

The Effects of Heat on Teachers and Their Students*

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Abstract

This paper provides the first evidence that extreme heat directly affects teachers, with consequences for student learning. Using matched student–teacher administrative data from North Carolina linked to high-resolution weather records, the analysis shows that older teachers, who are more sensitive to heat stress, experience greater productivity losses and higher absence rates during hot years. Students of older teachers see test score declines with each additional extreme heat day, effectively erasing the benefits of teaching experience. The cumulative impact of climate change–driven increases in heat is potentially large: equivalent to experiencing an event comparable to Hurricane Katrina every ten years.

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1 Introduction

As climate change leads to more extreme weather, research suggests we will see increased crime rates, lower labor supply, and, especially among older adults, increased illness and death (Luber and McGeehin, 2008; Dell et al., 2014; Graff Zivin and Neidell, 2014; Baysan et al., 2019; Somanathan et al., 2021; Cohen and Gonzalez, 2024; Costa et al., 2024). Extreme temperatures hinder human capital formation and worker productivity in a range of settings, from manufacturing in India to education in the United States (Park et al., 2020b; Somanathan et al., 2021). Understanding these relationships in elementary schools is particularly important given the returns to early childhood education reported extensively in the literature—returns that may be diminished by exposure to extreme heat (Angrist and Krueger, 1991; Card, 1999; Heckman et al., 2010; Hendren and Sprung-Keyser, 2020, and many others).

Human capital development in schools depends on students and teachers, both of whom are susceptible to harmful environmental factors. While previous research shows that extreme temperatures reduce student performance on standardized tests, the mechanisms driving these effects remain underexplored in the economics literature (Park et al., 2020b; Roach and Whitney, 2022). From the literature on environmental stressors' effects on workers, it is reasonable to expect negative impacts on teachers' instructional quality. However, it can be difficult to disentangle effects on teachers separately from students given that the two groups experience heat exposure simultaneously. By taking advantage of differences in teachers' sensitivity to heat by age, this paper documents the teacher mechanism underlying heat's effects on student academic performance.

In this paper, I provide the first evidence of heat effects on teachers by exploiting variation in temperature and heat sensitivity to examine how extreme heat exposure affects teacher productivity and behavior. The analysis combines matched student-teacher administrative data from the North Carolina Education Research Data Center with a balanced panel of interpolated weather data from the PRISM climatology group (Schlenker, 2024). This analysis leverages physiological and behavioral differences between younger and older

teachers. As humans age, we become more sensitive to heat-related stress and illness (Kenney, 1988). Additionally, older workers who are established in their careers may have more elastic responses to extreme heat due to the advantages of tenure, like extra vacation days. Using an interaction between cumulative heat shocks and teacher age, I compare the outcomes of students taught by older teachers, who are likely more negatively impacted by extreme heat, to those taught by less-impacted younger teachers. To examine a facet of teacher behavior with important spillovers to student learning, I investigate heat's impacts on teacher absences.

The analysis in this paper exploits cumulative weather shocks and examines the interaction of these shocks and teacher age to quantify the effects of a hotter learning environment on teachers and their students. To focus on yearlong learning rather than testing-day conditions, I use weather measures that span the entire school year and end-of-year standardized exam scores. The main independent variable, a measure of extreme heat, is defined as the number of days in a school year with temperatures above the 90th percentile, based on the empirical distribution of temperature at each location from 1997 to 2007, the decade prior to the sample period. This measure of extreme heat takes into account place-specific adaptation to heat—a factor that other heat measures, like number of days in a temperature range, cannot address. I use a two-way fixed effects model, regressing student test scores on this extreme heat measure and the interaction of extreme heat and an indicator for advanced teacher age.

For causal identification, I assume that conditional on fixed effects and control variables, variation in extreme heat is exogenous. This assumption relies on the randomness in weather after accounting for location and can only be violated if individuals could predict local weather shocks. Additionally, to identify the difference between older and younger teachers, I assume that the interaction of heat and teacher age is conditionally exogenous. Using balance tables and a regression framework, I argue that this is a reasonable assumption. Moreover, the findings in this paper are robust to varying the definition of extreme heat and the method of classifying teacher age.

This paper presents two main findings showing heat disproportionately affects older teachers' productivity and attendance. First, I find that students taught by older teachers score 0.002 standard deviations lower on end-of-year standardized exams for each additional extreme heat day—equivalent to losing 22% of a school day. Meanwhile, students of younger teachers are essentially unaffected. On average, students of older teachers score higher than those of younger teachers, a difference likely attributable to experience — but this advantage diminishes as the number of extreme heat days increases. The estimates imply that ten more extreme heat days would completely erase the benefits of having an older, more experienced teacher. These findings support those of previous studies on returns to experience for North Carolina teachers (Wiswall, 2013; Ladd and Sorensen, 2017). Secondly, I find that older teachers are twice as likely to be absent due to each additional extreme heat day, suggesting a direct behavioral response to heat exposure.

The current research on the effects of heat on student academic performance does not explore teacher effects, potentially due to the interconnectedness of student and teacher effects. This analysis uses heterogeneity in heat effects by teacher characteristics to elucidate the effects of heat on teachers. Since teacher productivity is often inferred from student test scores, isolating the effects on teachers themselves, independent of their students, can be difficult. Separating teacher and student effects is critical for policymakers to target mitigation strategies. I address this difficulty by proxying for teachers' heat sensitivity using teacher age and by analyzing teacher absenteeism. Additionally, this type of analysis requires matched student-teacher data with sufficient variation in temperature for credible identification. Along with rich longitudinal data, the state of North Carolina offers geographic variation missing in studies that focus on a single school district.

By analyzing the relationship between heat, learning outcomes, teachers' ages, and absences, this study aims to shed light on a mechanism underlying heat's effects. This research contributes to the growing body of work at the intersection of climate and education by highlighting an understudied mechanism, instructional quality, and how it varies with environmental conditions. Previous research indicates that students across the United States perform worse on standardized exams following periods of higher temperatures

(Park et al., 2020b; Roach and Whitney, 2022). Extreme temperatures also influence students' disciplinary referrals and attendance, which likely further affect test scores (McCor- mack, 2023). However, these studies do not consider teachers or how their characteristics and behaviors might influence the relationship between heat and learning.

By analyzing teacher absences, this paper addresses a key yet understudied factor of worker productivity in education, which plays a crucial role in the development of human capital. Recent studies show that adverse environmental conditions such as heat and pollution negatively impact worker productivity across various sectors, including outdoor industries like construction and agriculture, as well as indoor settings such as manufacturing and call centers. Some of these productivity losses can be attributed to increased worker absences (Graff Zivin and Neidell, 2014; Chang et al., 2019; Somanathan et al., 2021; Casey et al., 2024; Costa et al., 2024). In manufacturing, for example, the impact of heat on absenteeism persists even in workplaces with climate control, a feature likely present in many classrooms in my study context (Somanathan et al., 2021).

While heat affects productivity and learning in many contexts, older individuals are especially susceptible to heat-related illness, mortality, and productivity loss. Older, more experienced teachers face a different set of career incentives compared to younger teachers and thus may be more likely to reduce productivity and labor supply in extreme heat. Further, the medical and public health literature consistently identifies advanced age as a major risk factor for heat-related illness (Bouchama and Knochel, 2002; Luber and McGeehin, 2008). Han et al. (2024) presents a meta-analysis of recent studies on heat and productivity among construction workers, finding that middle-aged and older workers are particularly affected. My work bridges the public health and economics literature by examining the effects of heat on older workers in a new context. This work also speaks to the teacher productivity and absenteeism literature by highlighting how heat affects teacher absenteeism (Herrmann and Rockoff, 2012; Benhenda, 2022).

This work aims to inform evaluations of student and teacher performance, guide infrastructure investment decisions, and support policies related to school closures during heat

waves. In doing so, this work helps address inequities between students attending heat-vulnerable schools and those in better-equipped environments. These considerations are increasingly urgent in light of climate change, which is likely to exacerbate disparities between under-resourced schools with aging infrastructure and well-resourced schools with modern facilities.

2 Conceptual Framework

In this section, I present a brief conceptual framework describing how teachers and students contribute to educational outcomes. The education production function in this framework depends on two forms of labor inputs: student inputs, S , teacher inputs, T , and total factor productivity, A . Student and teacher labor inputs have an output elasticity of α and $1 - \alpha$, respectively. Student i with teacher type $j \in \{Y, O\}$ has output E_{ij} where

$$E_{ij} = AS_i^\alpha T_j^{1-\alpha} \quad (1)$$

Teacher inputs vary by teacher age in two age categories, younger, T_Y , and older, T_O . All inputs may be affected by heat. Heat, h , negatively impacts all teacher inputs, but may have a larger negative effect on older teacher inputs due to the physiological effects of heat as humans age and shifting career incentives. Written mathematically,

$$0 > \frac{\partial T_Y}{\partial h} > \frac{\partial T_O}{\partial h} \quad (2)$$

For ease of calculation, I take the natural logarithm of the production function. Taking the log of the production function and then finding the derivative with respect to h ,

$$\frac{\partial \log E_{ij}}{\partial h} = \frac{\partial \log A}{\partial h} \frac{1}{A} + \frac{\partial \log S_i}{\partial h} \frac{\alpha}{S_i} + \frac{\partial \log T_j}{\partial h} \frac{1-\alpha}{T_j} \quad (3)$$

Combining Equations 2 and 3 implies that test scores decrease more for students of older teachers compared to students of younger teachers.

$$0 > \frac{\partial E_{iY}}{\partial h} > \frac{\partial E_{iO}}{\partial h} \quad (4)$$

However, it is clear from the literature on the returns to experience for teachers in North Carolina that older, and thus, more experienced teachers have more successful students (Wiswall, 2013; Ladd and Sorensen, 2017). These returns to experience may mean that older teachers are better able to make up for the detrimental effects of heat shocks. This would imply the following:

$$0 > \frac{\partial T_O}{\partial h} > \frac{\partial T_Y}{\partial h} \Rightarrow 0 > \frac{\partial E_{iO}}{\partial h} > \frac{\partial E_{iY}}{\partial h} \quad (5)$$

Given this framework, it is unclear whether heat will have greater negative effects on students of older teachers compared to students of younger teachers. However, this is testable given data on heat, test scores, and teacher age.

3 Data and Empirical Strategy

I combine two main sources of data for this study: administrative records from the North Carolina Department of Public Instruction (with access provided by the North Carolina Education Research Data Center (NCERDC)) and a balanced panel of daily weather data from the PRISM climatology group (Schlenker, 2024).¹

3.1 Sample Selection

The NCERDC compiles annual datasets tracking students and teachers across North Carolina's public schools using unique identifiers. Using these identifiers, I construct a panel

¹Interpolated daily weather data is available at <https://zenodo.org/records/10625288>.

of annual test scores, teacher assignments, and student demographics for all third through fifth grade students from 2008 to 2018.²³ After fifth grade, students typically rotate among multiple classrooms rather than staying with one teacher all day, which reduces their exposure to any single teacher. For this reason, I focus on students in these grades. Within this student sample, I identify teachers who are assigned to third through fifth graders either for full-day, self-contained classrooms or for reading or math classes. I then match each student-teacher pair with the student's standardized test scores, total annual absences, and disciplinary incidents. The dataset does not directly include teacher age, so I calculate age based on the teacher's undergraduate graduation date, assuming individuals graduate at age 24. This estimate is based on an assumed six-year college trajectory beginning at age 18.

Following the sample restrictions I impose, the analysis sample remains large, with approximately 570,000 students and 22,000 teachers. While this sample generally spans 2008 to 2018, detailed records of teacher absences are only available to me for the 2006–2008 period. As a result, I am unable to link the teacher absence records to the larger, matched student-teacher sample used for the main analysis. However, these earlier data offer the advantage of monthly reporting frequency.

3.2 Weather Data and Extreme Heat Measure

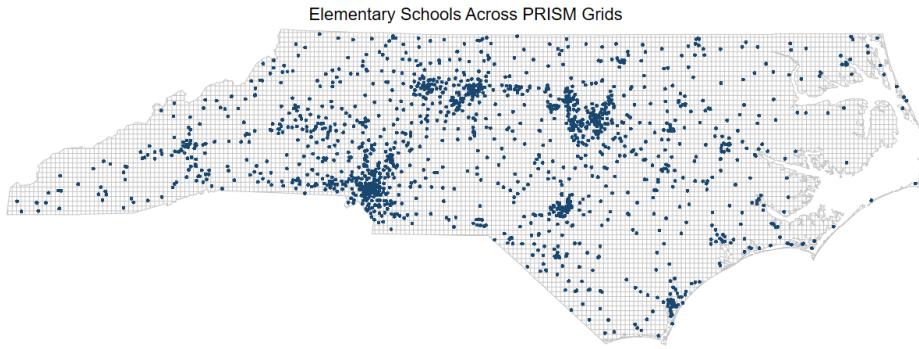
To assign weather conditions to schools as accurately as possible, I use interpolated weather data rather than relying solely on information from weather stations. Although North Carolina has many weather stations, schools are not always located near one—the average distance from a school to the nearest station in this sample is 6.9 miles. The PRISM climatology group creates daily weather data on a 2.5-mile by 2.5-mile grid across the United States by interpolating between stations which is then processed into a balanced panel

²Years refer to the spring of the academic year; for example, 2008 refers to the 2007–08 school year.

³Federal law, including the Every Student Succeeds Act and the preceding No Child Left Behind Act, requires states to administer annual standardized exams to students in grades three through eight. In North Carolina, these exams are conducted during the last ten days of each school year.

(Schlenker, 2024).⁴ Using a balanced panel helps prevent bias that could occur if weather stations are added or removed in ways correlated with local economic conditions, which might in turn impact test scores. Each school in my dataset is matched to the weather data grid cell in which it is located. Not every PRISM grid has an elementary schools and some have multiple schools, as shown in Figure 1.

Figure 1: Elementary Schools in North Carolina



Note: This map of North Carolina shows the geographic distribution of elementary schools. Each dot represents an elementary school in the sample. The overlaid grid represents the 2.5 mile by 2.5 mile PRISM grid.

From these weather data, I construct a measure of extreme heat days, defining such a day as one with temperatures above the 90th percentile of the grid-level heat distribution in the decade prior to the main sample, 1997 to 2007. This approach captures the effects of extreme heat in a way that accounts for local adaptation to typical climate conditions. For comparison with existing literature, I also categorize temperatures into ten-degree bins. In robustness checks, I vary the definition of an extreme heat day and use the number of days above the 85th or 95th percentile of the heat distribution.

This analysis uses extreme heat days to capture effects at the right tail of the temperature distribution, given the hot climate and the typical air-conditioning infrastructure present in North Carolina's buildings. In economics and related literature, researchers use a variety of measures of heat and temperature depending on the context and the relevant data frequency (Schlenker and Roberts, 2009; Auffhammer et al., 2013; Dell et al., 2014; Park et al., 2020a,b; McCormack, 2023; Sajid et al., 2024). Temperature measures include average maximum temperature (specified as a linear or polynomial function), cooling and heating

⁴Details about PRISM's modeling techniques are available at <https://prism.oregonstate.edu/>.

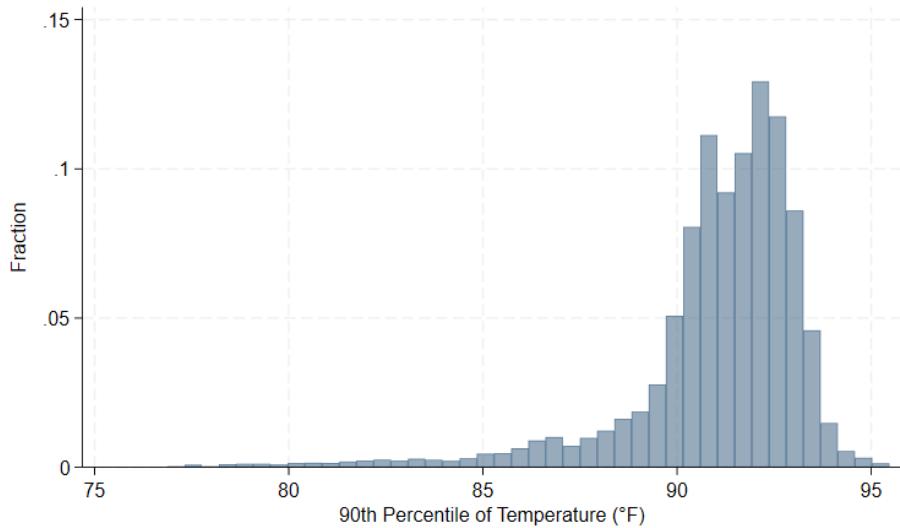
degree days, extreme degree days, and days in temperature bins. Studies in this literature that examine the effects of cumulative heat on learning typically use average maximum temperature or days in temperature bins (Park et al., 2020b; Roach and Whitney, 2022). Importantly, their setting—the United States as a whole—includes many schools that categorically lack air conditioning, and, indeed, the findings are concentrated among those schools. However, given North Carolina’s hot climate, buildings there are much more likely to have air conditioning. About 93–96% of homes in North Carolina’s climate region reported having air conditioning at the beginning of my sample period, compared to 83% for the United States as a whole (U.S. Energy Information Administration, 2013). Although air-conditioning data on schools specifically are unavailable, the near ubiquity of climate control in North Carolina homes suggests a higher likelihood of climate control in schools.

The climate and infrastructure of the study setting motivate the use of extreme heat days as the main measure of heat. Because air conditioning is likely present in most North Carolina schools, average maximum temperature changes during the school year may not reflect variation in actual classroom heat exposure. By focusing the analysis on extreme heat days, I measure the impacts of particularly hot periods when air-conditioning systems may be inadequate, outdoor supervision may be particularly uncomfortable, and nighttime heat may disrupt sleep, all of which could reduce teaching quality.

I measure extreme heat as the number of school days with daily maximum dry bulb temperature (DBT) above the local 90th percentile. Because DBT does not account for humidity, it may not fully capture physiological heat stress, which depends on both temperature and moisture. Wet bulb temperature (WBT), which incorporates humidity, is always less than or equal to DBT. Consequently, this measure may misclassify exposure: some dry days may exceed the DBT threshold without imposing meaningful heat stress, while humid days may impose substantial stress but fall below the threshold. Such misclassification is expected to attenuate the estimated effects of heat, implying that the results are conservative. WBT is not used in this analysis because it is unavailable in the interpolated,

high-resolution weather data.⁵

Figure 2: Extreme Heat Day Temperature Cutoffs



Note: This figure plots the 90th percentile (in °F) of each grid's temperature distribution. These percentiles are used to create the extreme heat days measure in this analysis: the number of days per school year above the 90th percentile. This figure shows that the majority of grids have a 90th percentile between 90 and 95°F (32-35°C).

3.3 Summary Statistics

The analysis sample contains more than 3.6 million individual third through fifth grade students. The sample contains a higher proportion of Black students (comprising 25% of the sample) and lower proportions of Hispanic and Asian students compared to the national average (NCES, 2022). Table 1, Panel A presents summary statistics for the education dataset. On average, each class has between 40 and 41 students. For every ten students, there are approximately three disciplinary incidents per school year. In this sample, disciplinary incidents most frequently result from disruptive behavior, fighting, bus misbehavior, and aggression. Students are absent an average of 6 days per school year. The mean teacher age is 39 years old. The average school year temperature, excluding June through August, is 64.5°F (18 °C). Test scores are standardized to have a mean of zero and

⁵WBT is available at the weather station level from NOAA's National Centers for Environmental Information Local Climatological Data service.

a standard deviation of one within each subject and year, as is standard practice in the education literature.

Table 1, Panel B presents summary statistics for school year weather data, excluding summers. It includes weather in the months of September through April of the 2007-08 through 2017-18 school years. This panel shows that, on average, a school year has about three extreme heat days and the same number of days above 90°F (32 °C). In fact, for much of the state, the 90th percentile of maximum temperature is close to 90°F, though the western mountain region is generally cooler. Panel C includes summary statistics for the county-level unemployment rate and median income. Panel D summarizes the monthly teacher absence data with a shorter sample of 2006 through 2008.

The analysis in this paper relies on variation in the number of extreme heat days in North Carolina, net of year- and place-specific averages. Figures 3a through 3j show the variation in extreme heat used in this paper. For each year of the sample, each map shows the number of extreme heat in a grid minus the average number of extreme heat days for that year. Blues indicate that a grid had a cooler year than the state average while reds indicate that a grid had a warmer year than the state average. Focusing on a particular location and looking across years gives a sense of the variation. Squares without data indicate grid areas without elementary schools during the sample period.

Table 2 presents descriptions of teacher absences along with the percentage of each type of absence by teacher age. Sick leave, the most common absence type, accounts for 54-58% of teacher absences. Annual leave and absences without deductions are the next most common types, each representing 17-22% of all absences. The remaining absences include absences with deduction or without pay, child involvement leave, and personal leave.

Table 1: Summary Statistics

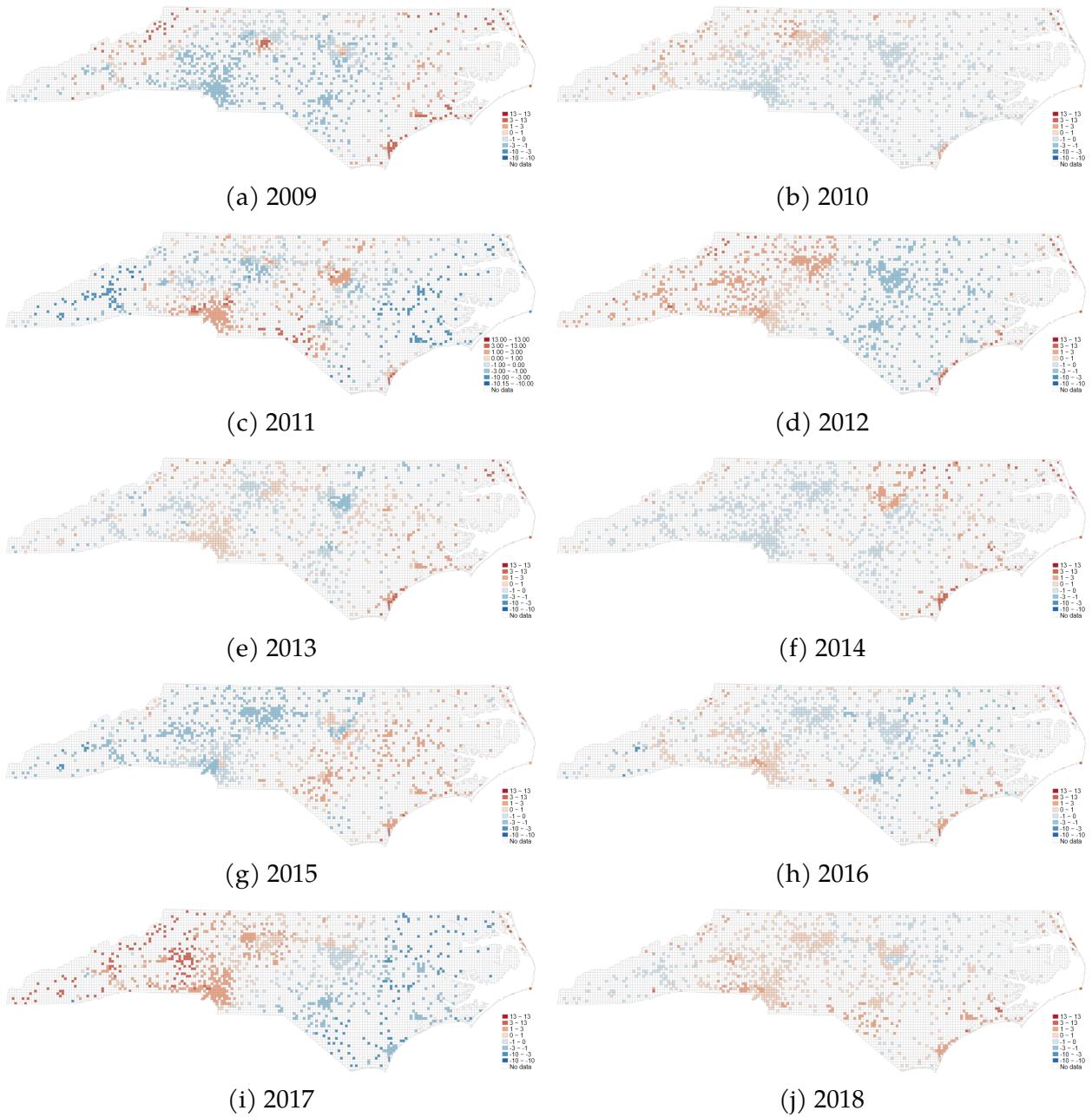
	Mean	SD
Panel A: Education Data		
Student Age	10.77	0.67
Percent Male	0.51	0.50
Percent Black	0.25	0.43
Class Size	41.37	13.45
Percent Native American	0.01	0.12
Incident Count	0.29	1.24
Days Absent	5.99	5.72
Teacher Age	38.87	10.14
Panel B: Weather Data (Excludes Summers)		
Max Temp °F	64.51	2.70
Extreme Heat Days	3.35	3.58
Days in 90s °F	3.30	3.95
Days in 80s °F	30.90	8.42
Panel C: County Labor Market Data		
Unemployment Rate	7.52	3.00
Median Income (2008 Dollars)	58,927.46	10,649.69
Panel D: Monthly Teacher Data		
Teacher Age	38.30	11.00
Absences Per Year	20.75	6.42
Observations, Panels A-C	3,663,375	
Observations, Panel D	165,841	

Note: Education and weather variables are at the school year level and span the 2007-08 through 2017-18 school years with the exception of student attendance which spans 2007-08 through 2012-13. Weather variables are calculated using September through April daily values. Monthly teacher variables span the 2005-06 through 2007-08 school years and exclude summer months.

Table 2: Percent of Absences By Description and Age

	Teacher Age [24,54)	≥ 54
Absent with Deduction	0.03	0.04
Absent without Deduction	21.72	18.96
Absent without Pay	0.82	1.24
Annual Leave	17.61	21.80
Child Involvement Leave	0.06	0.01
Donated Shared Leave	0.05	0.05
Extended Sick Leave	0.32	0.05
Personal Leave	3.33	4.01
Sick Leave	56.04	53.81
Sick Leave Bank	0.02	0.02
Total	100.00	100.00

Figure 3: Variation in Number of Extreme Heat Days



Note: This figure maps the number of extreme heat days by grid after subtracting that year's average. In this way, these maps represent the variation in extreme heat days after accounting for the yearly average. Figures a-j each show one year's variation from 2009 to 2018. Red and orange colors indicate a grid that had more extreme heat days than it had the previous year. Blues indicate the opposite. Missing data indicates grids in which there are no elementary schools.

3.4 Empirical Strategy

Students take annual exams at the end of each school year to measure their learning in mathematics and English language arts.⁶ These exams are designed to test grade-level standards developed by North Carolina educators. Thus, the exams focus on content learned throughout the school year. Yearlong learning conditions and teacher attributes likely influence students' test performance.

To estimate the effect of extreme heat on student performance, I use a panel data model with year and school fixed effects. I regress standardized test scores on the number of extreme heat days in a school year and an indicator for teacher age above the 90th percentile. I include the interaction of these two explanatory variables to capture differences in heat effects by teacher age. This regression is of the following form:

$$y_{its} = \beta_1 H_{t\tilde{s}} + \beta_2 H_{t\tilde{s}} \times A_{tj} + \beta_3 A_{tj} + \mathbf{X}_i^{-1} \alpha + \delta_t + \lambda_{\tilde{s}} + \varepsilon_{its} \quad (6)$$

where

$$A_j = \begin{cases} 1 & \text{if teacher } j \text{'s age } \in [24, 54] \\ 0, & \text{otherwise} \end{cases}$$

and y_{its} is the outcome of interest: student i 's standardized test score in year t and subject s . H_{ts} is the number of extreme heat days defined as the number of days in school year t that are above the 90th percentile for school \tilde{s} . \mathbf{X}_i is a vector of control variables including lagged test score, student race, gender, and grade level. δ_t and $\lambda_{\tilde{s}}$ represent year and school fixed effects. School and year fixed effects are included to control for school-specific or year-specific unobservable factors that may affect test scores. In the model of teacher absences, I also include month fixed effects but cannot include most controls due to data availability during this shorter sample of 2006 through 2008.

⁶End-of-grade science exams begin in the fifth grade and are excluded from this analysis because there are no past year scores.

I use the following panel data model to estimate the effects of extreme heat on teacher absences:

$$a_{jm} = \gamma_1 H_{m\tilde{s}} + \gamma_2 H_{m\tilde{s}} \times A_j + \gamma_3 A_j + \mathbf{C}^{-1} \kappa + \nu_y + \phi_m + \omega_{\tilde{s}} + u_{jm} \quad (7)$$

where A_j is defined as in Equation 9, a_{jm} is the number of absences that teacher j has in month m of school year t , $H_{m\tilde{s}}$ is the number of extreme heat days in the month at school \tilde{s} , and C is a vector of control variables including teacher education, county unemployment rate, real median income, CPI inflation, and yearly average precipitation.

3.5 Comparing Older and Younger Teachers

For causal identification, I assume that extreme heat days, conditional on fixed effects and observable characteristics, are uncorrelated with unobservables. To causally identify the effects of heat on younger and older teachers, I further assume that the interaction of age and extreme heat days, conditional on observables, is uncorrelated with unobservables. In this section, I provide suggestive evidence that these assumptions are reasonable.

Because the analysis compares outcomes between older and younger teachers, I must ensure that teacher age is not confounded with other systematic differences not captured by the fixed effects. For example, if older teachers are more likely to work in areas with more extreme heat days, any observed impacts might be attributable to location rather than age. However, I do not find evidence to support this concern.

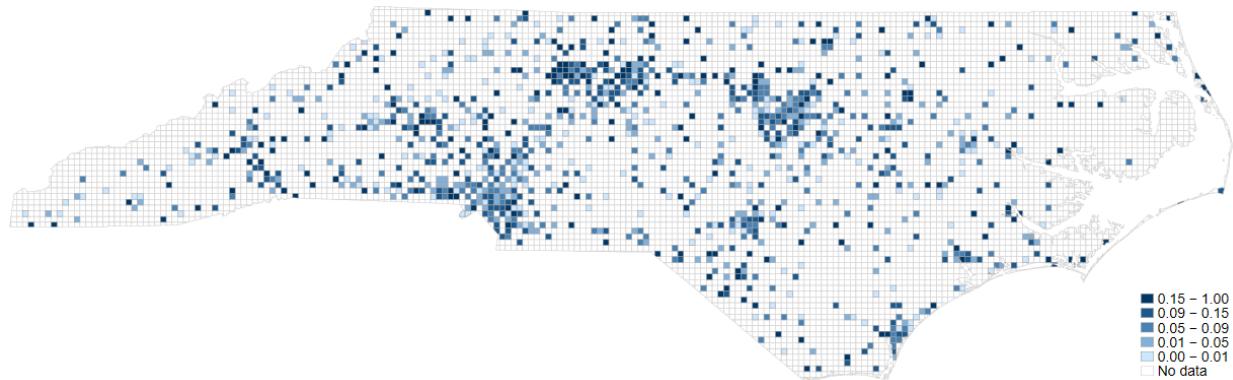
Table 3 presents average heat, student demographics, and county-level economic variables by teacher age category and the difference between the two. Column 1 shows the average values of extreme heat days, days between 80 and 90°F and 90 and 100°F, average maximum temperature for the school year, the percentage of Black, Native American, and male, students, county-level unemployment rate, median income, and rural status. On average, older teachers experience 3.41 extreme heat days per school year, while younger teachers experience 3.39 extreme heat days. The difference between these figures is not

significant. Older teacher work in schools with slightly fewer days in the 80s and 90s, with a slightly lower average maximum temperature. Though these differences are statistically significant, they are very small and represent less than a 1% difference in average maximum temperature, less than a 5% difference in days in the 80s and 90s. Older and younger teachers, on average, have very similar student demographics in terms of race and gender. However, older teachers tend to live in more rural areas with slightly higher unemployment rates and slightly lower median incomes. These differences are small but statistically significant. I include county economic variables in the main analysis to account for any differences in student outcomes stemming from economic differences that are not otherwise netted out.

Further, using a linear probability model, I show that teacher age categories are uncorrelated with extreme heat days conditional on school and year fixed effects. Appendix Table A.1 provides the full results of this analysis.

Teachers may also sort into schools based on the climate. Figure 4 displays the percentage of older teachers in each grid across North Carolina. The distribution appears generally even throughout the state. To further investigate this possibility, present descriptive results and an event study analysis to show that there is no evidence of differential climate sorting by teacher age. I focus on teachers who move from one school to another at least once during my sample. In a descriptive analysis presented in Appendix Table E.1, I find the mean temperature, extreme heat days, student demographics, unemployment rate, median income, and rurality of teachers' first, second, and third schools and show that there are very few significant differences between the change in characteristics from the one school to the next across teacher age, aside from median county-level income. Younger teachers move to schools in counties with higher median income relative to their prior school relative to older teachers (presented in balance table form in Appendix Tables E.2). Similarly, the event study plot show in Appendix Figure E.1 shows no difference in extreme heat between younger and older teachers who move.

Figure 4: Percentage of older teachers



Note: This figure maps the average percentage of teachers above the age of 54 in each grid. Missing data indicates grids in which there are no elementary schools.

Table 3: Difference Between Older and Younger Teachers

	(1) Age [24,54]	(2) ≥ 54	(3) Difference (1)-(2)
Days Above 90th Percentile	3.39 (3.91)	3.41 (4.03)	-0.02 (0.04)
Days in 80s °F	30.79 (8.21)	29.84 (8.46)	0.95*** (0.09)
Days in 90s °F	3.28 (4.08)	3.14 (4.17)	0.14** (0.05)
Max Temp °F	64.43 (2.66)	64.10 (2.78)	0.33*** (0.03)
Black Student %	0.28 (0.28)	0.28 (0.29)	0.00 (0.00)
Male Student %	0.52 (0.19)	0.52 (0.20)	-0.01** (0.00)
Native American Student %	0.01 (0.08)	0.02 (0.09)	-0.00** (0.00)
Unemployment Rate	7.87 (3.02)	8.35 (3.13)	-0.48*** (0.03)
Median Income	58811.03 (10546.41)	57877.04 (10370.08)	933.99*** (113.43)
Rural %	0.22 (0.42)	0.26 (0.44)	-0.04*** (0.00)
Observations	88,191	9,267	97,458

Columns 1 and 2 show means with standard deviations in parentheses. Column 3 shows the difference in means, with the standard error of the difference in parentheses and with stars specifying significance as follows: * for $p < .05$, ** for $p < .01$, *** for $p < .001$.

4 Heat's Impacts on Teachers and Their Students

4.1 Test Scores and Teacher Age

For students of older teachers, each additional day of extreme heat lowers test scores by an average of 0.002 standard deviations, a result that is significant at the 5% level and is consistent across choices of covariates. This decrease in scores is equivalent to a loss of 22% of a day's worth of instruction for an additional day of extreme heat.⁷ The effect of extreme heat is significantly weaker for students taught by younger teachers, whose scores are 0.001 standard deviations higher than those taught by older teachers in response to an extreme heat day. This difference is statistically significant at the 1% level. Overall, students of younger teachers have a small and statistically insignificant response to extreme heat. Table 4 presents these findings in Column 6, including controls for past year test scores, the temperature on the day of the exam, student age, ethnicity, and gender, county-level unemployment and median income, and classroom size. Columns 1 presents results with no covariates, only year and school fixed effects. Columns 2 through 6 each add an additional covariate.

Moreover, additional extreme heat days reduce returns to teacher experience. At the average number of extreme heat days, students of older teachers achieve much higher test scores overall, even when accounting for prior achievement, exam-day temperature, student characteristics, and fixed effects. On average, students of younger teachers score 0.02 standard deviations lower than those of older teachers, a highly statistically significant finding that is stable across choice of covariates. I interpret this achievement gap as reflecting differences in teaching quality due to experience. Based on this interpretation, my findings suggest that teaching quality among more experienced teachers declines when they are exposed to extreme heat. Younger teachers are essentially unaffected, with a remarkably flat response to extreme heat days. Ten additional extreme heat days would

⁷I calculate the average increase in test scores throughout a year using pre- and post-grade exams from third grade students that were administered for two years of the sample. This allows me to calculate the average increase for each day of instruction which makes for a useful benchmark against my estimated effects of an extra day of extreme heat.

completely erode the positive effect of having an older teacher. An additional ten extreme heat days would be a very large increase over the mean of three extreme heat days per school year; however, given estimates of climate change in the near-future, this increase may soon be in the realm of possibilities. (More on this in Section 4.6.)

Although the effects of extreme heat on scores are relatively stable across the choice of covariates, the magnitude of the effect for students of older teachers increases by nearly half when I do not include a student's past year test score as a covariate (as in Table 4, Column 1). At the same time, this specification results in a larger return to having an experienced teacher at the average of extreme heat days. These findings imply that when we do not account for a student's prior test scores, it appears that heat has greater effects on older teachers but at the same time, older teachers have larger returns. This result might be due to selection into older teachers' classes that is corrected by including past test scores and other student demographics in the regression specification.

Figure 5 plots mean test scores against bins of extreme heat days by teacher age category. This figure shows data residualized by the covariates included in regression Equation 9: past test scores, exam day weather, student and classroom characteristics, county economic variables, and fixed effects. The figure shows that the test scores of students taught by older and younger teachers converge as exposure to extreme heat increases.

To test the robustness of these findings, I also conduct regressions using alternative measures of heat, such as cooling degree days, temperature bins, and a modified version of extreme heat days. The results remain qualitatively similar and indicate that temperature extremes, specifically days above 90°F and below 30°F, have the greatest impact on older teachers. The full results of these robustness checks appear in Appendix Tables B.1 through B.4. In Appendix Tables B.3 and B.4, I use alternate definitions in which one extreme heat day is one day above the 85th and 95th percentiles of heat rather than the 90th percentile. The results of these robustness checks are consistent with the main analysis.

Additionally, I test the sensitivity of the results to the definition of teacher age categories. I find similar results to those using the 90th percentile of teacher age when I use the 85th

or 95th percentiles, though with somewhat noisier estimates. These results are presented in Appendix Tables C.2 and C.1. In another specification, I test whether the results are driven by the youngest, most inexperienced teachers having both worse outcomes and more heat resilience than other teachers. In Appendix Table C.3, I exclude the teachers below the tenth percentile of teacher age, that is, teachers below age 28. The results are again consistent with those in the main analysis.

Further, I investigate potential heterogeneous impacts to find whether any particular group drives the overall effects. If extreme heat affects some groups more than others, this finding provides a valuable insight to administrators and policy makers working to adapt classrooms to extreme heat.

To explore heterogeneous heat impacts, I conduct regression analyses of the form described in Equation 9 after splitting the sample by test subject, grade level, student demographics, county-level median income, or semester-level heat and present the results in Appendix Tables D.1 through D.7. I find similar results for math and reading standardized test scores, though the results for math scores are noisy. Given the smaller point estimate for math scores, it is possible that there is not enough power to precisely estimate a smaller effect due to a decrease in the sample size. Splitting the sample by grade level offers similar results for each grade, though each subsample yields noisy results. Similarly, heterogeneity analysis by student gender, county rural status, or county median income yields no sizable differences between subgroups.

Table D.6 presents regressions by students' racial group. Black students of older teachers appear to be especially affected by extreme heat. For this group, an additional day of extreme heat leads to a 0.003 standard deviation decrease in test scores, which is precisely estimated at the 5% confidence level. Black student with younger teachers have an effect about half this size, though this difference is noisy. Native American students also appear to be more strongly affected than other groups, though these findings are noisy. Hispanic and White students have effects that are about half the size of those of Black students.

Finally, I conduct regressions in which I use only extreme heat days in the fall semester or

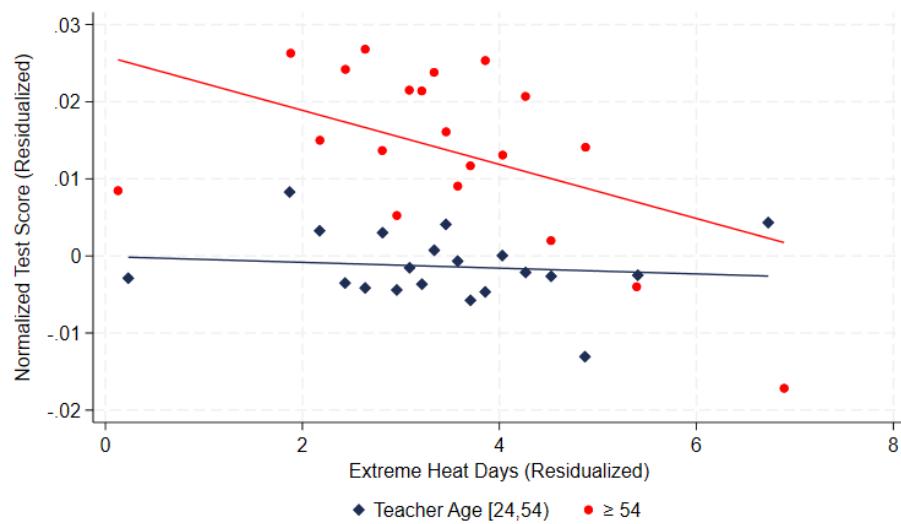
spring semester of each year preceding end-of-year exams. I find that extreme heat days in the fall semester seem to drive the main result. This may be due to the fact that extreme heat days are much more common during the early fall semester months of September and October compared to any of the spring months of January through April.

Table 4: Regression of Test Scores on Extreme Heat Days and Teacher Age

	(1)	(2)	(3)	(4)	(5)	(6)
Extreme Heat Days	-0.00322** (0.00119)	-0.00153* (0.000724)	-0.00153* (0.000724)	-0.00167* (0.000735)	-0.00173* (0.000735)	-0.00185* (0.000732)
Teacher Age [24,54)	-0.0539*** (0.00876)	-0.0212*** (0.00372)	-0.0212*** (0.00372)	-0.0208*** (0.00375)	-0.0208*** (0.00375)	-0.0208*** (0.00363)
Teacher Age [24,54) × Extreme Heat Days	0.00269** (0.000971)	0.00147** (0.000519)	0.00147** (0.000519)	0.00142** (0.000525)	0.00140** (0.000524)	0.00135** (0.000516)
Past Year Score	No	Yes	Yes	Yes	Yes	Yes
Day of Test Temperature	No	No	Yes	Yes	Yes	Yes
Student Demographics	No	No	No	Yes	Yes	Yes
County Economic Trends	No	No	No	No	Yes	Yes
Classroom Size	No	No	No	No	No	Yes
Observations	3,663,254	3,663,254	3,663,254	3,663,254	3,663,254	3,663,254

Note: Heteroskedasticity robust standard errors clustered at the grid level appear in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. This table presents the regression of normalized annual test scores on the number of extreme days in the school year, teacher age bins, and the interaction of the these explanatory variables. The first row presents the effect of one extreme heat day on students of older teachers on standard deviations of exam scores. The second row shows the effect of an indicator for younger teacher age at the average number of extreme heat days. The third row presents the difference in the effect of extreme heat days for students of younger versus older teachers. All regressions include year and school fixed effects. Column 1 does not include any covariates. Column 2 controls for a student's prior year test score. Column 3 adds the exam day temperature. Column 5 adds student gender, ethnicity, and age. Column 6 adds county-level yearly unemployment rates and average income. Column 6 adds the classroom size.

Figure 5: Extreme Heat and Scores Conditional on Teacher Age



Note: This figure plots average normalized test scores against the number of yearly extreme heat days by teacher age. Each point on the graph represents an average test score and an average number of extreme heat days for a range of extreme heat days, after both variables have been residualized by a set of controls. Test scores are normalized to have a mean of zero and standard deviation of one. Extreme heat days are defined as days above the 90th percentile of the empirical temperature distribution with a 2.5 mile by 2.5 mile grid.

4.2 Teacher Absences

Extreme heat may affect teachers through multiple channels. Teaching in a hot classroom or supervising outdoor activities during a heat wave can reduce teaching quality, though this effect is difficult to observe directly. Another channel is teacher absenteeism: extreme heat may exacerbate health conditions that cause teachers to miss school. At the same time, older, more experienced teachers who are advanced in their careers may face a smaller disincentive to miss work and may have more personal leave days. Such absences reduce instructional quality, as temporary substitute teachers typically fall in the 10th–20th percentile of teacher productivity (Herrmann and Rockoff, 2012).

To quantify the relationship between heat and teacher absences, I estimate a regression of teacher absences on extreme heat days as specified in Equation 7. On average, each additional extreme heat day results in 0.1 more absences per month for older teachers, a result that is highly statistically significant. This effect is about two times that of younger teachers—a result significant at the 0.01% level. Table 5 presents the full regression output. These results are stable across the choice of covariates. Column 1 presents this regression including only year, month, and school fixed effects. School fixed effects account for school- or location-specific factors that do not change over time, such as school culture, which may influence teacher absences. Year and month effects control for unobservable factors, like the adoption of new teacher leave policies, that can vary over time and affect teacher absences alongside the number of extreme heat days. Column 2 adds indicators for teacher education level. Column 3 introduces controls for county-by-month unemployment rates, real median income, and CPI inflation. The next two columns use subsamples to tease out whether these effects may differ by the type of absence. Column 5 uses the subsample of absences due to illness while column 6 uses the remainder of the sample, absences due to annual leave, personal leave, or unspecified reasons.

The effects of heat on absences for older teachers are stable across the choice of covariates, including using the subsample that includes only sick leave (shown in Table 5 Column 4). In this regression, the difference in the effects of heat between older and younger teachers

becomes noisier and loses statistical significance though the point estimate and standard deviation are similar across models. This regression also shows that older teachers take more absences due to illness than younger teachers. Column 6, which uses the subsample that does not include absences due to illness echoes the previous findings that older teachers take about 1.5 times as many non-illness absences during months with one more extreme heat days compared to younger teachers.

Figure 6 shows the average number of absences against binned extreme heat days, separately by teacher age category. This figure shows data residualized by the covariates included in regression Equation 7: teacher education level, county economic variables, and fixed effects. This figure shows that older teachers are more likely to miss school when there are more extreme heat days in a month compared to younger teachers.

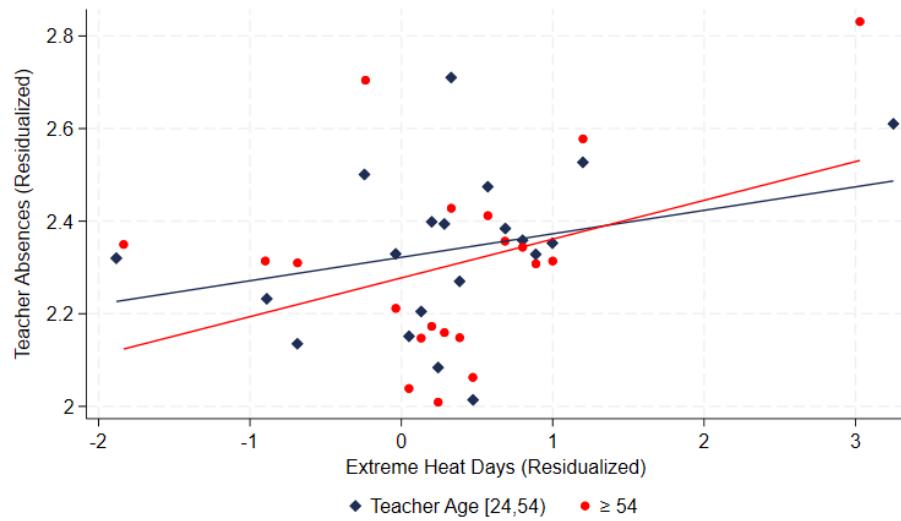
These findings indicate a pronounced behavioral response to heat, suggesting that additional mechanisms, such as reduced teaching effort on hot days, may also be at play. Given the magnitude of the observable behavioral effect, it is likely that other, less directly observable behaviors similarly contribute to the impact of heat on students' exam performance.

Table 5: Older teachers miss school more often during months with extreme heat

	(1)	(2)	(3)	(4)	(5)
Extreme Heat Days	0.0826*** (0.0111)	0.0824*** (0.0111)	0.0922*** (0.0113)	0.111*** (0.0207)	0.124*** (0.0135)
Teacher Age [24,54]	0.0439* (0.0176)	0.0514** (0.0176)	0.0530** (0.0176)	-0.0687* (0.0270)	0.0184 (0.0224)
Teacher Age [24,54) × Extreme Heat Days	-0.0406*** (0.00874)	-0.0405*** (0.00874)	-0.0414*** (0.00881)	-0.0226 (0.0185)	-0.0422** (0.0133)
Teacher Education	No	Yes	Yes	Yes	Yes
County Economic Trends	No	No	Yes	Yes	Yes
Sick Leave Indicator = 1	No	No	No	No	Yes
Sick Leave Indicator = 0	No	No	No	No	No
Observations	164,645	164,645	164,645	70,476	55,201

Note: Heteroskedasticity robust standard errors clustered at the grid level appear in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. This table presents regressions of teacher absences on the number of extreme days in the school year, teacher age bins, and the interaction of the these explanatory variables. All regression contain school, year, and month fixed effects. Column 3 includes a control for teacher education, county unemployment rate, real median income, and CPI inflation. Column 4 includes only absences due to sick leave and column 5 includes absences that are not due to illness.

Figure 6: Older teachers' attendance responds more in extreme heat



Note: This figure plots average residualized teacher absences over average residualized extreme heat days by teacher age. Each point on the graph represents the average absence and average extreme heat within a range of extreme heat days, after both variables are residualized by a set of controls. Extreme heat days are defined as days above the 90th percentile of the empirical temperature distribution with a 2.5 mile by 2.5 mile grid. Absences and heat days are at the monthly frequency.

4.3 Student Absences and Disciplinary Referrals

Previous literature indicates that extreme heat impacts student behaviors, though primarily in schools lacking air conditioning (McCormack, 2023). If this relationship holds in this setting, it may explain a separate channel through which heat impacts student outcomes.

In the following analysis, I regress student absences on extreme heat days, teacher age, and the interaction of these variables using a regression model akin to Equation 9, including school and year fixed effects and a set of control variables. These analyses do not show evidence of significant effects of extreme heat on student absences or discipline, potentially because of data limitations—all student absences and disciplinary incidents are at the year level.

At face value, my findings suggest that one additional day of extreme heat in a school year leads to 0.003 fewer absences for students of older teachers and 0.01 fewer absences for students of younger teachers. However, these result is not precisely estimated, with large standard errors. Table 6, column 4 presents the regression results, which include controls for student demographics, prior year test scores, county economic trends, and year and school fixed effects.

Table 6: No evidence of an effect of extreme heat on yearly absences

	(1)	(2)	(3)	(4)	(5)
Extreme Heat Days	0.00425 (0.00823)	0.00323 (0.00820)	-0.00581 (0.00870)	-0.00372 (0.00872)	-0.00300 (0.00873)
Teacher Age [24,54)	-0.0195 (0.0304)	-0.0395 (0.0297)	-0.0356 (0.0297)	-0.0351 (0.0299)	-0.0336 (0.0299)
Teacher Age [24,54) × Extreme Heat Days	-0.00600 (0.00523)	-0.00526 (0.00520)	-0.00646 (0.00514)	-0.00676 (0.00514)	-0.00671 (0.00514)
Past Year Score	No	Yes	Yes	Yes	Yes
Student Demographics	No	No	Yes	Yes	Yes
County Economic Trends	No	No	No	Yes	Yes
Classroom Size	No	No	No	No	Yes
Observations	3,658,774	3,658,774	3,658,774	3,658,774	3,658,774

Note: Heteroskedasticity robust standard errors clustered at the grid level appear in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. This table presents the regression of student absences on the number of extreme days in the school year, teacher age bins, and the interaction of the these explanatory variables. All regressions contain year and school fixed effects. Column 5 includes controls for lagged test score, student grade, ethnicity, gender, classroom size, and county-level unemployment rate and median income.

Table 7 presents the results from the regression of students' disciplinary referrals on the number of extreme heat days, teacher age, and the interaction of the two. I find very small and noisy results, with confidence intervals that surround zero.

Table 7: No evidence of extreme heat effect on disciplinary referrals

	(1)	(2)	(3)	(4)	(5)
Extreme Heat Days	0.000217 (0.00229)	-0.0000830 (0.00228)	-0.000129 (0.00231)	-0.000329 (0.00231)	-0.0000792 (0.00232)
Teacher Age [24,54]	0.00922 (0.00843)	0.00340 (0.00823)	0.00371 (0.00810)	0.00363 (0.00809)	0.00414 (0.00810)
Teacher Age [24,54) × Extreme Heat Days	-0.000600 (0.00141)	-0.000383 (0.00140)	-0.000248 (0.00139)	-0.000171 (0.00139)	-0.000153 (0.00139)
Past Year Score	No	Yes	Yes	Yes	Yes
Student Demographics	No	No	Yes	Yes	Yes
County Economic Trends	No	No	No	Yes	Yes
Classroom Size	No	No	No	No	Yes
Observations	3,663,254	3,663,254	3,663,254	3,663,254	3,663,254

Note: Heteroskedasticity robust standard errors clustered at the grid level appear in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. This table presents the regression of student disciplinary incidents on the number of extreme days in the school year, teacher age bins, and the interaction of the these explanatory variables. Column 5 includes controls for lagged test score, student grade, ethnicity, gender, and year and school fixed effects.

4.4 Exploring the Returns to Age in the Presence of Extreme Heat

To study the effects of heat on teachers, I rely on interactions between heat and aging, making a parametric choice to study the top 10% of teachers by age compared to their younger colleagues. To explore the non-parametric relationship between test scores and teacher age under different levels of heat exposure, I create a binned scatterplot with teacher age on the x-axis and standardized test scores on the y-axis, with two series: one for student-teacher pairs in years with an above-average number of extreme heat days and another for those below the average. Figure 7 includes data residualized by the covariates in regression Equation 7: teacher education level, county economic variables, and school and year fixed effects.

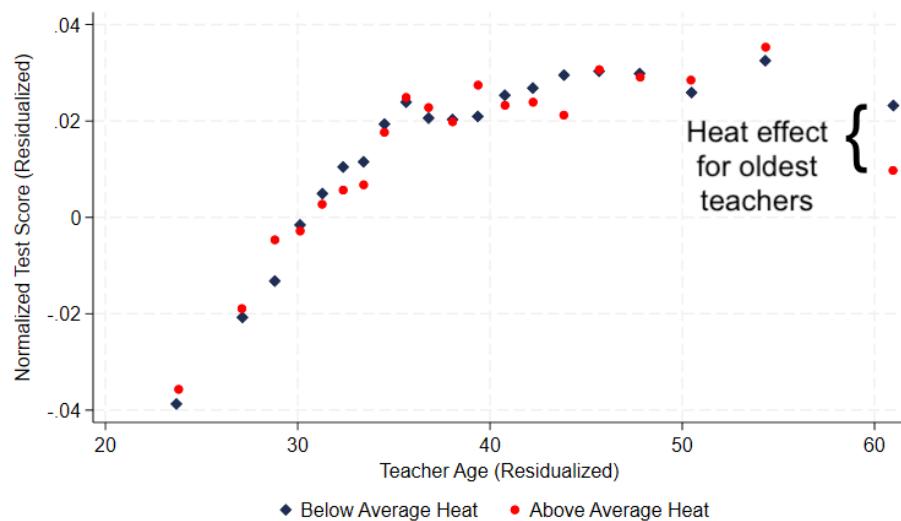
Figure 7 shows the descriptive relationship between test scores and teacher age by heat exposure level. The vertical distance between the red dots and blue diamonds illustrates how heat affects teacher performance by age. The largest difference appears for the oldest age group in the chart, teachers above age 54, validating the choice to focus on the top 10% of teachers by age.

The figure also shows that after about age 35, gains to experience flatten sharply, with the slope of the curve decreasing markedly in the early-to-mid 30s. While this is descriptive evidence only, it aligns with the literature on returns to teacher experience⁸.

Further, at the right tail of teacher age, there appears to be a drop to the returns to teacher age, particularly for teachers with above average heat exposure. These teachers' students have test scores below that of other teachers above 35 years old. I infer from this relationship that the oldest, most heat-exposed teachers lose some of the gains to teacher experience, though not all. These teachers still have students who perform higher than those of the youngest teachers.

⁸Earlier conventional wisdom suggested that teacher experience yielded little improvement after the first two or three years of teaching (Hanushek et al., 2005). However, more recent work shows that teachers continue to make gains beyond the first five years, with potential improvements extending into later decades of experience (Wiswall, 2013; Papay and Kraft, 2015; Ladd and Sorensen, 2017).

Figure 7: Test Scores by Teacher Age Above and Below Average Heat



Note: This figure plots average normalized test scores against teacher age by heat exposure level. Each point on the graph represents an average test score and an average teacher age with a range of ages, after both variables have been residualized by a set of controls. Test scores are normalized to have a mean of zero and standard deviation of one. The blue diamonds represent student-teacher pairs who experienced a below-average number of extreme heat days in a year while the red dots are those who had above-average heat. Teacher age is calculated using undergraduate graduation date, assuming age 24 at graduation.

4.5 Climate Control in Classrooms

Though I do not explicitly account for air conditioning in classrooms throughout this analysis, the baseline climate and building policies in North Carolina suggest that most classrooms have climate control. There is no statewide database that details which schools have climate control or when air conditioning systems were installed or upgraded. Given the hot and humid climate in much of North Carolina and the years covered by my sample, I assume that all elementary classrooms are equipped with air conditioning. I have some evidence to support this assumption. First, I compile a dataset of school maintenance requests beginning in 2008 for several of the largest school districts in my sample, and I find maintenance requests for existing air conditioning systems in every district included.⁹ Second, the state's 2014 Department of Public Instruction facilities guidelines specify the inclusion of central air conditioning, which suggests that schools built since at least 2014 are climate controlled. The analysis in this paper indicates that, despite the presence of air conditioning, teachers and students still experience declines in productivity and learning during periods of extreme heat. This may be due to a need for repairs and maintenance or it may be that older air-conditioning systems were not designed to handle current extremes.

4.6 Climate Change

With a warming climate, teachers and their students face an increasing number of extreme heat days. To predict the impacts of climate change, climate models often use climate scenarios proposed by the Intergovernmental Panel on Climate Change (IPCC), such as Representative Concentration Pathway (RCP) 4.5, a moderate climate change scenario, and RCP 8.5, a more severe scenario. RCP 4.5 requires enough technological innovation or industrial and climate policy to reduce increases in greenhouse gases, reaching stable levels shortly after the year 2100. The more severe climate change scenario, RCP 8.5, as-

⁹Data on school-level HVAC maintenance requests were collected through Freedom of Information Act requests.

sumes increasing global greenhouse gas emissions (United States Environmental Protection Agency, 2025). A peer-reviewed report on climate change in North Carolina predicts the prevalence of extreme weather in the coming decades using RCP 4.5 and 8.5 (Kunkel et al., 2020).¹⁰ For the 2041-2060 period, under moderate climate change, the report estimates that there will generally be up to 15 to 25 more days above 95°F per year compared to the 1996-2015 average, with larger increases in isolated areas. Under more severe climate change, the report projects around 25 or more very hot days per year for much of the state with even more hot days in the limited areas. At the same time, under both climate scenarios, the report finds an increase throughout the state in the number of very warm nights—nights above a minimum temperature of 75°F.

Further, the North Carolina climate report highlights the engineering design problems we face due to climate change, given that infrastructure like air-conditioning systems is engineered using historical extreme temperature data. Much of the current infrastructure may already be out-of-date and incapable of handling current extreme temperatures. Through technological innovation and improved design, buildings may become better at handling very hot temperatures over time. However, recent work shows there may be a limited scope for climate adaptation to extreme heat, at least in the short term (Costa et al., 2024).

Climate scientists estimate that, even under a moderate climate change scenario, North Carolina will have an increase of 15 to 25 days of extreme heat per year in 15 years' time—implying that the classroom environment will likely become hotter during the school year. Assuming the same relationship holds between learning and heat that I present in this work, ten more extreme heat days per school year leads to a yearly decrease in test scores of 0.02 standard deviations. If these effects are additive across years and there is no further climate adaptation, this decrease results in a loss of learning similar to the estimated loss in the immediate aftermath of Hurricane Katrina every ten years (Sacerdote, 2012). However, this estimate does not capture the increased sensitivity to extreme heat due to an aging workforce. In 2018, adults above 45 years old made up about 42% the US population

¹⁰Then-governor Roy Cooper commissioned this report under Executive Order 80.

5 Conclusion

While much of the literature on heat and learning focuses on students, this paper shows that teachers are themselves directly affected by extreme heat. I document how extreme heat undermines teacher productivity, particularly among older, more experienced educators, through both reduced instructional quality and increased absenteeism. In doing so, this work bridges two strands of research: the impact of climate on worker productivity and the economics of education, highlighting an overlooked mechanism through which environmental conditions shape student outcomes.

The results reveal a tension between teaching quality and sensitivity to heat. Older teachers, who typically deliver the greatest gains in student achievement in this analysis, are also the most sensitive to heat. In my setting, just ten additional extreme heat days are enough to erase the benefits of teacher experience. As climate change intensifies, this increased sensitivity threatens to erode one of the education system's key strengths—its experienced workforce. The fact that a relatively small group of teachers accounts for a large share of the climate-related loss in learning underscores both the scale of the challenge and the potential effectiveness of targeted mitigation strategies.

These findings also carry broader implications for inequality. Extreme heat effects are not distributed evenly: Black students and those in under-resourced schools with outdated infrastructure are more likely to learn in heat-vulnerable environments. If extreme heat disproportionately diminishes the effectiveness of experienced teachers in these schools, it could further widen achievement gaps across districts and communities. Investments in school infrastructure, workforce protections, and climate adaptation policies therefore have the potential to both improve resilience and reduce educational inequality.

Ultimately, this research shows that the costs of climate change extend beyond immediate health and labor market effects to the classroom, where they may compound over time by weakening the foundations of human capital. By identifying teachers as a critical channel through which heat influences learning, this paper provides new evidence to guide pol-

icy choices—whether in evaluating teacher performance, planning for climate-resilient schools, or deciding when to close schools during heat waves. These choices will shape whether the education system can continue to deliver high quality instruction in an era of rising temperatures.

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Appendices

A Teacher Age Bins Uncorrelated with Observables

In this section, I present the results of regressions of a teacher age bin indicator on extreme heat days, school and year fixed effects, and a set of control variables including students' past year test scores, student demographics, county unemployment rate, county median income, and classroom size. These regressions are based on linear probability models of the following form:

$$A_{jt} = \beta_0 + \beta_1 Heat + \mathbf{X}_i^{-1}\alpha + \gamma_k + v_t + \varepsilon_{jt} \quad (8)$$

where

$$A_j = \begin{cases} 1 & \text{if teacher } j\text{'s age } \in [24, 54] \\ 0, & \text{otherwise} \end{cases}$$

and *Heat* refers to the number of extreme heat days at a school during a school year. The variables γ_k and v_t refer to school and year fixed effects. Table A.1 presents the full results of these regression analyses. I find that teacher age bins are not correlated with extreme heat days. This result is stable across the choice of observable characteristics. Because teacher age and extreme heat days do not appear to be correlated, it is plausible that they are uncorrelated conditional on unobservables, an assumption needed for causal claims.

Table A.1: Regression of Teacher Age Bin Indicator on Observables

	(1)	(2)	(3)	(4)
Extreme Heat Days	0.000802 (0.000632)	0.000804 (0.000632)	0.000846 (0.000632)	0.000899 (0.000633)
Past Year Score	Yes	Yes	Yes	Yes
Student Demographics	No	Yes	Yes	Yes
County Economic Trends	No	No	Yes	Yes
Classroom Size	No	No	No	Yes
Observations	3663375	3663322	3663322	3663322

Note: Heteroskedasticity robust standard errors clustered at the grid level appear in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ This table presents the regression of teacher age bins on extreme heat days and observable characteristics. All regressions include year and school fixed effects. Column 1 includes the prior year test scores for a teacher's current students. Column 2 adds student demographics including ethnicity, gender, and age. Column 3 adds county-level unemployment rates and median income. Finally, column 4 adds class size.

B Test Score and Teacher Age Using Alternate Heat Measures

In the main analysis, the independent variable, the number of days above the 90th percentile of historic temperature, captures heat relative to baseline to account for adaptation by climate such as air-conditioning infrastructure. However, it may be useful to look at effects of absolute heat to compare to past literature and to investigate possible nonlinearities. To do this, I use the number of days in each school year below 30°F, between 30 and 40 °F, and so on, using the number of days between 60 and 70°F as the excluded category.

In this appendix, I regress standardized test scores on the number of days in each temperature bin in a school year and an indicator for teacher age above the 90th percentile. I include the interaction of these two explanatory variables to capture differences in heat effects by teacher age. This regression is of the following form:

$$y_{its} = \beta_a \sum_{a=1}^N DaysInBin_{ats} + \gamma_a \sum_{a=1}^N DaysInBin_{ats} \times A_{tj} \\ + vA_{tj} + \mathbf{X}_i^{-1}\alpha + \delta_t + \lambda_{\tilde{s}} + \varepsilon_{its} \quad (9)$$

where

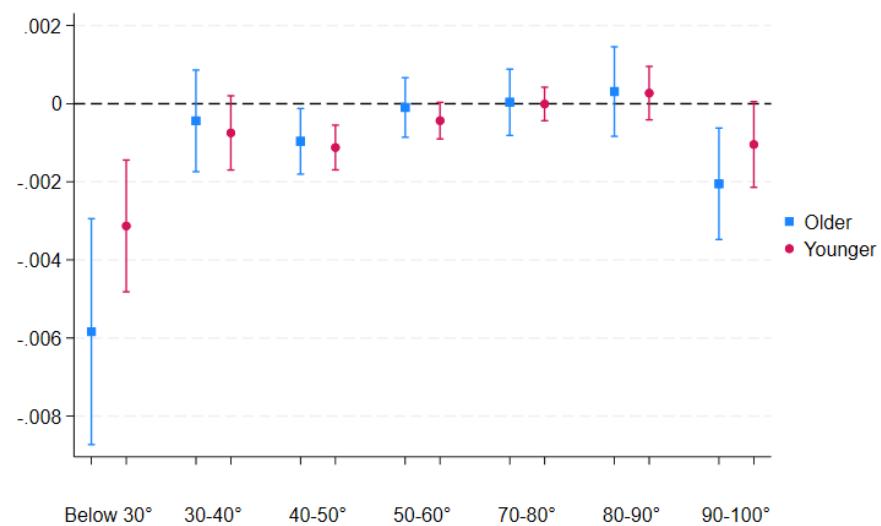
$$A_j = \begin{cases} 1 & \text{if teacher } j \text{'s age } \in [24, 54] \\ 0, & \text{otherwise} \end{cases}$$

and y_{its} is the outcome of interest: student i 's standardized test score in year t and subject s . $DaysInBin_{ats}$ is the number of days in bin a in school year t for school \tilde{s} . \mathbf{X}_i is a vector of control variables including lagged test score, student race, gender, and grade level. δ_t and $\lambda_{\tilde{s}}$ represent year and school fixed effects. School and year fixed effects are included to control for school-specific or year-specific unobservable factors that may affect test scores.

The results of this regression indicate that all teachers' students scores decrease with each additional day above 90°F and below 30°F—but older teachers' students seem to be especially affected. Table B.1, Column 6 presents the full regression output and Figure B.1 plots

the coefficients.

Figure B.1: Older teachers' quality suffers in heat above 90°F and below 30°F



Note: This figure plots the coefficients and standard errors from the regression of standardized test scores on the number of days in each temperature bin and teacher age.

Table B.1: Older teachers' quality suffers in heat above 90°F and below 30°F

	(1)	(2)	(3)	(4)	(5)	(6)
Days in 90s °F	-0.00195 (0.00124)	-0.00158* (0.000719)	-0.00159* (0.000718)	-0.00167* (0.000718)	-0.00193** (0.000725)	-0.00205** (0.000728)
Days in 80s °F	0.00148 (0.00112)	0.000400 (0.000586)	0.000385 (0.000586)	0.000477 (0.000574)	0.000244 (0.000583)	0.000311 (0.000584)
Days in 70s °F	0.000857 (0.000874)	0.0000172 (0.000440)	0.0000192 (0.000440)	0.000146 (0.000431)	0.0000718 (0.000433)	0.0000360 (0.000433)
50s °F	0.000852 (0.000813)	0.0000558 (0.000393)	0.0000408 (0.000392)	0.0000453 (0.000385)	-0.0000118 (0.000385)	-0.0000968 (0.000388)
40s °F	0.000580 (0.000794)	-0.000751 (0.000432)	-0.000770 (0.000432)	-0.000840* (0.000426)	-0.000839* (0.000426)	-0.000963* (0.000428)
30s °F	0.00220 (0.00134)	-0.000242 (0.000666)	-0.000276 (0.000664)	-0.000338 (0.000658)	-0.000222 (0.000663)	-0.000441 (0.000663)
< 30 °F	-0.00869** (0.00288)	-0.00535*** (0.00150)	-0.00536*** (0.00150)	-0.00527*** (0.00148)	-0.00560*** (0.00148)	-0.00584*** (0.00147)
Teacher Age [24,54) × < 30 °F	0.00720* (0.00290)	0.00306* (0.00151)	0.00306* (0.00151)	0.00275 (0.00147)	0.00268 (0.00147)	0.00271 (0.00147)
Teacher Age [24,54) × 30s °F	-0.000403 (0.00122)	-0.000388 (0.000536)	-0.000390 (0.000536)	-0.000321 (0.000531)	-0.000276 (0.000531)	-0.000306 (0.000531)
Teacher Age [24,54) × 40s °F	-0.000383 (0.000697)	-0.000152 (0.000351)	-0.000153 (0.000351)	-0.000201 (0.000342)	-0.000191 (0.000342)	-0.000158 (0.000344)
Teacher Age [24,54) × 50s °F	-0.000391 (0.000788)	-0.000355 (0.000367)	-0.000358 (0.000367)	-0.000365 (0.000359)	-0.000345 (0.000359)	-0.000337 (0.000361)
Teacher Age [24,54) × Days in 70s °F	-0.0000889 (0.000878)	0.0000297 (0.000430)	0.0000269 (0.000431)	-0.0000716 (0.000422)	-0.0000473 (0.000421)	-0.0000436 (0.000421)
Teacher Age [24,54) × Days in 80s °F	-0.000220 (0.00110)	-0.0000549 (0.000524)	-0.0000544 (0.000524)	-0.0000477 (0.000512)	-0.0000443 (0.000513)	-0.0000397 (0.000513)
Teacher Age [24,54) × Days in 90s °F	0.00150 (0.00108)	0.00110* (0.000540)	0.00109* (0.000540)	0.00103 (0.000533)	0.00101 (0.000532)	0.00101 (0.000531)
Teacher Age [24,54)	-0.00945 (0.127)	0.00385 (0.0617)	0.00417 (0.0617)	0.0119 (0.0605)	0.00872 (0.0604)	0.00674 (0.0606)
Past Year Score	No	Yes	Yes	Yes	Yes	Yes
Day of Test Temperature	No	No	Yes	Yes	Yes	Yes
Student Demographics	No	No	No	Yes	Yes	Yes
County Economic Trends	No	No	No	No	Yes	Yes
Classroom Size	No	No	No	No	No	Yes
Observations	3,663,254	3,663,254	3,663,254	3,663,254	3,663,254	3,663,254

Note: Heteroskedasticity robust standard errors clustered at the grid level appear in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
This table presents the regression of normalized test scores on ten-degree temperature bins, teacher age bins, and the interaction of these explanatory variables. Column 6 includes controls for lagged test score, the temperature on the day of the exam, student grade, ethnicity, gender, and year and school fixed effects.

Table B.2: Younger teachers' students perform relatively better than older ones during hotter years

	(1)	(2)	(3)	(4)	(5)
Cooling Degree Days (100s)	-0.000992 (0.00466)	-0.000949 (0.00466)	-0.00138 (0.00456)	-0.000986 (0.00457)	-0.00207 (0.00459)
Heating Degree Days (100s)	-0.00489** (0.00150)	-0.00515*** (0.00152)	-0.00587*** (0.00149)	-0.00605*** (0.00151)	-0.00630*** (0.00150)
Teacher Age [24,54)	-0.0633* (0.0256)	-0.0636* (0.0255)	-0.0702** (0.0247)	-0.0727** (0.0249)	-0.0717** (0.0248)
Teacher Age [24,54) × Cooling Degree Days (100s)	0.00738* (0.00305)	0.00741* (0.00305)	0.00786** (0.00298)	0.00797** (0.00299)	0.00786** (0.00299)
Teacher Age [24,54) × Heating Degree Days (100s)	0.000701 (0.000570)	0.000708 (0.000570)	0.000882 (0.000548)	0.000930 (0.000552)	0.000913 (0.000551)
Past Year Score	Yes	Yes	Yes	Yes	Yes
Day of Test Temperature	No	Yes	Yes	Yes	Yes
Student Demographics	No	No	Yes	Yes	Yes
County Economic Trends	No	No	No	Yes	No
Classroom Size	No	No	No	No	Yes
Observations	3663375	3663375	3663322	3663322	3663322

Note: Heteroskedasticity robust standard errors clustered at the grid level appear in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table presents the regression of normalized test scores on heat and cooling degree days, teacher age bins, and the interactions of the these explanatory variables. All regressions include year and school fixed effects. Column 5 includes controls for lagged test score, the temperature on the day of the exam, student grade, ethnicity, and gender.

Table B.3: Findings robust to alternate definition of extreme heat using 85th Percentile

	(1)	(2)	(3)	(4)	(5)	(6)
Extreme Heat Days (85th Percentile)	-0.00301** (0.00101)	-0.00195*** (0.000559)	-0.00194*** (0.000560)	-0.00182** (0.000562)	-0.00189*** (0.000561)	-0.00199*** (0.000563)
Teacher Age [24,54]	-0.0568*** (0.0101)	-0.0228*** (0.00437)	-0.0229*** (0.00437)	-0.0221*** (0.00430)	-0.0222*** (0.00430)	-0.0224*** (0.00429)
Teacher Age [24,54] × Extreme Heat Days (85th Percentile)	0.00182* (0.000769)	0.00100* (0.000408)	0.00101* (0.000408)	0.000962* (0.000405)	0.000972* (0.000405)	0.000938* (0.000405)
Past Year Score	No	Yes	Yes	Yes	Yes	Yes
Day of Test Temperature	No	No	Yes	Yes	Yes	Yes
Student Demographics	No	No	No	Yes	Yes	Yes
County Economic Trends	No	No	No	No	Yes	Yes
Classroom Size	No	No	No	No	No	Yes
Observations	3,663,254	3,663,254	3,663,254	3,663,254	3,663,254	3,663,254

Note: Heteroskedasticity robust standard errors clustered at the grid level appear in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
This table presents the regression of normalized annual test scores on the number of extreme days beyond the 85th percentile in the school year, teacher age bins, and the interaction of the these explanatory variables. All regressions include year and school fixed effects. Column 1 includes no other covariates. Column 2 controls for a student's prior year test score. Column 3 adds the exam day temperature. Column 4 adds student gender, ethnicity, and age. Column 5 adds county-level yearly unemployment rates and average income. Column 6 adds the classroom size.

Table B.4: Findings robust to alternate definition of extreme heat using 95th Percentile

	(1)	(2)	(3)	(4)	(5)	(6)
Extreme Heat Days (95th Percentile)	-0.00551* (0.00256)	-0.00157 (0.00142)	-0.00155 (0.00142)	-0.00156 (0.00139)	-0.00154 (0.00140)	-0.00157 (0.00140)
Teacher Age [24,54]	-0.0511*** (0.00851)	-0.0194*** (0.00350)	-0.0194*** (0.00350)	-0.0189*** (0.00341)	-0.0189*** (0.00342)	-0.0193*** (0.00341)
Teacher Age [24,54] × Extreme Heat Days (95th Percentile)	0.00552* (0.00238)	0.00275* (0.00120)	0.00274* (0.00120)	0.00275* (0.00118)	0.00268* (0.00117)	0.00267* (0.00118)
Past Year Score	No	Yes	Yes	Yes	Yes	Yes
Day of Test Temperature	No	No	Yes	Yes	Yes	Yes
Student Demographics	No	No	No	Yes	Yes	Yes
County Economic Trends	No	No	No	No	Yes	Yes
Classroom Size	No	No	No	No	No	Yes
Observations	3,663,254	3,663,254	3,663,254	3,663,254	3,663,254	3,663,254

Note: Heteroskedasticity robust standard errors clustered at the grid level appear in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
This table presents the regression of normalized annual test scores on the number of extreme days beyond the 95th percentile in the school year, teacher age bins, and the interaction of the these explanatory variables. All regressions include year and school fixed effects. Column 1 includes no other covariates. Column 2 controls for a student's prior year test score. Column 3 adds the exam day temperature. Column 4 adds student gender, ethnicity, and age. Column 5 adds county-level yearly unemployment rates and average income. Column 6 adds the classroom size.

C Using Alternate Definitions of Teacher Age

Table C.1: Similar Findings Using Age 50 Cutoff (85th Percentile of Teacher Age)

	(1)	(2)	(3)	(4)	(5)	(6)
Extreme Heat Days	-0.00189 (0.00104)	-0.000901 (0.000653)	-0.000897 (0.000654)	-0.000968 (0.000657)	-0.00104 (0.000657)	-0.00121 (0.000661)
Teacher Age [24,50]	-0.0538*** (0.00724)	-0.0229*** (0.00305)	-0.0229*** (0.00305)	-0.0225*** (0.00297)	-0.0224*** (0.00296)	-0.0226*** (0.00296)
Teacher Age [24,50) × Extreme Heat Days	0.00136 (0.000788)	0.000848* (0.000431)	0.000848* (0.000431)	0.000764 (0.000429)	0.000747 (0.000429)	0.000720 (0.000430)
Past Year Score	No	Yes	Yes	Yes	Yes	Yes
Day of Test Temperature	No	No	Yes	Yes	Yes	Yes
Student Demographics	No	No	No	Yes	Yes	Yes
County Economic Trends	No	No	No	No	Yes	Yes
Classroom Size	No	No	No	No	No	Yes
Observations	3,663,254	3,663,254	3,663,254	3,663,254	3,663,254	3,663,254

Note: Heteroskedasticity robust standard errors clustered at the grid level appear in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. This table presents the regression of normalized annual test scores on the number of extreme days in the school year, teacher age bins, and the interaction of the these explanatory variables, where the cutoff age between younger and older teachers is age 50, or the 85th percentile of teacher age. All regressions include year and school fixed effects. Column 1 does not include any covariates. Column 2 controls for a student's prior year test score. Column 3 adds the exam day temperature. Column 4 adds student gender, ethnicity, and age. Column 5 adds county-level yearly unemployment rates and average income. Column 6 adds the classroom size.

Table C.2: Similar Findings Using Age 59 Cutoff (95th Percentile of Teacher Age)

	(1)	(2)	(3)	(4)	(5)	(6)
Extreme Heat Days	-0.00350* (0.00151)	-0.00177 (0.000927)	-0.00176 (0.000928)	-0.00176 (0.000941)	-0.00181 (0.000941)	-0.00202* (0.000937)
Teacher Age [24,59]	-0.0567*** (0.0114)	-0.0182*** (0.00503)	-0.0182*** (0.00503)	-0.0167*** (0.00495)	-0.0168*** (0.00494)	-0.0171*** (0.00492)
Teacher Age [24,59) × Extreme Heat Days	0.00287* (0.00133)	0.00166* (0.000783)	0.00165* (0.000783)	0.00150 (0.000779)	0.00147 (0.000778)	0.00147 (0.000772)
Past Year Score	No	Yes	Yes	Yes	Yes	Yes
Day of Test Temperature	No	No	Yes	Yes	Yes	Yes
Student Demographics	No	No	No	Yes	Yes	Yes
County Economic Trends	No	No	No	No	Yes	Yes
Classroom Size	No	No	No	No	No	Yes
Observations	3,663,254	3,663,254	3,663,254	3,663,254	3,663,254	3,663,254

Note: Heteroskedasticity robust standard errors clustered at the grid level appear in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. This table presents the regression of normalized annual test scores on the number of extreme days in the school year, teacher age bins, and the interaction of the these explanatory variables, where the cutoff age between younger and older teachers is age 59, or the 95th percentile of teacher age. All regressions include year and school fixed effects. Column 1 does not include any covariates. Column 2 controls for a student's prior year test score. Column 3 adds the exam day temperature. Column 4 adds student gender, ethnicity, and age. Column 5 adds county-level yearly unemployment rates and average income. Column 6 adds the classroom size.

Table C.3: Similar Findings Excluding Youngest Teachers

	(1)	(2)	(3)	(4)	(5)	(6)
Extreme Heat Days	-0.003* (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001* (0.001)	-0.001* (0.001)	-0.002* (0.001)
Teacher Age [28,54)	-0.042*** (0.009)	-0.015*** (0.004)	-0.015*** (0.004)	-0.014*** (0.004)	-0.014*** (0.004)	-0.014*** (0.004)
Teacher Age [28,54) × Extreme Heat Days	0.002* (0.001)	0.001** (0.001)	0.001** (0.001)	0.001* (0.001)	0.001* (0.001)	0.001* (0.001)
Past Year Score	No	Yes	Yes	Yes	Yes	Yes
Day of Test Temperature	No	No	Yes	Yes	Yes	Yes
Student Demographics	No	No	No	Yes	Yes	Yes
County Economic Trends	No	No	No	No	Yes	Yes
Classroom Size	No	No	No	No	No	Yes
Observations	3,241,374	3,241,374	3,241,374	3,241,374	3,241,374	3,241,374

Note: Heteroskedasticity robust standard errors clustered at the grid level appear in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. This table presents the regression of normalized annual test scores on the number of extreme days in the school year, teacher age bins, and the interaction of the these explanatory variables, excluding teachers below the age of 28. All regressions include year and school fixed effects. Column 1 does not include any covariates. Column 2 controls for a student's prior year test score. Column 3 adds the exam day temperature. Column 4 adds student gender, ethnicity, and age. Column 5 adds county-level yearly unemployment rates and average income. Column 6 adds the classroom size.

D Heterogeneity

Table D.1: Heterogeneity By Test Subject

	(1) Math	(2) Reading	(3) All
Extreme Heat Days	-0.000882 (0.00100)	-0.00270*** (0.000719)	-0.00185* (0.000732)
Teacher Age [24,54)	-0.0156** (0.00521)	-0.0251*** (0.00335)	-0.0208*** (0.00363)
Teacher Age [24,54) \times Extreme Heat Days	0.00103 (0.000705)	0.00153** (0.000554)	0.00135** (0.000516)
Observations	1,845,537	1,817,679	3,663,254

Note: Heteroskedasticity robust standard errors clustered at the grid level appear in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. This table presents the regression of normalized annual test scores on the number of extreme days beyond the 90th percentile in the school year, teacher age bins, and the interaction of the these explanatory variables. All regressions include year and school fixed effects and controls for student's prior year test score, exam day temperature, student gender, ethnicity, and age, county-level yearly unemployment rates and average income, and classroom size. Column 1 includes only math standardized test scores. Column 2 includes only reading standardized test scores. Column 3 includes all test scores.

Table D.2: Heterogeneity by Grade Level

	(1) Grade 4	(2) Grade 5	(3) All
Extreme Heat Days	-0.00169 (0.000937)	-0.00218* (0.00104)	-0.00185* (0.000732)
Teacher Age [24,54)	-0.0218*** (0.00481)	-0.0189*** (0.00468)	-0.0208*** (0.00363)
Teacher Age [24,54) × Extreme Heat Days	0.00158* (0.000731)	0.00113 (0.000720)	0.00135** (0.000516)
Observations	1,760,149	1,875,729	3,663,254

Note: Heteroskedasticity robust standard errors clustered at the grid level appear in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. This table presents the regression of normalized annual test scores on the number of extreme days beyond the 90th percentile in the school year, teacher age bins, and the interaction of the these explanatory variables. All regressions include year and school fixed effects and controls for student's prior year test score, exam day temperature, student gender, ethnicity, and age, county-level yearly unemployment rates and average income, and classroom size. Column 1 includes only fourth grade. Column 2 includes only fifth grade. Column 3 includes all test scores.

Table D.3: Heterogeneity by Semester of Extreme Heat Days

	(1) Fall	(2) Spring	(3) All
Extreme Heat Days	-0.00202** (0.000734)	0.0130 (0.00842)	-0.00185* (0.000732)
Teacher Age [24,54)	-0.0209*** (0.00360)	-0.0157*** (0.00325)	-0.0208*** (0.00363)
Teacher Age [24,54) × Extreme Heat Days	0.00140** (0.000509)	-0.00956 (0.00793)	0.00135** (0.000516)
Observations	3,663,322	3,663,322	3,663,322

Note: Heteroskedasticity robust standard errors clustered at the grid level appear in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. This table presents the regression of normalized annual test scores on the number of extreme days beyond the 90th percentile in the school year, teacher age bins, and the interaction of the these explanatory variables. All regressions include year and school fixed effects and controls for student's prior year test score, exam day temperature, student gender, ethnicity, and age, county-level yearly unemployment rates and average income, and classroom size. Column 1 includes heat days from each fall semester. Column 2 includes heat days from the spring semesters only. Column 3 includes all extreme heat days.

Table D.4: Heterogeneity By Student Gender

	(1) Girls	(2) Boys	(3) All
Extreme Heat Days	-0.00183* (0.000811)	-0.00187* (0.000818)	-0.00185* (0.000732)
Teacher Age [24,54)	-0.0171*** (0.00386)	-0.0245*** (0.00400)	-0.0208*** (0.00363)
Teacher Age [24,54) × Extreme Heat Days	0.00146* (0.000592)	0.00127* (0.000599)	0.00135** (0.000516)
Observations	1,845,537	1,817,679	3,663,254

Note: Heteroskedasticity robust standard errors clustered at the grid level appear in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. This table presents the regression of normalized annual test scores on the number of extreme days beyond the 90th percentile in the school year, teacher age bins, and the interaction of the these explanatory variables. All regressions include year and school fixed effects and controls for student's prior year test score, exam day temperature, student gender, ethnicity, and age, county-level yearly unemployment rates and average income, and classroom size. Column 1 includes only female students' test scores. Column 2 includes only male students' test scores. Column 3 includes all test scores.

Table D.5: Heterogeneity By Rurality

	(1) Rural	(2) Suburban	(3) Urban
Extreme Heat Days	-0.000699 (0.00130)	-0.00181 (0.00201)	-0.00228* (0.00101)
Teacher Age [24,54)	-0.00203 (0.00791)	-0.0219 (0.0117)	-0.0280*** (0.00425)
Teacher Age [24,54) × Extreme Heat Days	0.000373 (0.00110)	0.00109 (0.00149)	0.00180** (0.000640)
Observations	819,807	469,295	2,374,152

Note: Heteroskedasticity robust standard errors clustered at the grid level appear in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. This table presents the regression of normalized annual test scores on the number of extreme days beyond the 90th percentile in the school year, teacher age bins, and the interaction of the these explanatory variables. All regressions include year and school fixed effects and controls for student's prior year test score, exam day temperature, student gender, ethnicity, and age, county-level yearly unemployment rates and average income, and classroom size. Column 1 includes only schools in rural counties. Column 2 includes only suburban counties and Column 3 uses only urban counties.

Table D.6: Heterogeneity By Student Race

	(1) American Indian	(2) Asian and Pacific Islander	(3) Hispanic	(4) Black	(5) White	(6) Multi-Racial	(7) N/A
Extreme Heat Days	-0.00235 (0.00424)	-0.00124 (0.00245)	-0.00120 (0.00128)	-0.00313* (0.00131)	-0.00139 (0.000853)	-0.00170 (0.00223)	0.00560 (0.120)
Teacher Age [24,54)	0.0170 (0.0291)	-0.0310*** (0.00911)	-0.0172** (0.00585)	-0.0152** (0.00517)	-0.0227*** (0.00426)	-0.0277** (0.00926)	-0.126 (0.139)
Teacher Age [24,54) × Extreme Heat Days	0.00267 (0.00309)	0.00204 (0.00203)	0.000970 (0.000986)	0.00170 (0.000901)	0.000999 (0.000679)	0.00216 (0.00185)	0.0101 (0.0107)
Observations	50,185	96,919	567,961	883,830	1,862,873	144,499	56,936

Note: Heteroskedasticity robust standard errors clustered at the grid level appear in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. This table presents the regression of normalized annual test scores on the number of extreme days beyond the 90th percentile in the school year, teacher age bins, and the interaction of the these explanatory variables. All regressions include year and school fixed effects and controls for student's prior year test score, exam day temperature, student gender, ethnicity, and age, county-level yearly unemployment rates and average income, and classroom size.

Table D.7: Heterogeneity By County Median Income

	(1) \$30-40K	(2) \$40-50K	(3) \$50-60K	(4) \$60-70K	(5) >\$70-80K
Extreme Heat Days	-0.00296 (0.00490)	-0.00298 (0.00165)	-0.000131 (0.00115)	-0.00293 (0.00155)	-0.00442 (0.00292)
Teacher Age [24,54]	0.0199 (0.0237)	-0.0126 (0.00814)	-0.0206*** (0.00560)	-0.0284*** (0.00735)	-0.0294*** (0.00816)
Teacher Age [24,54] × Extreme Heat Days	-0.000108 (0.00222)	0.00128 (0.00129)	0.00112 (0.000885)	0.00194* (0.000948)	0.00138 (0.00146)
Observations	92,096	603,716	1,481,712	880,954	604,776

Note: Heteroskedasticity robust standard errors clustered at the grid level appear in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. This table presents the regression of normalized annual test scores on the number of extreme days beyond the 90th percentile in the school year, teacher age bins, and the interaction of the these explanatory variables. All regressions include year and school fixed effects and controls for student's prior year test score, exam day temperature, student gender, ethnicity, and age, county-level yearly unemployment rates and average income, and classroom size. Column 1-5 each include schools in counties a given median income level, with Column 1 including only counties with a median income between \$30,000 and \$40,000, for example.

E Movers Analysis

This analysis explores whether younger and older teachers geographically sort by extreme heat in different ways. If older teachers choose to live in hotter climates compared to younger teachers, we would expect to see these teachers moving from a relatively cooler place to a warmer one, compared to younger teachers. Table E.2 presents the average changes in weather between a teacher's school and the next school where she works. For example, on average, younger teachers relocate to schools that have 1.57 fewer extreme heat days compared to their prior workplace. Older teachers on average relocate to schools that have 2.88 fewer extreme heat days than their prior school. The difference between these two figure is statistically significant, indicating that older teachers who relocate indeed move to cooler places than younger teachers. Table E.2 also shows these average differences between schools by teacher age for the number of days in the 80-90°F range and 90-100°F range, the average maximum temperature, student demographics, the county-level unemployment rate, and the median income. On average, younger teachers move to schools in slightly hotter places, with lower unemployment rates and higher median income. Younger teachers relocate to schools in counties with a median income that is on average \$2,470 higher than their prior school; older teachers relocate to areas with a median income that is \$1,280 higher on average. This difference hints at a potential reason for the move. Teacher may switch schools for better-resourced school districts earlier in their careers.

The descriptive analysis shown in Tables E.1 and E.2 indicate underlying differences between younger and older teachers who move. In addition, I implement an event study to investigate whether there is any causal evidence of geographic sorting by teacher age. This event study framework uses a regression of the following form,

$$y_{st} = \alpha + \sum_{j=2}^J \beta_j (\text{Lag } j)_{st} + \sum_{k=1}^K \gamma_k (\text{Lead } k)_{st} + \mu_s + \lambda_t + X'_{st} \Gamma + \varepsilon_{st}, \quad (10)$$

where y_{st} is the number of extreme heat days at school s in year t and $\text{Lag } j_{st}$ and $\text{Lead } k_{st}$

are indicators for the number for years preceding or following a move. The regression includes school and year fixed effects, μ_s and λ_t and a vector of covariates, X_{st} including percentage of a teacher's students who are male, percentage of students who are Black, student age, and student grade-level.

I find no evidence that older teachers move to cooler places compared to younger teachers. I present these finding in Figure E.1, which has the number of school years relative to a move on the horizontal axis and the estimated effect of that year on the number of extreme heat days on the vertical axis. These point estimates correspond with β_j and γ_k in Equation 10. The point estimates in red are those for younger teachers while those in yellow are those for older teachers. The figure also includes the 95% confidence intervals around each of point estimate.

Table E.1: Summary Table For Teachers Who Move

	First School mean	sd	Second School mean	sd	Third School mean	sd
Panel A: Teacher Age <54						
Extreme Heat Days	5.08	4.11	3.29	2.54	3.28	2.32
Days in 80s	30.64	6.52	31.72	7.24	32.38	7.81
Days in 90s	5.24	4.56	3.36	2.91	3.33	2.61
Average Maximum Temperature	64.50	2.27	64.58	2.27	64.83	2.32
Black Student Percent	0.30	0.26	0.29	0.25	0.30	0.26
Female Student Percentage	0.01	0.09	0.00	0.07	0.01	0.07
Unemployment Rate	8.11	2.52	6.59	2.62	5.50	1.93
Median Income	58,927.17	10,305.55	61,407.93	10,808.20	62,968.37	10,879.01
Rural	0.19	0.39	0.17	0.37	0.12	0.33
Number of Teachers, First School					4,083	
Second School					4,083	
Third School					569	
	First School mean	sd	Second School mean	sd	Third School mean	sd
Panel B: Teacher Age ≥54						
Extreme Heat Days	6.03	4.12	2.89	2.64	4.11	3.36
Days in 80s	31.31	7.56	30.45	8.37	35.64	6.45
Days in 90s	6.16	4.41	2.94	2.96	5.04	3.77
Average Maximum Temperature	64.73	2.71	64.23	2.56	65.27	2.22
Black Student Percent	0.27	0.27	0.34	0.30	0.40	0.33
Female Student Percentage	0.02	0.14	0.01	0.12	0.00	0.00
Unemployment Rate	7.90	2.41	7.78	3.20	6.13	3.48
Median Income	57,869.21	9,964.29	58,990.05	10,943.22	60,207.16	11,562.44
Rural	0.22	0.42	0.22	0.42	0.41	0.51
Number of Teachers, First School					209	
Second School					209	
Third School					17	

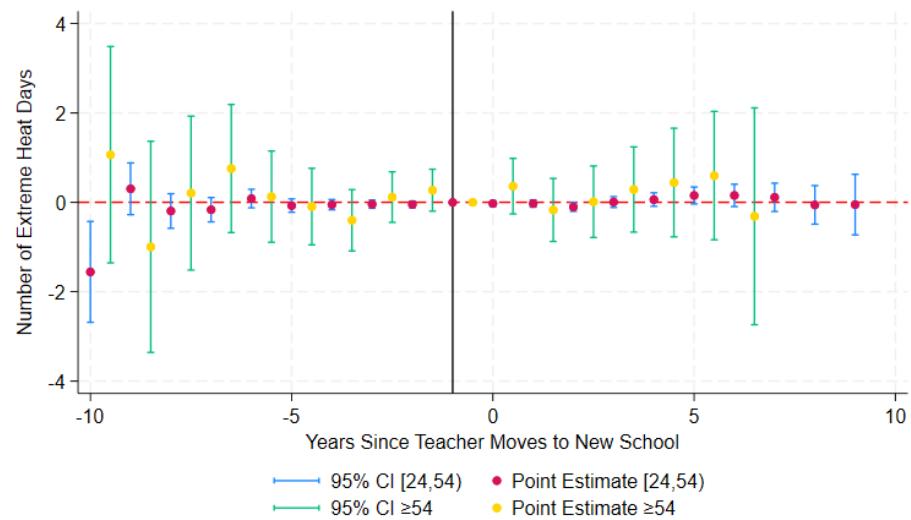
Note: This table presents summary statistics, including the mean, standard deviation, and number for teachers who change schools throughout the sample. All variables are at the school year level and span the 2007-08 through 2017-18 school years.

Table E.2: Differences Between Older and Younger Teachers Who Move

	(1) Age [24,54]	(2) ≥ 54	(3) Difference (1)-(2)
Change in Extreme Heat Days	-1.57 (5.01)	-2.80 (5.35)	1.23*** (0.36)
Change in Days in 80s	1.25 (7.46)	-0.48 (8.35)	1.73** (0.57)
Change in Days in 90s	-1.66 (5.30)	-2.82 (5.51)	1.15** (0.37)
Change in Average Maximum Temperature	0.16 (2.56)	-0.42 (2.61)	0.58** (0.18)
Change in Black Student Percent	-0.01 (0.28)	0.06 (0.36)	-0.07** (0.02)
Change in Male Student Percent	0.00 (0.15)	0.00 (0.20)	0.00 (0.01)
Change in Unemployment Rate	-1.64 (2.94)	-0.25 (3.34)	-1.39*** (0.23)
Change in Median Income	2467.06 (8322.48)	1283.71 (5961.31)	1183.35** (414.58)
Change in Rural	-0.03 (0.33)	-0.00 (0.24)	-0.02 (0.02)
Observations	4734	226	4960

Note: The sample in this table includes teachers who change schools at least once. Columns 1 and 2 show the mean difference in each variable between a teacher's prior and following school, with standard deviations in parentheses. Column 3 shows the difference in mean differences, with the standard error of this difference in parentheses and with stars specifying significance as follows: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure E.1: No evidence of sorting by heat and teacher age



Note: This event study plot presents estimates for the number of extreme heat days relative to a move from one school to another. The x-axis shows the number of years since the move to a new school.