# Heat and Learning in Elementary and Middle School

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**Abstract**

Changing weather patterns and extreme events are not the only outcomes of global climatic change. We investigate the impact of changing weather conditions on human capital development by studying achievement on standardized tests in Math and English/Language Arts for students in grades 3-8. Here we show, that increasing average temperature levels and particularly hot days reduce student learning and achievement. We find that achievement consistently decreases as temperatures increase, and that each additional day above 100F degrees decreases student achievement. This study confirms many findings in the received literature on global climate change and human capital acquisition and productivity.

JEL Classification Codes: H23, I21, J24, Q51, R11

Keywords: Climate Change, Student Achievement, Human Capital

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# 1 Introduction and Background

Despite more than a century of scientific evidence discussing the effect of accumulating greenhouse gasses on temperature (Foote, 1856), policies intended to limit these emissions have been slow to pass or are, at least in some countries, a political non-starter. Regardless of the political appetite to limit greenhouse gas accumulation, the effects of global climate change have already taken shape. These impacts can be seen in the heightened severity of droughts, hurricanes, and (of course) extreme temperatures. Beyond changing meteorological conditions, the effects of global climate change stand to impact human interactions and development in fundamental ways. These effects are sometimes extreme, for instance the lost economic value of one's home being destroyed in a fire or hurricane, and these effects are sometimes a little more banal, for instance difficulty paying attention or motivating one's self on a hot day. Regardless of the emotions drawn when discussing these differing impacts, they matter economically. And much like the accumulation of emissions from individual decisions have global consequences, the accumulation of climate-driven impacts stand to have long-lasting and non-trivial economic impacts.

There is a small but growing literature on the impacts of climatic change and "human capital" that has established a causal link between hot days or climbing temperatures and negative learning or productivity outcomes. We contribute to this literature by studying achievement on standardized tests for young students from 3rd through 8th grade for the entire United States. Our paper is the first to study this young of an age group without being limited geographically. Using nationally-comparable data on achievement in math and english/language arts at the school district and grade level, we determine how changes in average temperatures and weather extrema during school days impact learning. Figure 1 provides a first highlight of the relationship between hot weather and student achievement. The top panel shows how the standardized achievement statistic was distributed in 2013. The statistic is normalized such that schools that perform above average have a positive value (dark red), and schools that perform below average have a negative value (light yellow). Below that, we see the same year of data but now the amount of days that were above 90F are plotted with more hot days showing in dark red and areas with few or no 90F days are in a pale yellow. Although anecdotal at this point, the figure points to an inverse relationship between average temperatures and achievement.

In this paper, we find consistent evidence that rising average temperatures harm student learning. Using data collected from more than 58,000 weather stations we link observed average temperatures and weather extrema to school-district level data on academic achievement on math and english/language arts tests from third through eighth grade over a period of seven years. Using panel data methods, we are able to identify the effect of exogenous variation in temperature changes on student achievement while also controlling for demographic differences. We find that each 1F increase in average temperatures harms student performance on standardized tests, and further find that days over 100F are harmful to student learning. These results are robust to multiple specifications that vary in demographic controls, the subject tested, as well as the inclusion or exclusion of key parameters. We couple these findings with a recent report by the Intergovernmental Panel on Climate Change which described the likelihood of average temperature increases of 1.5C (IPCC (2018)). Our estimates indicate that if warming of this degree were to occur, mean student achievement would decrease by about 10.5%[1]

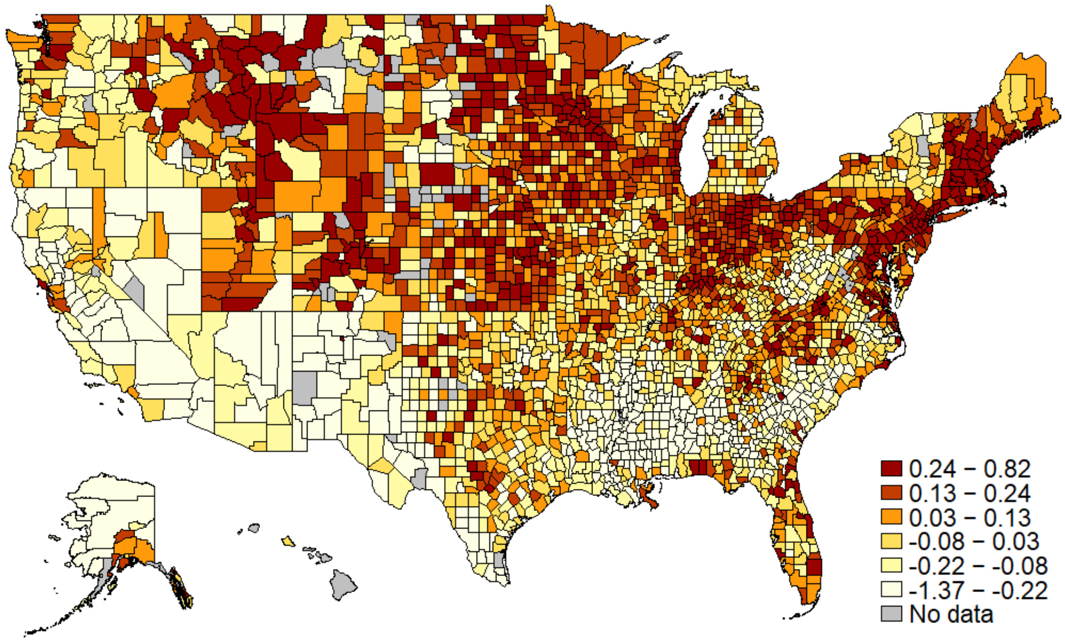
The balance of this paper continues accordingly: section two describes prior research on climate change and human capital and productivity; section three discusses the data sources and modeling strategy; section four presents our primary results; section five provides a robustness exercise that includes modeling temperatures non-linearly; and section six concludes.

## 2 Climate Change and Human Capital

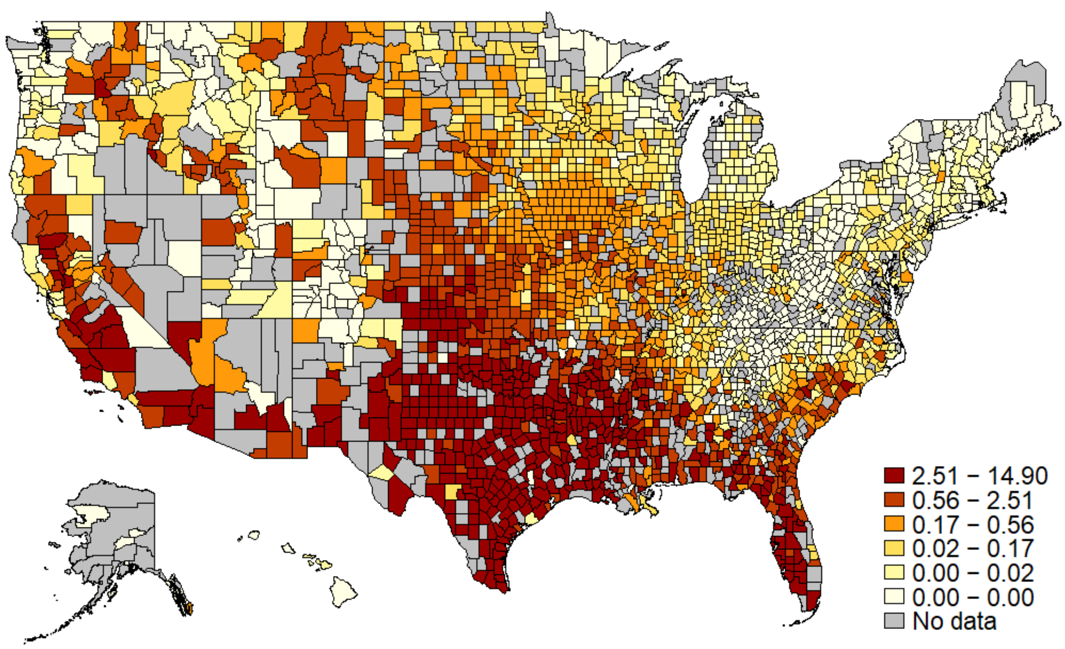
Brain imaging and psychometric testing have shown that heat and thermal stress cause heightened brain stress to fulfill cognitive processes like attention, memory, verbal learning, information processing and concentration (Hocking et al. (2001)). Without technology to directly detect how thermal stress inhibits brain function, economists have studied how thermal stress manifests in our daily lives by linking temperature anomalies to changes in performance and human capital development. Zivin et al. (2015) study the impact of short-run weather and long-run achievement using data from the National Longitudinal Survey of Youth (NLSY) and meteorological conditions on the

[1]Calculation explained below.

Figure 1: Relationship between Test Scores and Hot Days




(a) Average Test Scores in 2013




(b) Amount of Days above 90F in 2013

day of the assessment. They find that math scores decline at temperatures above 21C. Park (n.d.) also finds a negative impact of hot days on learning (and achievement) using data on students in NYC public schools that take exams that are needed to graduate in June. Specifically, Park (n.d.) finds that hot temperatures during an exam result in reduced performance. They show that taking an exam on a 90-degree day reduces performance by 14 percent of a standard deviation, which also impacts a students chance to graduate by 10.9%. Garg et al. (n.d.) show that 10 or more days in a year with an average daily temperature above 29C lowered both math and reading scores. In a study closely related to the methodology used here, Goodman et al. (2018) provides causal evidence of both the impact of heat on student learning, and the mitigating effects of air conditioning using a nationally representative sample of high school PSAT takers. They find that 1-degree higher temperature in the previous school year reduces learning by 1% of a years worth of learning. They deduce that heat reduces academic achievement by reducing the productivity of instructional time. To show this, the authors use a unique data set on the quality of air conditioning in schools and show that air conditioning appears to offset nearly all of the damages of heat exposure.

Rising average temperatures have also been linked to lower productivity and income growth. Heal and Park (2013) show that years with warmer than average temperatures are associated with lower output per-capita in hot climates, and higher output per-capita for countries in cold ones. The authors find an effect size of approximately 3%-4% per degree. Dell et al. (2009) show that a negative relationship exists between temperature and income, even within regions and states of a country, and that a 1-degree Celsius rise in temperature is associated with a 1.2-1.9% decline in municipal per-capita income. Deryugina and Hsiang (2014) go beyond linking hot temperatures and income and find temperature ranges that maximize income. They find that total personal income per capita is highest when the temperature is between 9-15C (48.2-59F). They further find that a day with an average daily temperature of 29C decreases productivity by .065% relative to a day with an average daily temperature of 15C, which means that a 29C day is 23.6% less productive than an average day. The same relative change lowers annual earnings by 0.11%.

# 3 Modeling Strategy

Prior authors have established a causal link between heat, heat exposure, and human capital and productivity. We aim to examine this link for young students in the United States, which would be a new population (at the national level) to study this effect of global climatic change. We are able to identify the causal impact of heat on learning because there is exogenous variation in weather events across space and time, and this variation even impacts cohorts of students within the same school district at different periods in their academic careers. Using panel data methods we are able to account for fixed factors that impact student learning over time that are related to place (access to parks, air conditioning availability, proximity to quality grocery stores, or other neighborhood-level effects) and idiosyncratic differences in state governance that are uncorrelated with warm or cool temperatures (e.g. state funding formulas that dictate funding for education). The two data sets we draw from are described separately below. Figure 1 visually shows the connection we investigate, and summary statistics for all model parameters are included in Table 1.

## 3.1 Weather Data

We use information on daily temperature averages from the National Oceanic and Atmospheric Administration's (NOAA) global monitoring system. This data is collected by 58,578 individual stations in the United States which yield over 149 million daily observations for the time sample studied here.[2] To construct the geographic school district-level estimates, we take the median temperature reading from all stations within a 20 km radial distance from each county centroid, and link each school district to the county it is located within. We also restrict temperature anomalies to those that would impact in-class learning. To do this we only use observations on Monday-Friday during school months as in Goodman et al. (2018). Finally, for each academic school year (and each school) we build variables that will capture the effect of heat on student learning at both the extensive and intensive margins. First, we calculate the average temperature observed which captures changes along the extensive margin, and then we calculate the amount of days that the temperature fell within a temperature range, above 100F, above 90F (but below

[2]This data includes information on the daily temperature average, minimum, and maximum, and any precipitation.

100F), above 80F (but below 90F), and so on. These variables capture changes along the intensive margin which is similar to the method used in Goodman et al. (2018).

### 3.2 Education Data

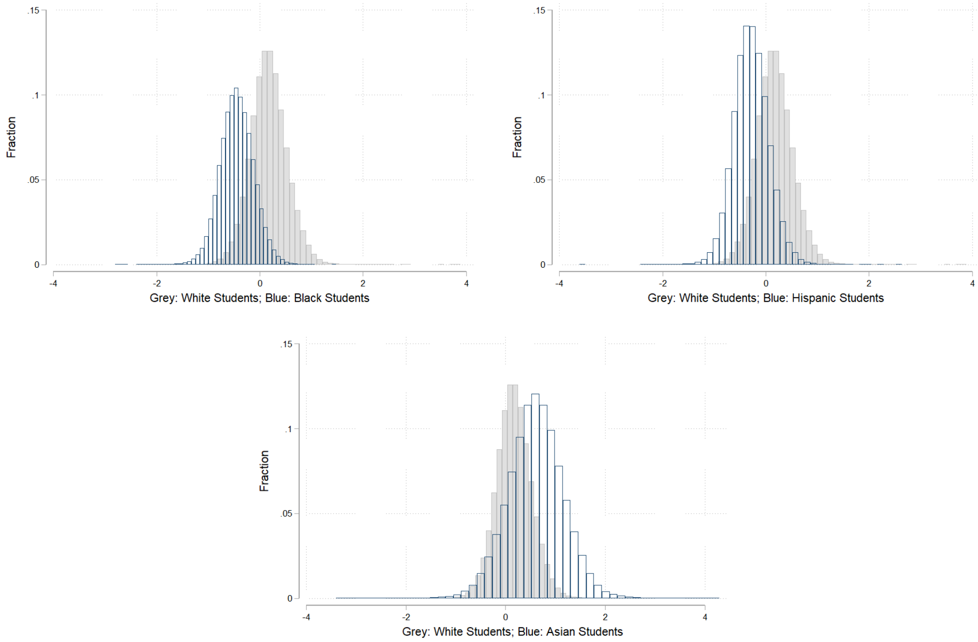
To gauge student learning and achievement we use data from the Stanford Educational Data Archive (SEDA) that has been constructed to compare proficiency outcomes nationally. These data include assessment outcomes from the 2008-09 school year to the 2014-15 school year for students in 3rd grade through 8th grade for both English/Language Arts and Math tests.

Under federal legislation, each state is required to test every student in grades 3-8 and in one high school grade in Math and English/Language Arts (ELA) each year.[3] Each state is allowed to administer the test of their choice that measures student achievement relative to the state's standards for each subject. States also determine standards regarding the level of performance considered "proficient" for each grade and subject. The SEDA (2.1) achievement data is constructed using state-recorded counts of students deemed proficient which are reported to the U.S. Department of Education. To nationally standardize achievement and proficiency, the SEDA data is constructed such that the estimated means and standard deviations at the school-level summarize the achievement represented by the observed counts in the raw (student-level) data. To do this, ordered probit models are fit at a 'geographic school district' or GSD-level.[4] The process is documented in Ho and Reardon (2012), Reardon, Shear, Castellano and Ho (2017), and Reardon et al. (2018). The scale used for this paper is the 'cohort scale' which is standardized by dividing by the national grade-subject-specific standard deviation for a given cohort in the data (for example, students in 4th grade in 2009 and 8th grade in 2013). Ho and Reardon (2012) note that this metric can be interpreted as an effect size which can be used to describe change over time in test scores.

A perennial issue that we must account for in our model is the 'achievement gap' among white and minority students. White students have historically performed better on standardized tests relative to black students (Vanneman et al. (2009)) and Hispanic students (Hemphill and Vanneman

[3]The law requires measuring achievement in one high school year, but the SEDA data excludes the high school year that is tested because of inconsistencies in when the tests are administered.

[4]Most traditional public schools have the same geographic and administrative district. There are a number of other types of schools (e.g. charter schools, virtual schools) that belong to an administrative district but do not have a geographic boundary. The SEDA data assigns each such school to a GSD.




(2011)), and this gap is persistent over time. While there is a large literature devoted to discussing and determining the causes of these gaps, one possible explanation that is related to our study is that of instructional time. Lavy (2015) shows that each additional hour of instructional time yields a 0.15 standard deviation improvement in student achievement. Given the received literature on the mitigating effects of air conditioning (Goodman et al. (2018), Garg et al. (n.d.), Laurent et al. (2018)), part of the achievement gap may be due to climate adaptation and school funding.

Much like the findings of prior authors, we recognize an achievement gap in the SEDA data, which is discussed in greater detail in Reardon, Kalogrides and Shores (2017). Figure 2 shows the histogram of student achievement outcomes for black, Hispanic and Asian students (blue bars) compared to white students (grey bars).[5] We account for this achievement gap by including the percentage representation of black, white, Hispanic, and Asian students for each grade in each school district as a regressor. Our dependent variable is the average score for each grade in each school district in a year, so we do this to account account for the effect that race and ethnicity may play in average scores that are independent of the observed weather.

[5]The SEDA data is normalized such that a score of 0 indicates performance on par with the rest of the cohort. Lower scores indicate lower proficiency and achievement, and vice versa.

Table 1: Summary Statistics

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Average Proficiency | 825,814 | 0.04522 | 0.400055 | -3.18686 | 3.80456 |
| Median Income | 799,894 | 62.02792 | 26.43517 | 12.4995 | 228.5294 |
| Average Temp. | 701,624 | 65.49427 | 8.901525 | 24.34941 | 101.1936 |
| Days over 100 | 701,624 | 1.669123 | 5.21492 | 0 | 68 |
| Days over 90 | 701,624 | 9.019023 | 11.14708 | 0 | 94 |
| Days over 80 | 701,624 | 30.13792 | 15.00081 | 0 | 189 |
| Days over 70 | 701,624 | 32.84046 | 11.36682 | 0 | 176 |
| Days Under 60 | 701,624 | 89.89703 | 42.82277 | 0 | 216 |
| % Black | 825,461 | 0.085485 | 0.173608 | 0 | 1 |
| % White | 825,461 | 0.740867 | 0.275585 | 0 | 1 |
| % Hispanic | 825,461 | 0.127164 | 0.20034 | 0 | 1 |
| % Asian | 825,461 | 0.021662 | 0.049384 | 0 | 0.8 |

Table 1: Cross-sectional unit of observation is a grade-level in a school district (3rd-8th), over time from 2009-2015. Median income is in $1,000 units.

### 3.3 Empirical Model

The SEDA data includes information on average achievement within a school district for each grade (3rd-8th) from 2009 to 2015. Thus, there are repeat observations for (mostly) the same group of students as they progress over time and are witness to differing weather and temperatures while still being impacted by school-district (neighborhood) fixed effects. Our identification is achieved by controlling for grade, state, school district, and year fixed effects in addition to a grade-by-year linear trend. These variables capture unobserved heterogeneity that include differences in how achievement is measured by grade, or state-to-state, while exogenous temperature anomalies vary over space and time within geographic boundaries. Our main estimating equations are presented below, where the dependent variable, $Score_{igsy}$, is the average score in school district $i$, for grade $g$, on subject $s$, in year $y$.

$$\begin{aligned} Score_{igsy} &= \beta_0 + \beta_1 AvgTemp_{iy} + \beta_2 MedianIncome_{iy} \\ &+ \sum_{i=0}^{n} \pi_{0+i} RacePercent_{igy} + \mu_d + \phi_s + \gamma_g + \omega_y + \xi_{gy} + \varepsilon_{igsy} \end{aligned} \tag{1}$$

$$Score_{igsy} = \beta_0 + \beta_1 Over100_{iy} + \beta_2 Over90_{iy} + \beta_3 Over80_{iy} + \beta_4 Over70_{iy} + \beta_5 Under60_{iy} \quad (2)$$
$$+\beta_6 MedianIncome_{iy} + \sum_{i=0}^{n} \pi_{0+i} RacePercent_{igy} + \mu_d + \phi_s + \gamma_g + \omega_y + \xi_{gy} + \varepsilon_{igsy}$$

The primary variables of interest are the count variables $Over100_{iy}$ (and others) which measure the impact that days above a threshold temperature have on performance (i.e. the amount of days within a temperature bin)[6] For example, the variable $Over90_{iy}$ is the amount of school days in that year that were above 90F but below 100F.[7] Additionally, we separately estimate models that use the average temperature, $AvgTemp_{iy}$, to measure the effect of average temperatures on performance. In a later robustness exercise we include the square (and cube) of this variable.

While we do not explore the impetus for lower or higher average grades by ethnicity, we account for the percentage of white, black, Hispanic, and Asian students in each grade so that our results are not biased due to spatial sorting of these students that may coincide with hotter or cooler areas. We also account for the median income in a school area, $MedianIncome_{iy}$. The variables, $\mu_d$, $\phi_s$ $\gamma_g$, $\omega_y$ and $\xi_{gy}$ denote various fixed effects that we toggle for robustness.[8] We are not able to control for specific adaptation measures like air conditioning as in Goodman et al. (2018) or Laurent et al. (2018). Thus, we include school district fixed effects ($\mu_d$) in each of the model specifications presented below to proxy for these adaptation measures. All standard errors are clustered by geographic school district (GSD).

# 4 Results

Our primary results are presented in tables 2 and 3 with average temperatures serving as our primary independent variable in the former, and days in temperature bins in the latter. We begin by exploring the simple effect of temperature on scores while only controlling for school district fixed effects (specification 1). Here we see that each 1f degree increase in average temperatures over a year

[6] Before reducing the temperature observations to school months and days we check that these variables and the excluded group add up to 365.
[7] Our excluded group are days when temperatures are between 60F and 70F as in Goodman et al. (2018).
[8] In order: district, subject, grade, and year fixed effects with grade-year linear trend

Table 2. Average Temperature

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Avg. Temperature | -0.00184*** | -0.00125*** | -0.00343*** | -0.00070*** | -0.00167*** |
| | (0.00027) | (0.00019) | (0.00049) | (0.00016) | (0.00039) |
| Median Income | | 0.00938*** | 0.00927*** | 0.00752*** | 0.00747*** |
| | | (0.00064) | (0.00063) | (0.00055) | (0.00053) |
| % Black | | | | -0.09494 | -0.04996 |
| | | | | (0.07666) | (0.07847) |
| % White | | | | 0.47343*** | 0.46248*** |
| | | | | (0.06213) | (0.06586) |
| % Hispanic | | | | 0.40071*** | 0.16113** |
| | | | | (0.06907) | (0.07965) |
| % Asian | | | | 0.96528*** | 0.82522*** |
| | | | | (0.11546) | (0.11750) |
| School District FE | Y | Y | Y | Y | Y |
| Subject FE | Y | Y | Y | Y | Y |
| Grade FE | N | N | Y | N | Y |
| Year FE | N | N | Y | N | Y |
| Grade · Year | N | N | Y | N | Y |
| $R^2$ | 0.691 | 0.704 | 0.713 | 0.707 | 0.716 |
| N | 695320 | 673495 | 673495 | 673495 | 673495 |

Robust standard errors clustered at the school-district level. ***, ** indicate statistical significance at the 1% and 5% level, respectively.

decreases student achievement. When we control for the median income in the school district area (specification 2) the effect of a 1F degree change becomes more muted, however it remains negative and statistically significant. Once we control for grade, year, and state fixed effects (specification 3), the effect of temperature changes on student achievement actually strengthens compared to when there are no other fixed effects are in the model. Specifications 4 and 5 both include controls for the racial makeup of the school while the additional controls are toggled. In these models we see that the impact of an additional 1F degree in average school day temperatures is negative and statistically significant at the 1% level. Our preferred model specification is specification (5), this is the coefficient we use in our discussion section that follows. We note that the estimated effects for each race conforms with prior authors' research on achievement gaps, as well as the raw data plotted in comparison with one another (Figure 2). We note, too, that the marginal effect of an increase in median income is lower when race controls are included. We expect that when race is not included as a control variable the estimated effect of a change in median income is biased upwards because white and Asian students score better than black or Hispanic students on average, and that failing to include these measures picks up an endogenous relationship between the median income of an area and a school's racial composition. The effect of an additional day above 100F remains negative and statistically significant across model specifications. The scaling of coefficients is difficult to interpret as they measure the change in a variable that has been standardized. We thus compare the estimated effect of an additional 1F on average achievement.[9] We find that an area with temperatures that are 1F hotter on average will witness a decrease of 0.00167, or a 3.76% reduction in the mean[10].

We also examine effects that may be happening on the intensive margin by measuring the effect that additional days above threshold temperatures have on student achievement and find that additional hot days negatively impact student learning. These estimates are shown in table 3. Specifically, we find that additional days above 100F harm student learning. This finding is statistically significant in all models. Here we see that each additional day above 100F decreases average student achievement, a 2.3% reduction in the mean. We also find that more days below 60F

[9] The mean level of achievement is .0452

[10] This effect size is 0.417% of a standard deviation

Table 3. Temperature Bins

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Over 100 | -0.00209*** | -0.00178*** | -0.00126*** | -0.00170*** | -0.00105*** |
| | (0.00021) | (0.00018) | (0.00019) | (0.00017) | (0.00019) |
| Over 90 | -0.00153*** | -0.00085*** | -0.00067*** | -0.00037*** | -0.00013 |
| | (0.00021) | (0.00016) | (0.00017) | (0.00013) | (0.00015) |
| Over 80 | -0.00052*** | -0.00025*** | -0.00028*** | -0.00004 | -0.00007 |
| | (0.00011) | (0.00009) | (0.00009) | (0.00008) | (0.00009) |
| Over 70 | -0.00062*** | -0.00053*** | -0.00016 | -0.00039*** | -0.00011 |
| | (0.00010) | (0.00007) | (0.00009) | (0.00007) | (0.00008) |
| Under 60 | 0.00023*** | 0.00014*** | 0.00032*** | 0.00006** | 0.00016*** |
| | (0.00004) | (0.00003) | (0.00006) | (0.00002) | (0.00005) |
| Median Income | | 0.00929*** | 0.00927*** | 0.00749*** | 0.00747*** |
| | | (0.00064) | (0.00064) | (0.00055) | (0.00053) |
| % Black | | | | -0.09982 | -0.05637 |
| | | | | (0.07602) | (0.07865) |
| % White | | | | 0.46349*** | 0.46195*** |
| | | | | (0.06138) | (0.06603) |
| % Hispanic | | | | 0.37621*** | 0.15862** |
| | | | | (0.06871) | (0.07991) |
| % Asian | | | | 0.94581*** | 0.82458*** |
| | | | | (0.11489) | (0.11774) |
| School District FE | Y | Y | Y | Y | Y |
| Subject FE | Y | Y | Y | Y | Y |
| Grade FE | N | N | Y | N | Y |
| Year FE | N | N | Y | N | Y |
| Grade · Year | N | N | Y | N | Y |
| $R^2$ | 0.692 | 0.704 | 0.712 | 0.708 | 0.716 |
| N | 695320 | 673495 | 673495 | 673495 | 673495 |

Robust standard errors clustered at the school-district level. ***, ** indicate statistical significance at the 1% and 5% level, respectively.

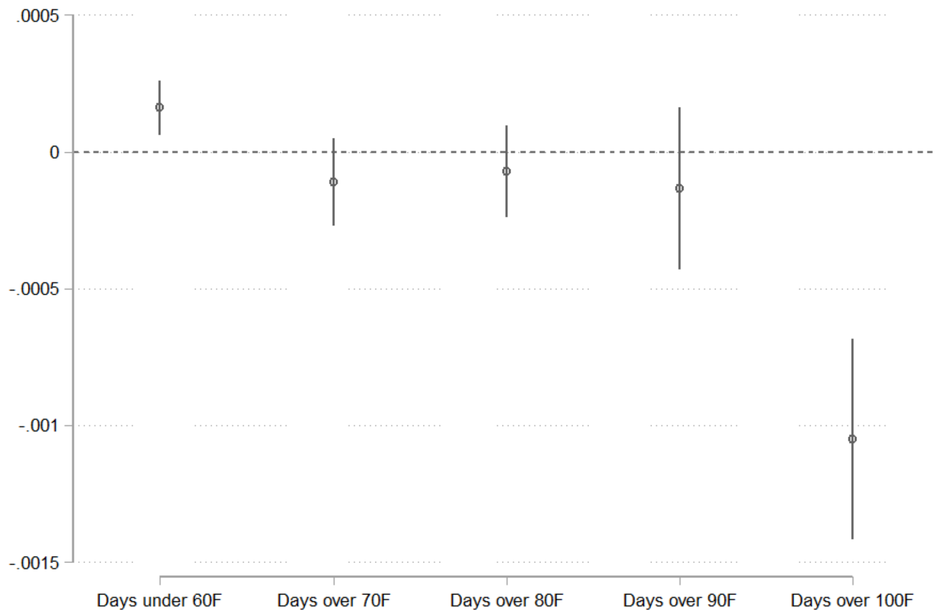



Figure 2: Estimated Coefficients for Degree-Bin Days

are associated with higher scores. This variable is positive and statistically significant in all model variations. These estimated effects are plotted alongside the coefficients for the other temperature degree days variables in Figure 3.

## 5 Robustness

Here we briefly comment on how the inclusion or exclusion of key fixed effects affect the estimates associated with changes in temperature, and, further, discuss an alternative modeling strategy. Recall, that we achieve identification by controlling for unobserved heterogeneity while observing exogenous variation in temperature. In table 3, we present our full model estimates in the first and fourth column for comparison (equivalent to specification 5 in tables 2 and 3). Now, we toggle the inclusion of the grade specific trend (table3, specification 2) as well as include a new interaction fixed effect, grade-by-state (table 3, specification 3). Here we see that the primary results of this paper remain essentially unchanged. The only difference between the models appears to be that slightly more of the variation in student learning is explained by the newly included fixed effects in column 3, though further inspection shows that the adjusted R-squared statistic is nearly identical

Table 3. Robustness

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Average Temp. | | | | -0.00167*** | -0.00168*** | -0.00100*** |
| | | | | (0.00039) | (0.00039) | (0.00025) |
| Over 100 | -0.00105*** | -0.00106*** | -0.00092*** | | | |
| | (0.00019) | (0.00019) | (0.00017) | | | |
| Over 90 | -0.00013 | -0.00013 | 0.00005 | | | |
| | (0.00015) | (0.00015) | (0.00012) | | | |
| Over 80 | -0.00007 | -0.00007 | -0.00007 | | | |
| | (0.00009) | (0.00009) | (0.00007) | | | |
| Over 70 | -0.00011 | -0.00011 | -0.00009 | | | |
| | (0.00008) | (0.00008) | (0.00008) | | | |
| Under 60 | 0.00016*** | 0.00016*** | 0.00009** | | | |
| | (0.00005) | (0.00005) | (0.00004) | | | |
| Median Income | 0.00747*** | 0.00747*** | 0.00772*** | 0.00747*** | 0.00747*** | 0.00774*** |
| | (0.00053) | (0.00053) | (0.00056) | (0.00053) | (0.00053) | (0.00056) |
| % Black | -0.05637 | -0.05660 | -0.30980*** | -0.04996 | -0.05011 | -0.30490*** |
| | (0.07865) | (0.07865) | (0.06560) | (0.07847) | (0.07848) | (0.06571) |
| % White | 0.46195*** | 0.46218*** | 0.22696*** | 0.46248*** | 0.46275*** | 0.23015*** |
| | (0.06603) | (0.06603) | (0.05340) | (0.06586) | (0.06586) | (0.05354) |
| % Hispanic | 0.15862** | 0.15952** | -0.03621 | 0.16113** | 0.16211** | -0.03212 |
| | (0.07991) | (0.07990) | (0.06007) | (0.07965) | (0.07963) | (0.06030) |
| % Asian | 0.82458*** | 0.82204*** | 0.58117*** | 0.82522*** | 0.82267*** | 0.58376*** |
| | (0.11774) | (0.11774) | (0.09238) | (0.11750) | (0.11750) | (0.09252) |
| School District FE | Y | Y | Y | Y | Y | Y |
| Subject FE | Y | Y | Y | Y | Y | Y |
| Grade FE | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y |
| Grade · Year | Y | N | Y | Y | N | Y |
| Grade · State FE | N | N | Y | N | N | Y |
| $R^2$ | 0.716 | 0.716 | 0.722 | 0.716 | 0.716 | 0.722 |
| N | 673495 | 673495 | 673495 | 673495 | 673495 | 673495 |

Robust standard errors clustered at the school-district level. ***, ** indicate statistical significance at the 1% and 5% level, respectively.

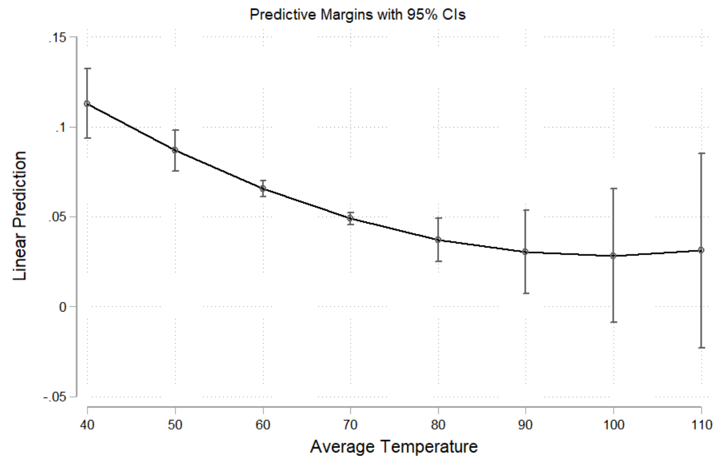



Figure 3: Quadratic Temperature Model

at 0.718. Moreover, we still see persistent estimates on the effect of days above 100F, and for all demographic control variables.

The primary results in this paper are that average scores are decreasing in the average school-day temperature for the year, and that hot days (100F+) reduce student learning. The method of measuring how temperatures effect student learning has been used to conform to existing studies in the literature, and specifically to conform with the model presented in Goodman et al. (2018) because they also have a nationally representative sample. An alternative to this modeling strategy is to remove the temperature degree day bins and include average school-day temperatures non-linearly by adding quadratic or cubic regressors (while also controlling for the full set of fixed effects and race and income controls). This alternative modeling strategy yields a similar result to before – that increasing temperatures harm student learning. Figure 3 shows this estimated relationship over the range of 40F-110F when school-day temperature and its square are included.[11,12]

# 6 Policy Implications and Conclusion

The impacts of global climate change and increasing temperatures are already being felt globally. The present research shows that failing to limit further greenhouse gas accumulation will lead to

[11] Cubic models yield similar curvature with a local maximum occurring near 40F.

[12] Estimates for this model and a cubic version of the model are available in the appendix.

negative outcomes for student learning. Using grade and school district specific data on student achievement on standardized tests for the entire United States, we find that each 1F increase in average temperatures results in lower student achievement. We further find that each additional day above 100F results in lower student achievement. These results are robust to the inclusion and exclusion of fixed effects and linear time trends, as well as alternative modeling strategies. We interpret these results as reinforcement of prior authors' work on the impacts of climate change on productivity and human capital, and are able to add to this literature by expanding the sample from single cities or school districts to a national sample, and we also expand the existing literature by focusing on learning at younger ages.

To put some of the core findings of this paper into context, we couple our estimates with the recent IPCC report (IPCC (2018)) which states that a 1.5C average temperature increase is nearly eminent (barring substantial changes to current practices). This change in average temperatures is equivalent reducing the mean by 0.004951 or 10.5%.[13] For an area that might be in the upper tail of average temperature increases (4.5C or 8.1F), this is tantamount to a decrease in the mean achievement measure by 0.01353 or 35.2%.[14]

A shortcoming of this paper that should be addressed in future work is the effect that humidity and heat have together. Most can relate to the disparate feeling of high temperatures with high humidity versus high temperatures with low humidity. This relates to another issue that we are not able to account for due to data limitations – adaptation and mitigation. We lean on the findings of Goodman et al. (2018) who show that adaptation measures matter, and that air conditioning can reduce the harmful effects of hot temperatures on student learning. However, we must also recognize that these adaptation measures also contribute to further accumulation of carbon dioxide and greenhouse gas emissions. Another adaptation measure that is worthy of study is the effect that tree canopy and vegetation coverage have on student learning outcomes. Loughner et al. (2012) and Tan et al. (2016) show that increased vegetation reduces temperatures in micro climates and reduce urban heat island effects. These adaptation measures should be linked to student performance as well, because we can only approximate these effects with school-district fixed effects.

[13] Using the midpoint method.

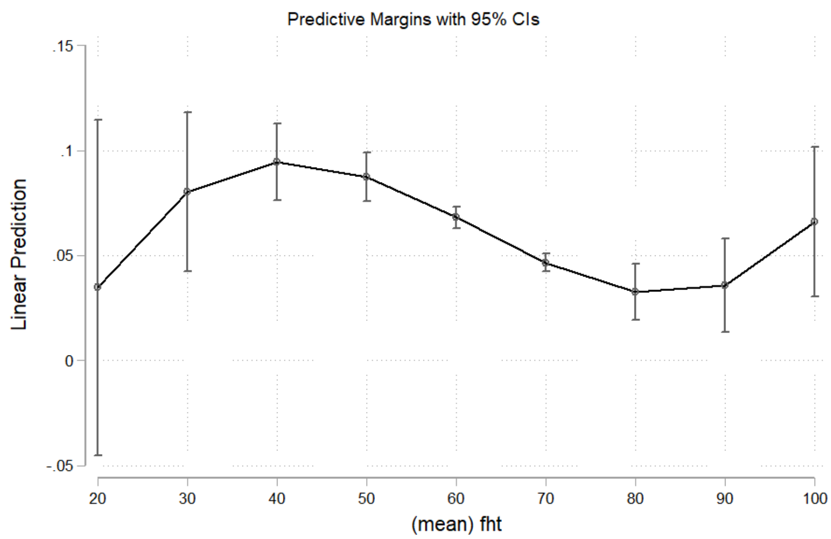
[14] 3.4% of a standard deviation

# 7 Appendix

Table A1. Quadratic and Cubic Temp.

| | | |
|---|---|---|
| Avgerage Temp | -0.00474 | 0.01664 |
| | (0.00112) | (0.00607) |
| $(\text{Avgerage Temp})^2$ | 0.00002 | -0.00030 |
| | (8.9E-06) | (9.3E-05) |
| $(\text{Avgerage Temp})^3$ | | 1.6E-06 |
| | | (4.6E-07) |

Notes: Full set of fixed effects included. All variables are statistically significant at the 1% level



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