledge of the exact day of the test in YLS to estimate the effect of day-of-test temperature on test scores. To the extent that other channels manifest over a duration longer than a single, the day-of-test effects represent a short-term physiological effect of temperature on test scores. We find that having day of test average temperature above 27C relative to below 21C reduces math test scores by 0.3 standard deviations (table 5, column 2; figure 11(a)). Second, consistent with the portion of the brain responsible for mathematical functions being more temperature sensitive, we find that higher temperatures on the day of the test reduce math scores, but have no effect on reading scores (table 5, column 4; figure 11(b)).

However, we find the physiological effect of temperature on test scores to be short-lived. We find no evidence for the persistence of the short-run effects of temperature on test scores; over the week prior to the test, extra hot days have no effect on test performance (figure 8). The large day-of-test effect and the null week-of-test effect are consistent with a model of internal self-regulation where the human body self-regulates higher temperatures. We find no evidence to support a scenario where students are distracted due to the discomfort of higher temperatures and therefore exerting lower effort on tests. Instead, we find that students spend marginally more time on the test under hotter temperatures (table A.2). Likewise, hotter days don't alter the time-of-the-day when the test takes place (table A.3). Together, the evidence is therefore consistent with a model where the body self-regulates higher temperatures and in line with prior work (Taylor, 2006).

4.3 Heterogeneity

In this section we investigate the heterogenous impacts of extreme temperatures across different population sub-groups. First, we find that the effects of temperature on performance are most acute amongst younger children, with the effects decreasing linearly in age and no discernible effects of temperature on performance for the oldest children in our sample (figure 9). Younger children may be more susceptible to the effects of temperature on performance either because of the phase in physical development where the body is particularly sensitive to higher temperatures or on account of low levels of prior human capital accumulation where the temperature-performance damage function could be conditional on existing stock of human capital as in equation (1).

Second, interestingly we find no gender dimension to our core result; hot days affect boys marginally more than they do girls, although these differences are not statistically significant (figure A.6). The absence of heterogeneity is consistent with a unitary household model protecting itself from heat shocks and inconsistent with a model where temperature-induced income shocks disproportionately impact the girls in the household.

Third, we dichotomously divide districts into hot and cold districts based on historical temperatures. We find that the effects of temperature on test scores are most pronounced in districts that are not historically the hot districts. By contrast, in the historically hot districts, an extra hot day has no measurable impact on test performance (figure 10). This source of heterogeneity is also consistent with a model where households engage in self-protection against high temperatures when they have had a historically compelling reason to do so.

4.4 Effect of Pro-social programs

In this section we examine the bi-directionality of the income mechanism and in particular whether the effects of temperature on test scores are attenuated by the introduction of NREGA, a workfare pro-social program that is in effect, a conditional cash transfer program. We exploit the staggered rollout of NREGA across India's 650 districts to perform an event study. We set the omitted category to be the concurrent year of the introduction of NREGA in a district. We find that the introduction of NREGA attenuates the impact of an extra hot day above 29C on math and reading scores by 31-38%. Specifically, prior to NREGA rollout in a district, an extra 10 days above 29C (relative to between 15C and 17C) reduces math and reading scores by 0.05 standard deviations (table 6). Figure 11 pictorially depicts the event study and shows that the introduction of NREGA attenuates the effect of those extra 10 hot days above 29C on test scores by 0.016 and 0.02 standard deviations on math and reading respectively.

These results are important on two accounts. First, they reinforce the underlying income mechanism linking higher temperatures to lower test score performance. Not only do higher temperatures lower test performance by adversely affecting household agricultural income, but also income stabilizing pro-social programs can build resilience and attenuate the negative effects of higher temperatures. In poor countries, where adaptation strategies such as air conditioners are unaffordable for large portions of the population, building resilience through pro-social programs can be an important tool in combating the harmful effects of increasing temperatures.

Second, recent work has identified an opportunity cost mechanism linking adverse weather and pro-social programs to lower test performance (Shah and Steinberg, 2016). In sharp contrast, we find that the income stabilization provided by pro-social allows households to self-protect against the adverse effects of temperatures.

5 Conclusion

As weather, in the age of climate change, becomes more pronounced in the tropics, it is likely to disproportionately impact the poor. We report three key findings. First we find strong evidence for the negative effects of extreme temperatures on human capital accumulation; 10 extra days in a year with average daily temperature above 29C relative to 15-17C reduces math and reading test performance by 0.03 and 0.02 standard deviations respectively, equivalent to erasing one-fourth of the gains from smaller class sizes. Second, we find strong evidence for an income mechanism. In particular we find that (a) hot days during the agricultural growing season have large effects on test score performance whereas hot days in the non-growing season have minimal effects, (b) the effects are concentrated in areas that don't grow heat resistant crops, and (c) hot days have large effects on agricultural yields. Third, we exploit the rollout of the world's largest workfare program, NREGA to examine the role of the safety net program in modulating the effect of temperature on test scores. Importantly, we find that NREGA attenuates the effect of hot days on math and reading scores by 31-38%.

Our results have important implications for climate and social policy in developing countries. Given the central role of human capital accumulation as a pathway out of poverty in developing countries (Barrett, Garg and McBride, 2016), climate change will not only disproportionately affect the rural poor but also likely perpetuate persistent poverty.

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Figures

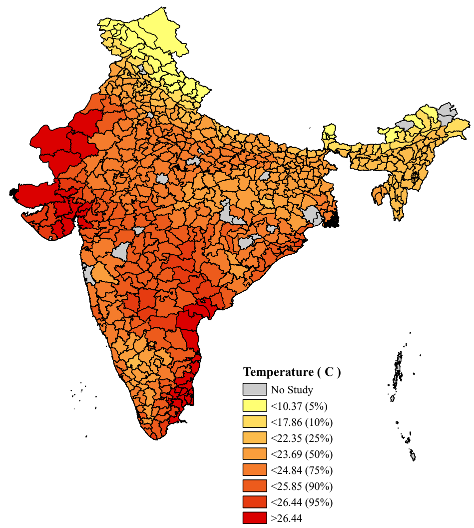


Figure 1: Average Daily Temperature by District

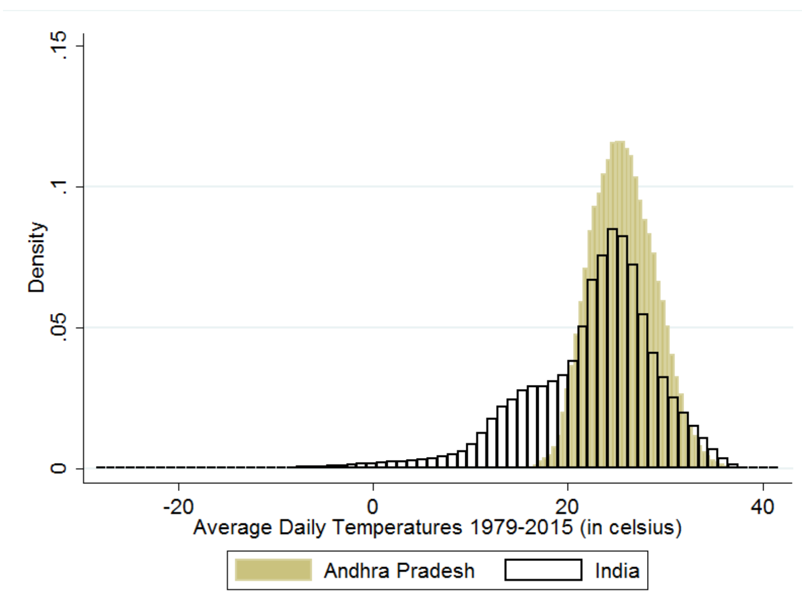
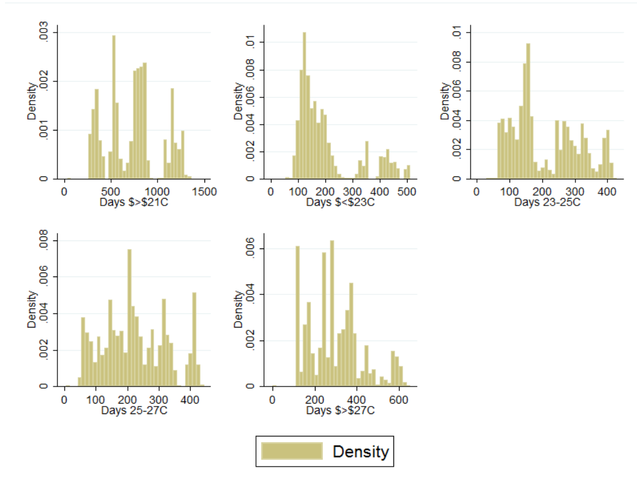
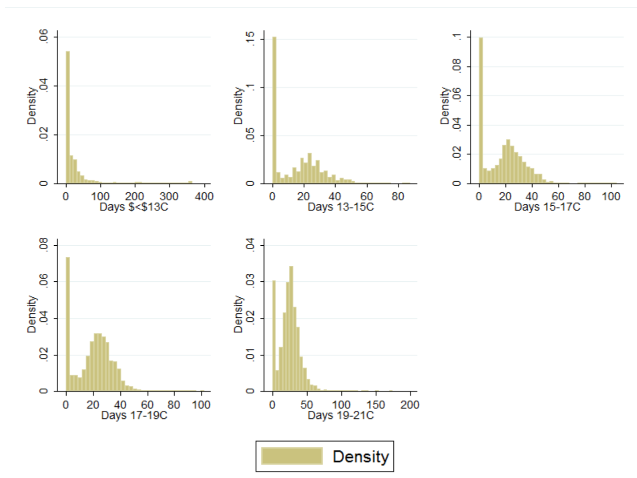


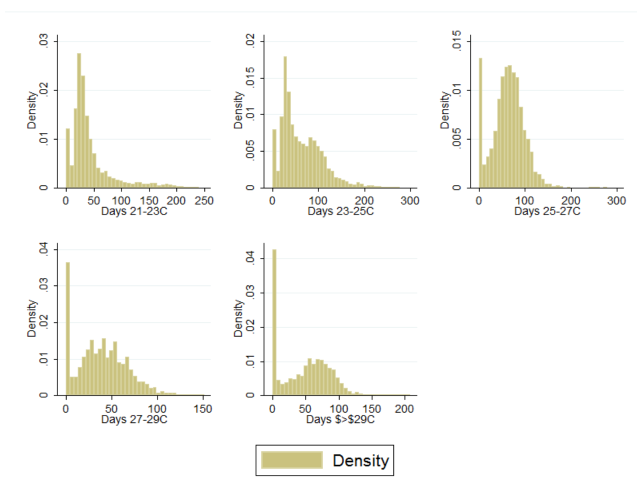
Figure 2: Distribution of Daily Temperatures for India and Andhra Pradesh



(a) Andhra Pradesh

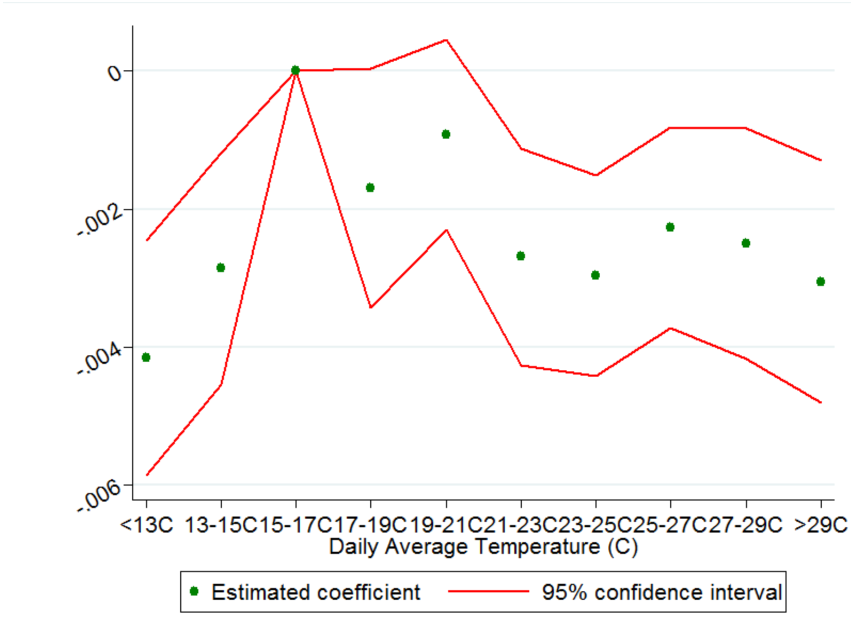


(b) All India

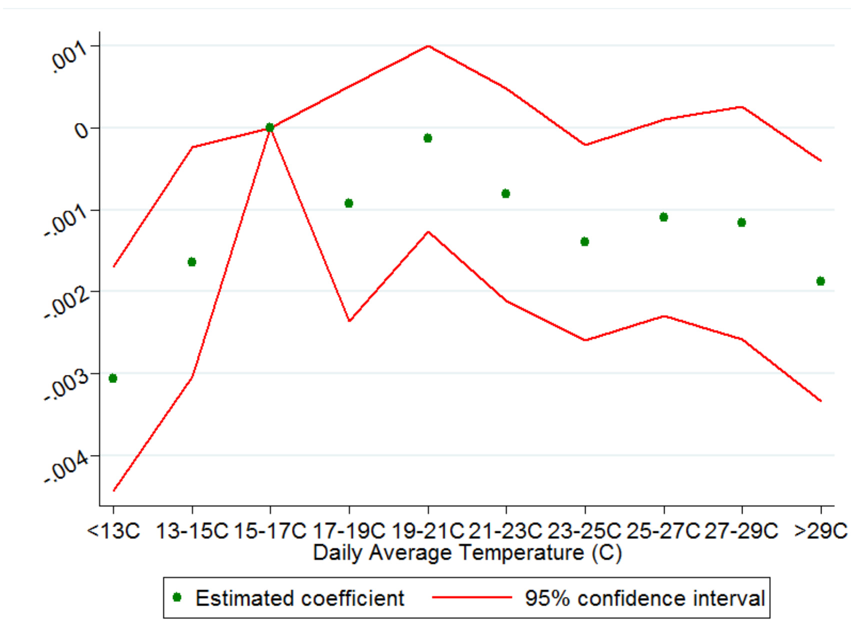


(c) All India (continued)

Figure 3: Long Run Temperature Variation

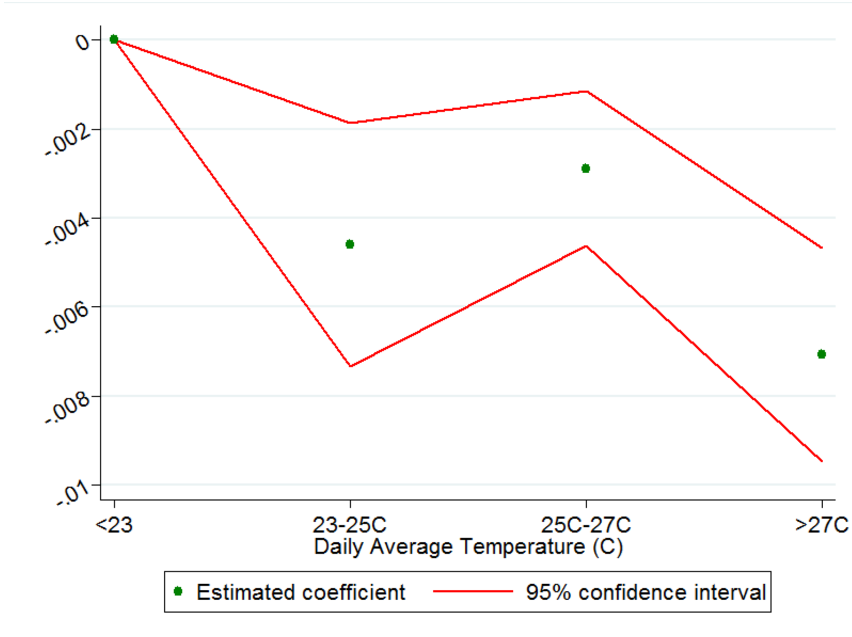


(a) Math Scores

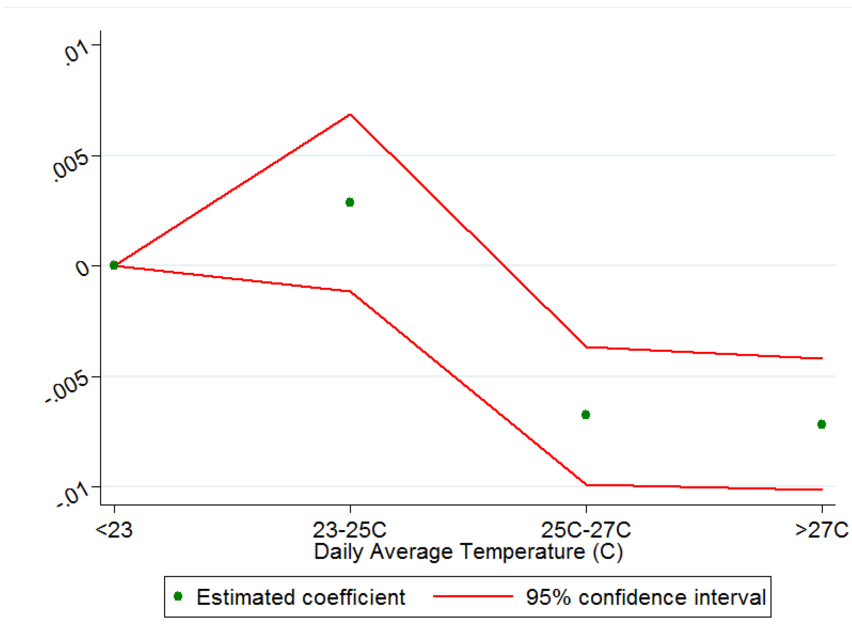


(b) Reading Scores

Figure 4: Long Run Temperature and Test Scores (ASER)

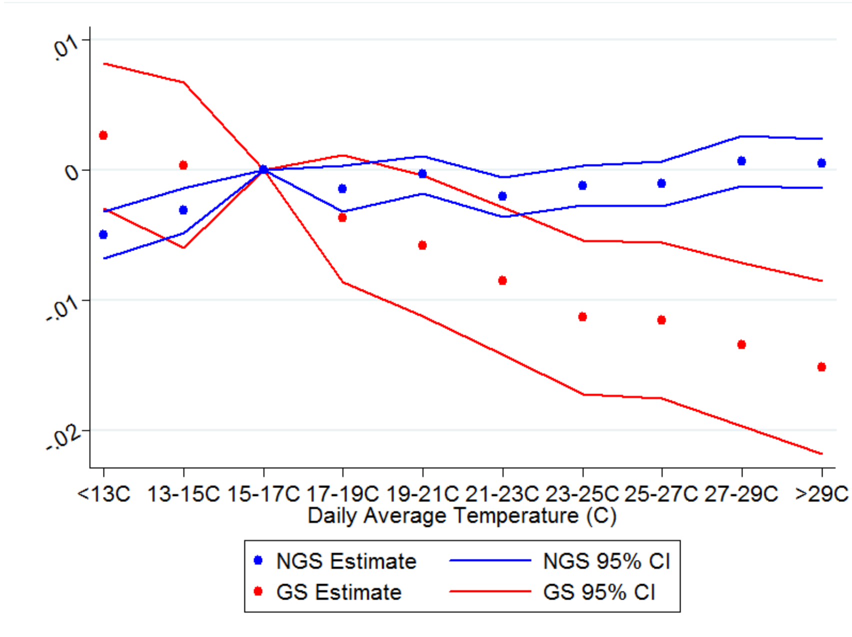


(a) Math Scores

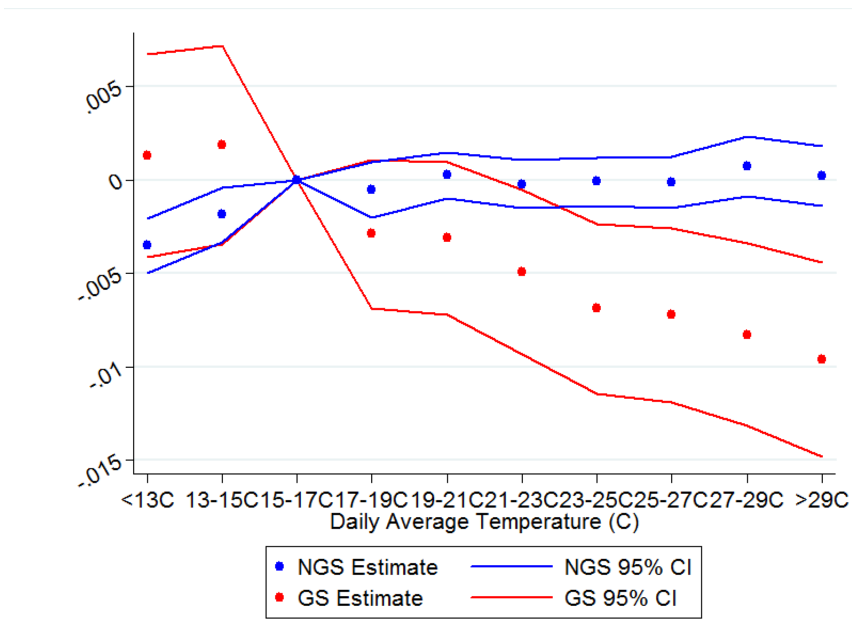


(b) Reading Scores

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

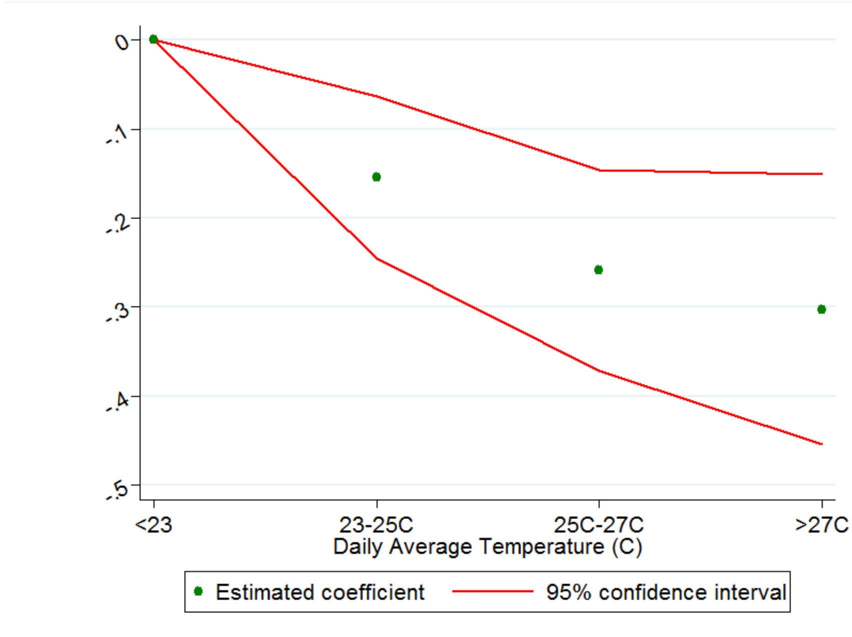


(a) Math Scores

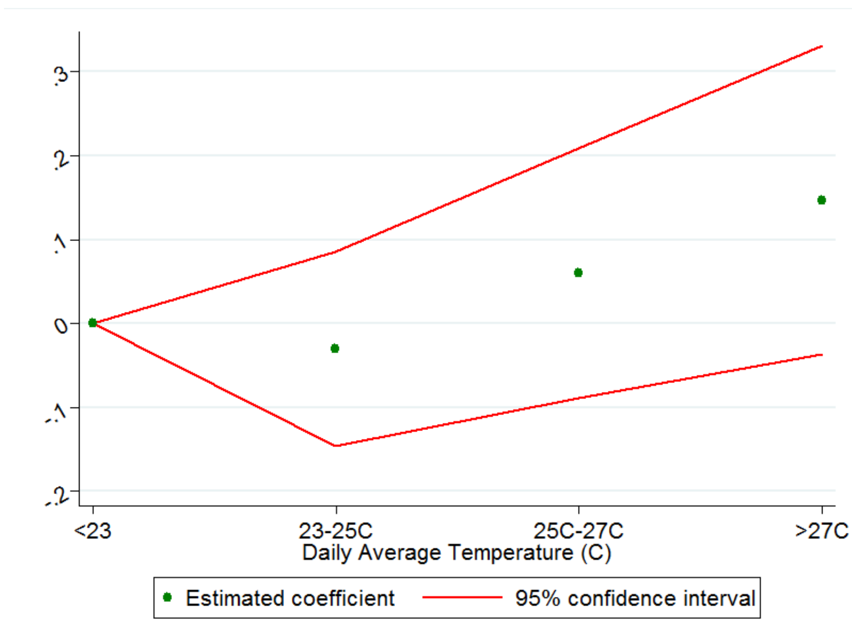


(b) Reading Scores

Figure 6: Growing vs. Non-Growing Season: Long Run Temperature and Test Scores



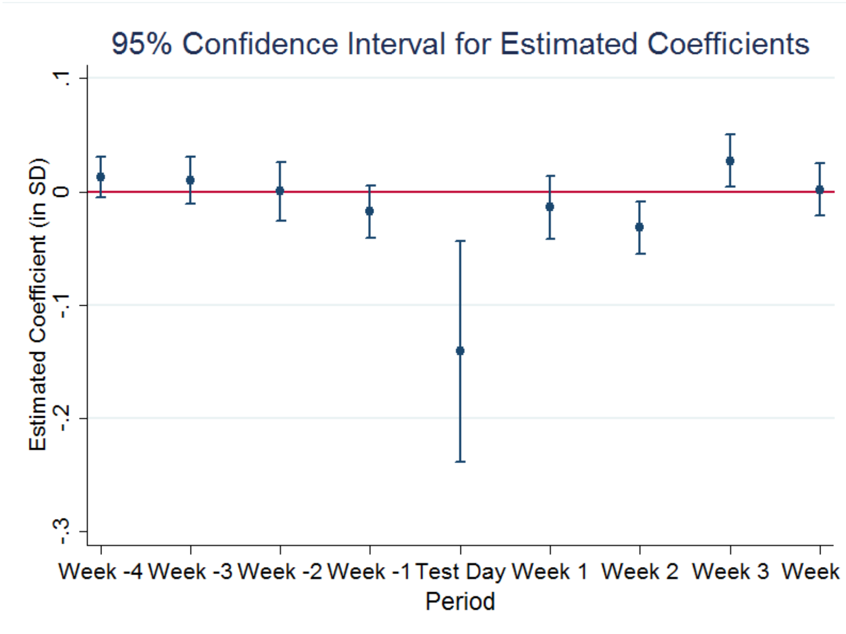
(a) Math Scores



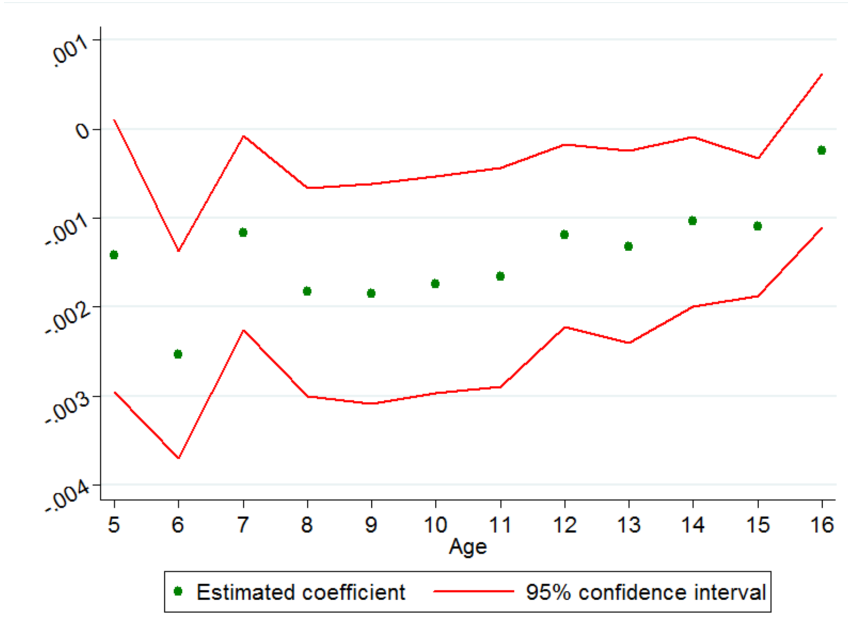
(b) Reading Scores

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

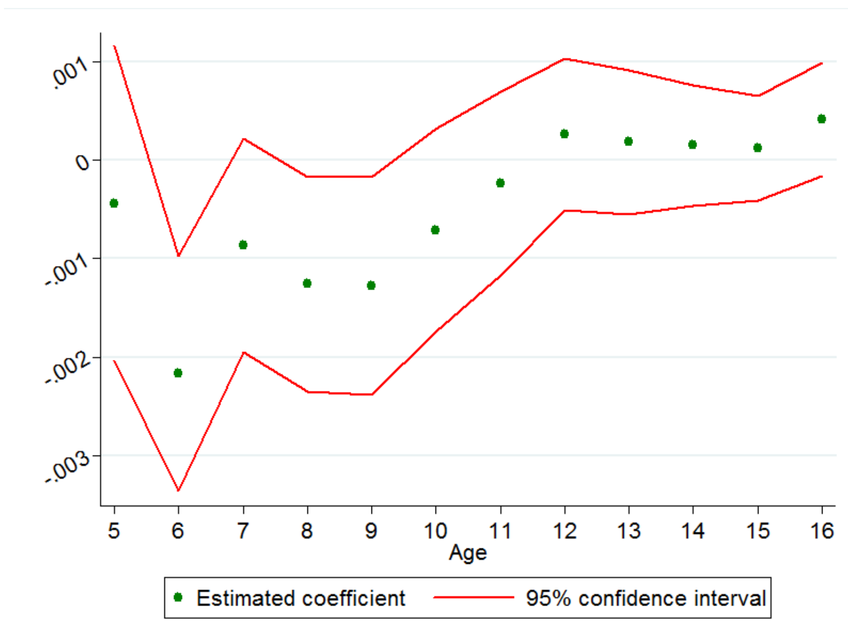
Figure 8: Leads and Lags in Weeks: Short Run Temperature and Math Scores



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

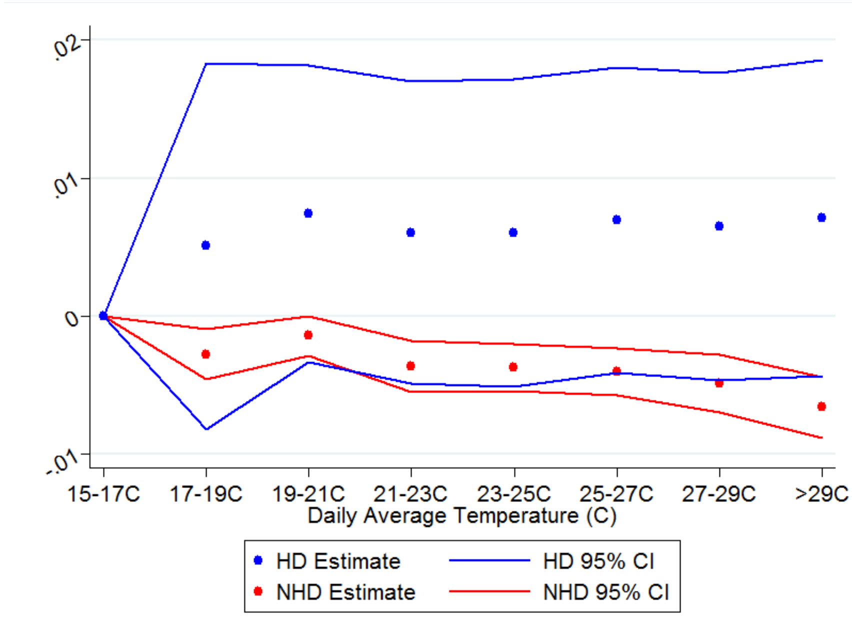


(a) Math Scores

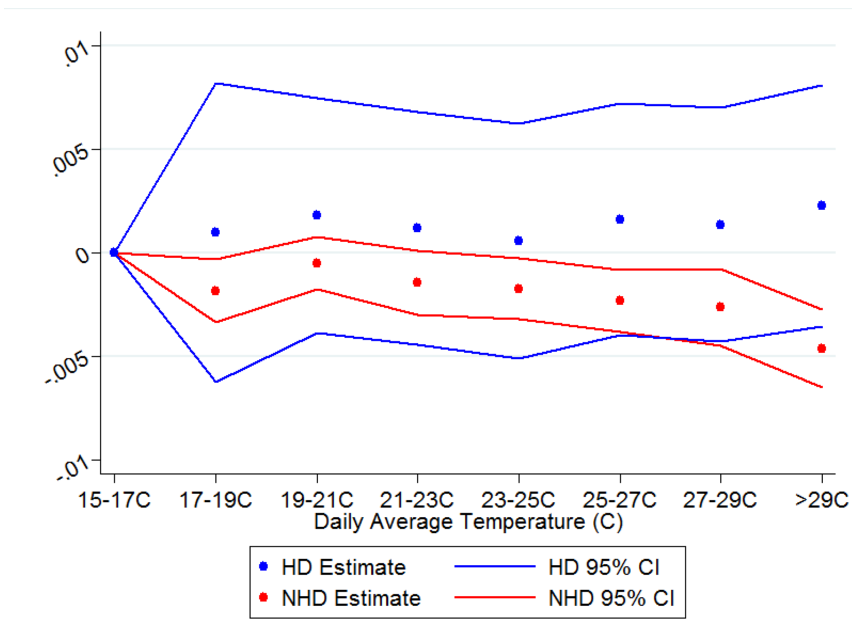


(b) Reading Scores

Figure 9: Effect of Long Run Temperature on Test Scores by age (ASER)

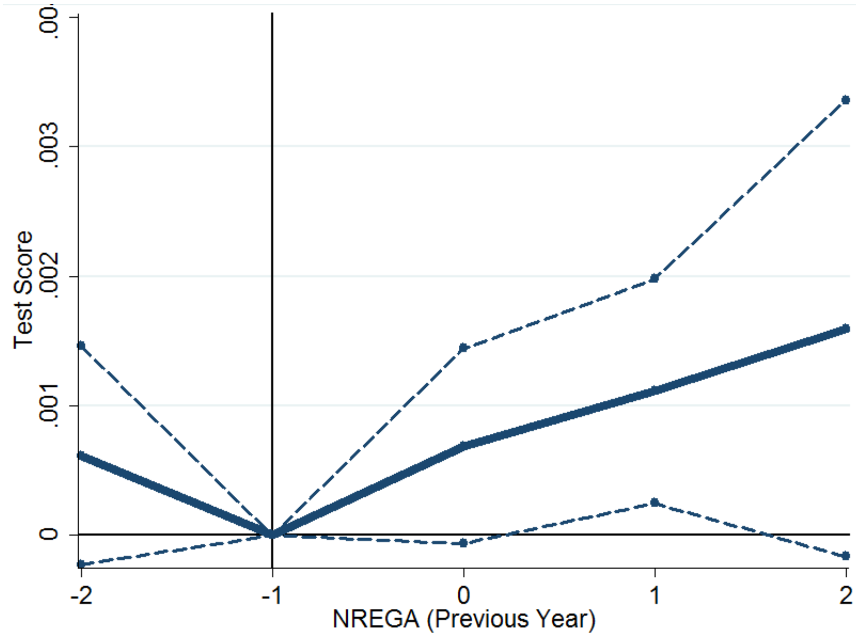


(a) Math Scores

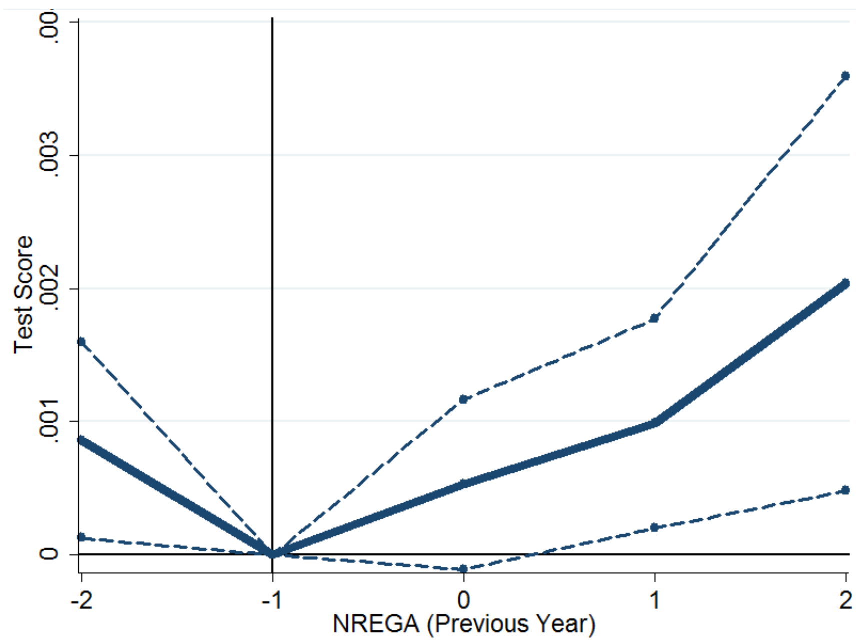


(b) Reading Scores

Figure 10: Hot vs. Not-so Hot Districts: Long Run Temperature and Test Scores



(a) Math Scores



(b) Reading Scores

Figure 11: Event Study: Long Run Temperature, NREGA and Test Scores

Tables

Table 1: Long Run Temperature and Test Scores (ASER)

	(1) Math Score (in SD) β / SE	(2) Math Score (in SD) β / SE	(3) Read Score (in SD) β / SE	(4) Read Score (in SD) β / SE
Days <15C	-0.0015**		-0.0012*	
	(0.0007)		(0.0006)	
Days >21C	-0.0021***		-0.0011**	
	(0.0005)		(0.0005)	
Days <13C		-0.0023**		-0.0020**
		(0.0009)		(0.0008)
Days 13-15C		-0.0013*		-0.0010
		(0.0008)		(0.0007)
Days 17-19C		-0.0005		-0.0006
		(0.0008)		(0.0007)
Days 19-21C		-0.0006		-0.0007
		(0.0009)		(0.0007)
Days 21-23C		-0.0026***		-0.0018**
		(0.0009)		(0.0008)
Days 23-25C		-0.0028***		-0.0018**
		(0.0010)		(0.0008)
Days 25-27C		-0.0030***		-0.0019**
		(0.0010)		(0.0009)
Days 27-29C		-0.0029**		-0.0017*
		(0.0011)		(0.0009)
Days >29C		-0.0030**		-0.0019*
		(0.0012)		(0.0010)
Observations	3446230	3446230	3446230	3446230
R^2	0.110	0.110	0.078	0.078

Notes: This table presents the impact of temperature in the previous year (captured via temperature bins) on test scores in the current year for children between the ages of 5-16 for 2006-2014. All specifications include district, year, and age fixed effects. We control for precipitation in all specifications. The sample only includes on-track children between the age 5-16. Standard errors are in parentheses, clustered by district.
*Significant at 10%.
**Significant at 5%.
***Significant at 1%.

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

	(1) Math Score (in SD)	(2) Math Score (in SD)	(3) Read Score (in SD)	(4) Read Score (in SD)
Days >21C	-0.004***		-0.004***	
	(0.001)		(0.001)	
Days 23-25C		-0.005***		0.003
		(0.001)		(0.002)
Days 25-27C		-0.003***		-0.007***
		(0.001)		(0.002)
Days >27C		-0.007***		-0.007***
		(0.001)		(0.002)
Observations	2604	2604	2541	2541
R^2	0.039	0.055	0.023	0.044

Notes: Includes individual, day of week, month and survey round fixed effects. We control for precipitation in all specifications. The sample includes only those children who were tested thrice in both Math and PPVT. Standard errors are in parentheses, clustered by district-week.
*Significant at 10%.
**Significant at 5%.
***Significant at 1%.

Table 3: Growing vs. Non-Growing Season: Long Run Temperature and Test Scores

	(1) Math Score (in SD) β / SE	(2) Read Score (in SD) β / SE
GS Days <15C	0.0022	0.0021
	(0.0023)	(0.0020)
GS Days >21C	-0.0035***	-0.0020**
	(0.0013)	(0.0010)
NGS Days <15C	-0.0031***	-0.0024***
	(0.0007)	(0.0006)
NGS Days >21C	-0.0013***	-0.0005
	(0.0005)	(0.0004)
Observations	3446230	3446230
R^2	0.088	0.065

Notes: This table presents the impact of temperature in the previous year (captured via temperature bins) on test scores in the current year for children between the ages of 5-16 for 2006-2014. All specifications include district, year, and age fixed effects. We control for precipitation in all specifications. The sample only includes on-track children between the age 5-16. Standard errors are in parentheses, clustered by district.
*Significant at 10%.
**Significant at 5%.
***Significant at 1%.

Table 4: Heat Resistant Crops: Long Run Temperature and Test Scores

	(1) Math Score (in SD) β / SE	(2) Read Score (in SD) β / SE
Days <15C	-0.0033***	-0.0024***
	(0.0007)	(0.0006)
Days >21C	-0.0022***	-0.0007
	(0.0006)	(0.0005)
Days >21C * HRC	0.0019***	0.0004
	(0.0007)	(0.0006)
Observations	3333541	3333541
R^2	0.086	0.065

Notes: This table presents the impact of temperature in the previous year (captured via temperature bins) on test scores in the current year for children between the ages of 5-16 for 2006-2014. All specifications include district, year, and age fixed effects. We control for precipitation in all specifications. The sample only includes on-track children between the age 5-16. Standard errors are in parentheses, clustered by district.
*Significant at 10%.
**Significant at 5%.
***Significant at 1%.

Table 5: Short Run Temperature and Test Scores

	(1) Math Score (in SD) β / SE	(2) Math Score (in SD) β / SE	(3) PPVT Score (in SD) β / SE	(4) PPVT Score (in SD) β / SE
Day >21C	-0.168***		-0.012	
	(0.046)		(0.058)	
Day 23-25C		-0.154***		-0.030
		(0.046)		(0.059)
Day 25-27C		-0.259***		0.060
		(0.057)		(0.076)
Day >27C		-0.303***		0.147
		(0.077)		(0.094)
Observations	2604	2604	2541	2541
R^2	0.023	0.027	0.009	0.012

Notes: Includes individual, day of week, month and survey round fixed effects. We control for precipitation in all specifications. The sample includes only those children who were tested thrice in both Math and PPVT. Standard errors are in parentheses, clustered by district-week.
*Significant at 10%.
**Significant at 5%.
***Significant at 1%.

Table 6: Event Study: Long Run Temperature, NREGA and Test Scores

	(1) Math Score (in SD) β / SE	(2) Read Score (in SD) β / SE
Time = -3	-0.1404	-0.1750**
	(0.0873)	(0.0759)
Time = -2	-0.0959*	-0.1282***
	(0.0504)	(0.0449)
Time = 0	-0.0381	0.0020
	(0.0476)	(0.0415)
Time = 1	-0.0234	0.0376
	(0.0850)	(0.0748)
Time = 2	0.0356	0.0808
	(0.1154)	(0.1021)
Days <13C	-0.0011	0.0000
	(0.0022)	(0.0019)
Days 13-15C	-0.0003	0.0003
	(0.0016)	(0.0015)
Days 17-19C	0.0011	-0.0000
	(0.0016)	(0.0015)
Days 19-21C	-0.0004	-0.0015
	(0.0017)	(0.0015)
Days 21-23C	-0.0034**	-0.0038**
	(0.0017)	(0.0016)
Days 23-25C	-0.0038**	-0.0039**
	(0.0017)	(0.0016)
Days 25-27C	-0.0038*	-0.0041**
	(0.0019)	(0.0017)
Days 27-29C	-0.0043**	-0.0044**
	(0.0020)	(0.0018)
Days >29C	-0.0052**	-0.0052***
	(0.0022)	(0.0019)
Time = -3 * Days >29C	0.0002	0.0000
	(0.0005)	(0.0004)
Time = -2 * Days >29C	0.0006	0.0009**
	(0.0004)	(0.0004)
Time = 0 * Days >29C	0.0007*	0.0005
	(0.0004)	(0.0003)
Time = 1 * Days >29C	0.0011**	0.0010**
	(0.0004)	(0.0004)
Time = 2 * Days >29C	0.0016*	0.0020**
	(0.0009)	(0.0008)
Observations	1417422	1417422
R^2	0.122	0.094

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

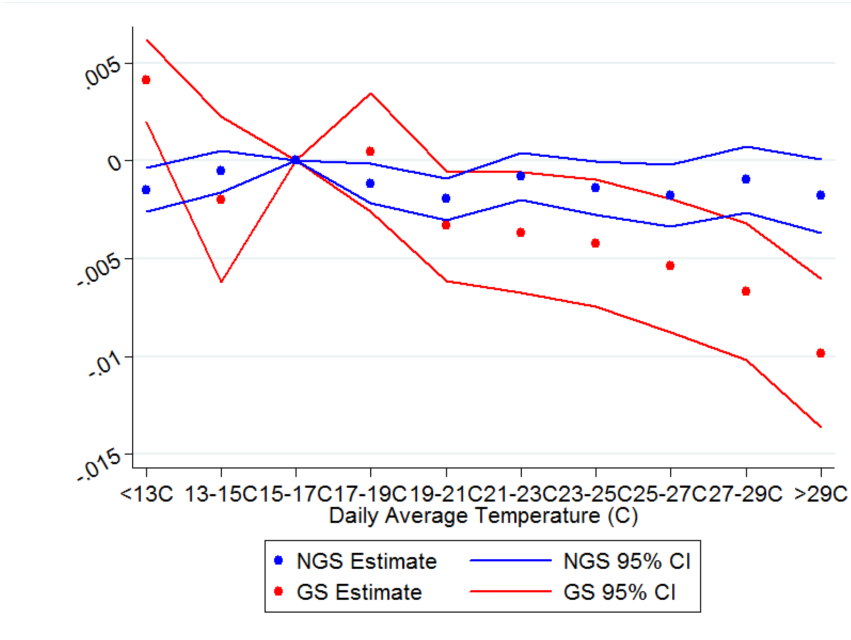
A Appendix

A.1 Temperatures and Agricultural Yields

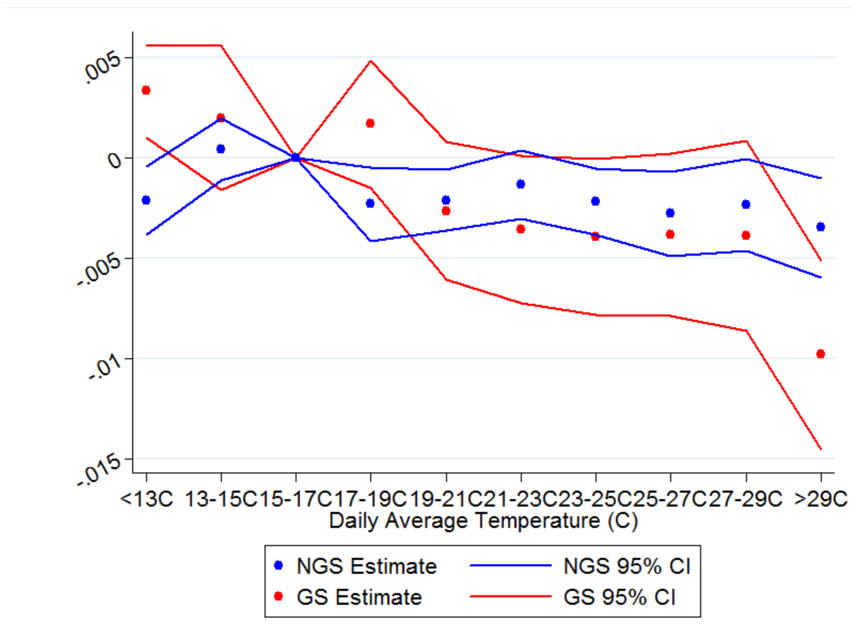
Table A.1: Current Year Growing Season Temperature and Agriculture Yields

	(1) Log Yield: Top 6 Crops β / SE	(2) Log Yield: Top 5 Monsoon Crops β / SE
GS Days <13C	0.0041***	0.0033***
	(0.0011)	(0.0012)
GS Days 13-15C	-0.0020	0.0020
	(0.0021)	(0.0018)
GS Days 17-19C	0.0004	0.0017
	(0.0016)	(0.0016)
GS Days 19-21C	-0.0033**	-0.0026
	(0.0014)	(0.0017)
GS Days 21-23C	-0.0037**	-0.0036*
	(0.0016)	(0.0019)
GS Days 23-25C	-0.0042**	-0.0039**
	(0.0016)	(0.0020)
GS Days 25-27C	-0.0054***	-0.0038*
	(0.0017)	(0.0021)
GS Days 27-29C	-0.0067***	-0.0039
	(0.0018)	(0.0024)
GS Days >29C	-0.0098***	-0.0098***
	(0.0019)	(0.0024)
NGS Days <13C	-0.0015**	-0.0021**
	(0.0006)	(0.0009)
NGS Days 13-15C	-0.0005	0.0004
	(0.0005)	(0.0008)
NGS Days 17-19C	-0.0012**	-0.0023**
	(0.0005)	(0.0009)
NGS Days 19-21C	-0.0020***	-0.0021***
	(0.0006)	(0.0008)
NGS Days 21-23C	-0.0008	-0.0013
	(0.0006)	(0.0009)
NGS Days 23-25C	-0.0014**	-0.0022**
	(0.0007)	(0.0008)
NGS Days 25-27C	-0.0018**	-0.0028***
	(0.0008)	(0.0011)
NGS Days 27-29C	-0.0010	-0.0024**
	(0.0009)	(0.0012)
NGS Days >29C	-0.0018*	-0.0035***
	(0.0010)	(0.0013)
Observations	9479	9475
R^2	0.886	0.879

Notes: This table presents the impact of temperature in the current growing season (captured via temperature bins) on agriculture yields in the current year for 1980-2011. All specifications include district and year fixed effects. We control for precipitation in all specifications. Standard errors are in parentheses, clustered by district.
*Significant at 10%.
**Significant at 5%.
***Significant at 1%.



(a) 6 major crops

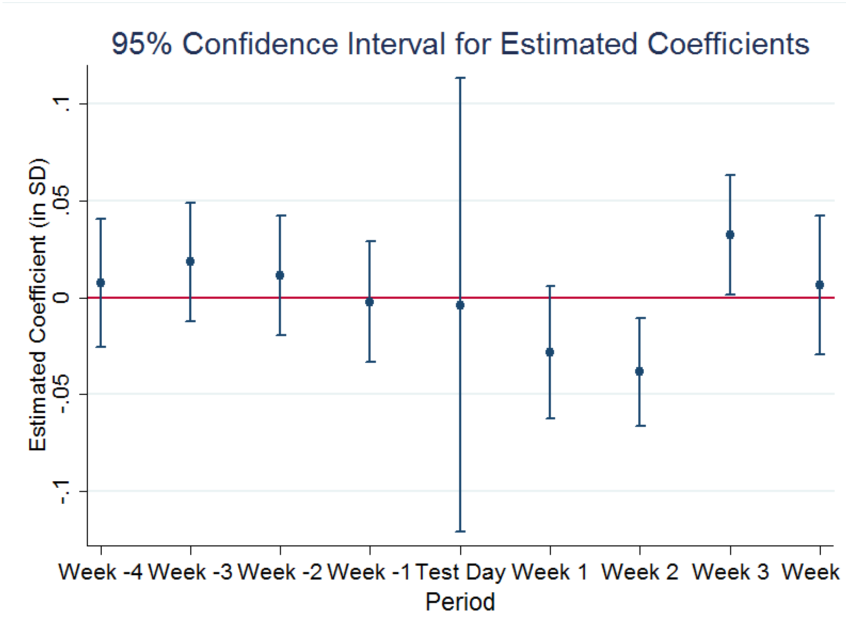


(b) 5 major monsoon crops

Figure A.6: Growing vs. Non-Growing Season: Current Year Temperature and Yields

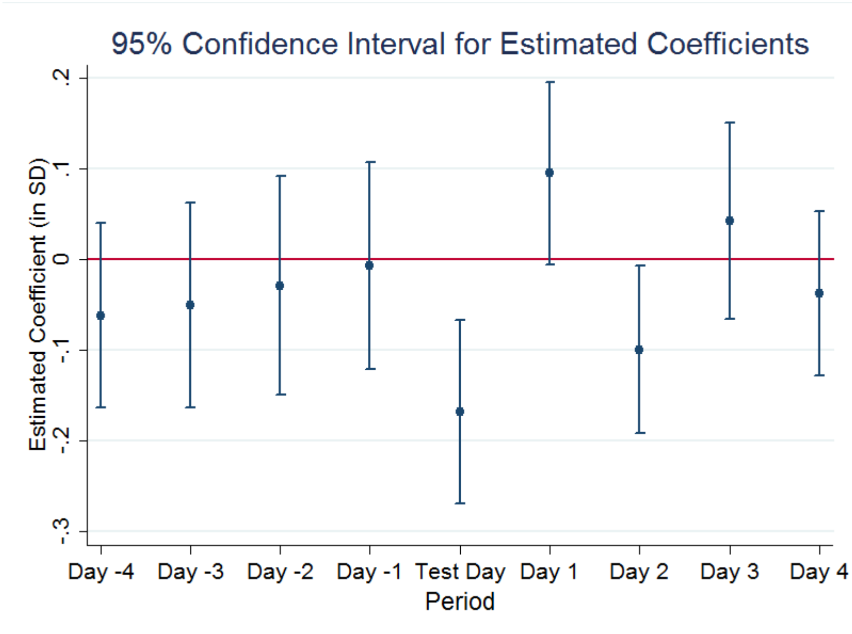
A.2 No Persistence in Short Run Physiological Effects

Figure A.6: Leads and Lags in Weeks: Short Run Temperature and PPVT Scores



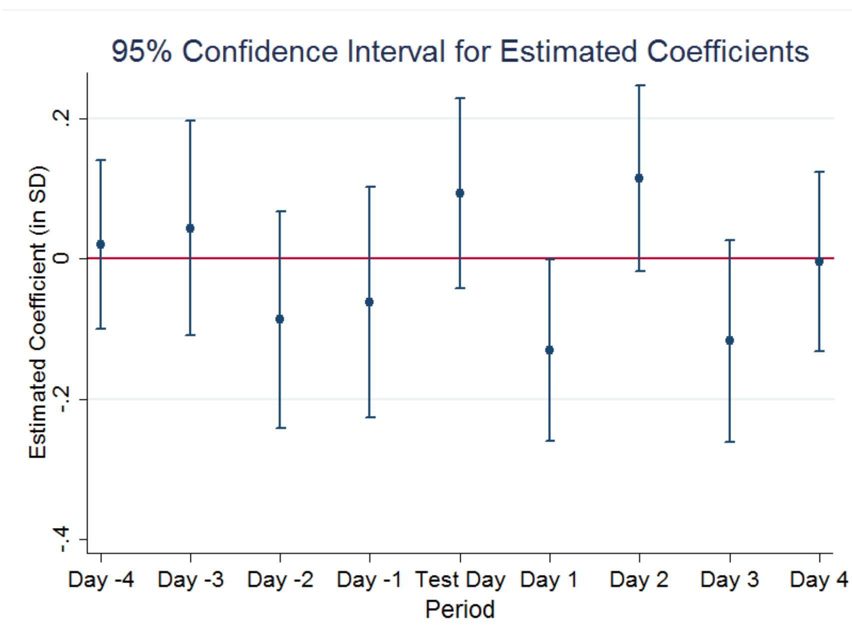
Notes: The figure present the impact of short-run temperature from 4 weeks before test day to 4 weeks after the test. Temperature is captured as the number of days when the temperature is >23C during a week for '$No.$ Week', and if temperature is $>$ 23 on the day of the test for 'Test Day'. Includes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

Figure A.6: Leads and Lags in Days: Short Run Temperature and Math Scores



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

Figure A.6: Leads and Lags in Days: Short Run Temperature and PPVT Scores



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

A.2.1 Test Times and Timing of Test

Table A.2: Short Run Temperature and Test Duration

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

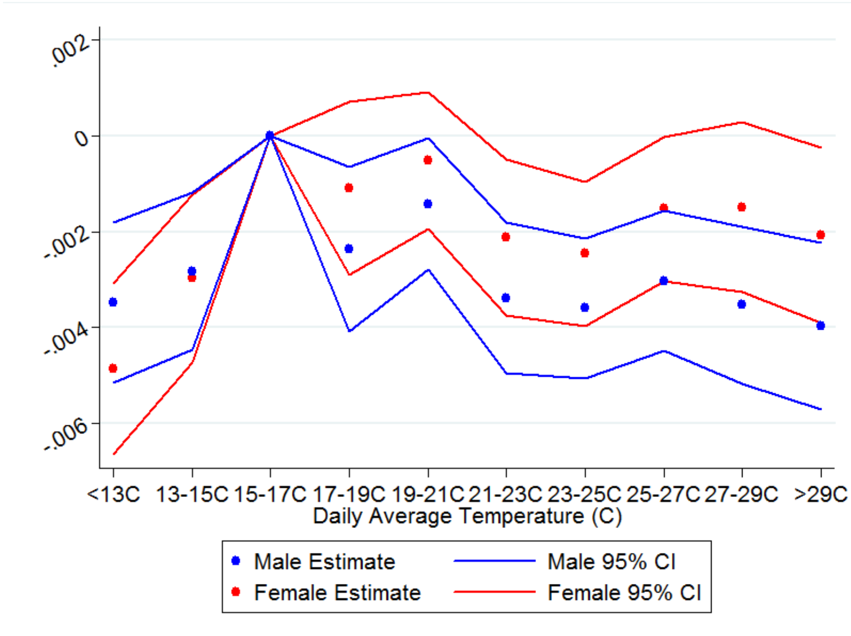
Notes: Includes individual, day of week, month and survey round fixed effects. We control for precipitation in all specifications. The sample includes only those children who were tested thrice in both Math and PPVT. Standard errors are in parentheses, clustered by district-week.
*Significant at 10%.
**Significant at 5%.
***Significant at 1%.

Table A.3: Short Run Temperature and Test Timing

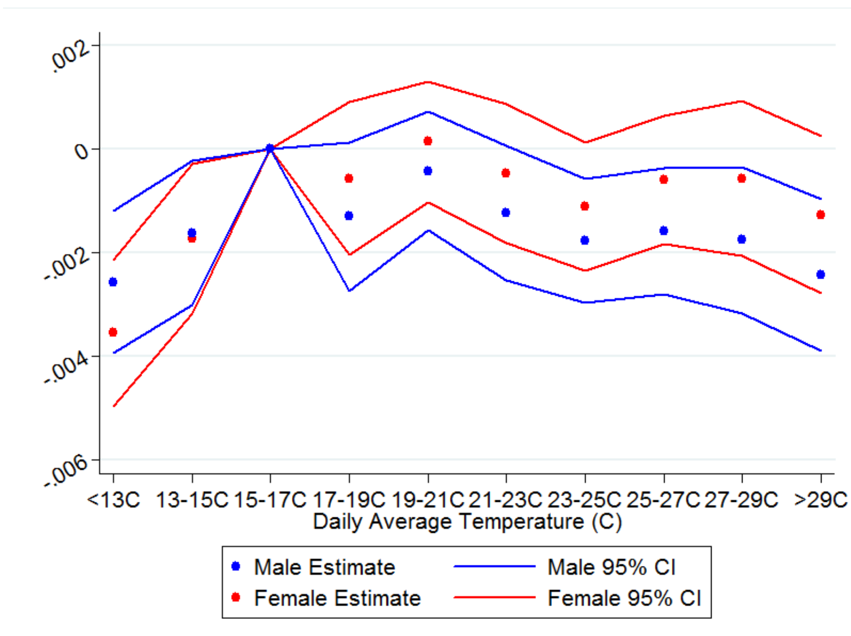
	(1) Math Start Time β / SE	(2) PPVT Start Time β / SE
Day 23-25C	0.187	0.165
	(0.372)	(0.213)
Day 25-27C	0.211	0.235
	(0.381)	(0.296)
Day >27C	0.449	0.288
	(0.588)	(0.348)
Observations	2604	2541
R^2	0.595	0.839

Notes: Includes individual, day of week, month and survey round fixed effects. We control for precipitation in all specifications. The sample includes only those children who were tested thrice in both Math and PPVT. Standard errors are in parentheses, clustered by district-week.
*Significant at 10%.
**Significant at 5%.
***Significant at 1%.

A.3 Heterogeneity - Gender



(a) Math Scores



(b) Reading Scores

Figure A.6: Female vs. Male: Long Run Temperature and Reading Scores