# Education Under Extremes: Temperature, Student Absenteeism, and Disciplinary Infractions

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This Draft: May 29, 2024

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**Abstract**

How does student behavior respond to extreme temperatures and who is most affected? Using daily student-level data from a large urban school district, I estimate the causal effect of temperature on two dimensions of student behavior that are predictive of academic and later life outcomes: school absences and disciplinary referrals. Absenteeism increases in response to both hot and cold conditions, particularly for Black, Hispanic, and lower-income students. Hot conditions also increase the likelihood that a student will receive a disciplinary referral, an effect found only among students attending schools without air conditioning. Results suggest that warming temperatures may lead to more student behavioral problems and that unequal access to air conditioning may exacerbate racial, ethnic, and socioeconomic disparities in school.

*I thank David Cutler, Joe Aldy, Marcella Alsan, and Ed Glaeser for their continued guidance and support. I am grateful to the partnering school district for providing data access and assistance throughout this research process. I am also grateful to Josh Goodman, Jisung Park, Mark Shepard, and Joshua Linn for their valuable feedback, as well as the participants of the Harvard Environmental Economics Workshop and Seminar, the Harvard Public Finance/Labor Workshop and Seminar, the Harvard Economics and Social Policy Workshop and Seminar, and the Northeast Workshop on Energy Policy and Environmental Economics. I have also benefited from feedback from seminar attendees at Resources for the Future, the University of Colorado Department of Economics and Renewable and Sustainable Energy Institute, Pomona College, Barnard College, Claremont McKenna College, the Environmental Protection Agency, the National Center for Environmental Economics, the Government Accountability Office, the Federal Trade Commission, and the U.S. Treasury Office of Tax Analysis. I gratefully acknowledge the support of the Joseph Crump Fellowship, the Christopher and Silvana Pascucci Graduate Student Dissertation Fellowship, and the Harvard Kennedy School's Taubman Center for State and Local Government. This research was conducted while McCormack was an employee of the U.S. Department of the Treasury. The findings, interpretations, and conclusions expressed in this paper are entirely those of the author and do not necessarily reflect the views or the official positions of the U.S. Department of the Treasury.

# 1 Introduction

In the United States, many schools are facing an unprecedented number of hot days, a trend that is expected to continue given the rapidly changing climate. At the same time, many school districts have deteriorating or outdated HVAC systems that are expensive to update.[1] Warming conditions are also experienced unequally; on average, Black, Hispanic, and low-income students live in hotter areas and have less access to air conditioning at school and at home (Park *et al.*, 2020; Hsu *et al.*, 2021). These patterns, along with evidence that students exposed to hotter conditions tend to perform worse on tests and to graduate at lower rates (Park *et al.*, 2020; Park, 2022; Park *et al.*, 2021; Graff Zivin *et al.*, 2018), contribute to concerns that climate change will exacerbate existing disparities in student outcomes and childhood and later life-well-being.

Much remains unknown about how temperature affects student experiences, outcomes, and well-being. This paper focuses on two important aspects of student behavior, absences and disciplinary referrals, which are both disruptive to learning, predictive of worse academic and later life outcomes, and characterized by large racial/ethnic and socioeconomic disparities (Liu *et al.*, 2021; Gottfried, 2010; Gershenson *et al.*, 2017; Cattan *et al.*, 2023; Craig and Martin, 2019; Bacher-Hicks *et al.*, 2019; Morris and Perry, 2016; Lacoe and Steinberg, 2019; Noltemeyer *et al.*, 2015). Understanding how absences and disciplinary referrals respond to extreme temperatures and who is most affected may offer valuable insight into the effect of warming temperatures on childhood experiences and the potential benefits of school infrastructure investments.

To estimate the causal impact of extreme temperatures on absences and disciplinary referrals, I leverage a highly-detailed panel of tens of millions of daily, student-level observations from a large urban school district. Data include approximately 80,000 K-12 students enrolled annually during the 2011/12 to 2018/19 school years. These data allow me to observe individual students over time and to link these students with local weather data, school air conditioning information, and a measure of access to air conditioning at home, which I construct at the census block level from housing-unit level air conditioning information. The resulting data set provides a rich picture of student behavior, exposure to extreme temperatures, and access to adaptive technology. School- and student-fixed effects regressions identify the temperature-behavior relationship by leveraging exclusively between-year variation in environmental conditions, while accounting for the exact day of the school year as well as time-invariant student and school characteristics.

My identification strategy relies on the assumption that, across different school years,

[1] Approximately a quarter of the 50 largest US school districts lacked full air conditioning in 2017 (Barnum, 2017), and in 2020, GAO found that that 41% of districts reported the need to update or replace heating, ventilation, and air conditioning (HVAC) systems in at least half of their schools (GAO, 2020).

environmental conditions on a specific day of the school year are uncorrelated with unobserved determinants of student behavior. Several features of the school setting lend support to this assumption. First, changes in school schedules that might affect behavior are rarely made in response to environmental conditions, and when changes are made (e.g., snow days), those changes are easily observed. Second, student-level attendance data identify which students are absent and therefore unable to receive a behavioral referral on a given day. These two features of the school setting allow me to avoid a common challenge faced by observational studies of the effect of temperature on behavior, in which temperature may affect not only the type of behavior occurring but also the number of interactions people have and the observability of those interactions.

I present three key findings about the effect of extreme temperatures on student behavior. First, extreme temperatures exacerbate absenteeism, especially for minority and lower-income students. Relative to school days with temperatures between 60 and 70°F, students are 34% more likely to be absent on days with temperatures below 30°F. Absences also increase in response to moderately and extremely hot temperatures; students are 8%, 10%, and 16% more likely to be absent on days where the temperature is in the 70s, 80s, and over 90°F, respectively. This increase in absenteeism may be the result of heat-induced discomfort or illness experienced by students or their families, a mechanism proposed by papers documenting the effect air pollution on absences (Currie *et al.*, 2009; Chen *et al.*, 2018). Consistent with Goodman (2014), I find that absences also increase in response to snow, particularly for Black, Hispanic, and lower-income students.

Results suggest that hot, cold, and snowy conditions exacerbate existing racial/ethnic and socioeconomic disparities in absences, reducing instructional time for the most disadvantaged students. On average, Black and Hispanic students are more than 30% more likely to be absent on a given day than white students, which translates into a substantial disparity in instructional time (more than 2.5 days over a typical school year). Results suggest that the absences of Black and Hispanic students are about twice as sensitive to hot conditions as the absences of white students, and over three times as sensitive to cold and snow.

Second, I find that disciplinary referrals increase in response to heat. On days with temperatures between 80 and 90°F and exceeding 90°F, students are 4% and 9% more likely to receive a disciplinary referral than on school days with temperatures between 60 and 70°F. This result may reflect changes in student behavior, teacher discretion in responding to student behavior, or a combination of the two, which is an important consideration given evidence of the effect of heat on harsher or less favorable decision-making by authority figures (Behrer and Bolotnyy, 2022; Heyes and Saberian, 2019). While a separate examination of the effect of temperature on each referral type is under-powered, I find the increase in behavioral referrals on hot days to be largely composed of behavior the district categorizes as "disruptive," "defiant," or "disobedient," categories of referrals that often reflect teacher-student interactions and are understood to be more affected by teacher bias (Okonofua and Eberhardt, 2015; Morris, 2007; Nolan, 2011).

Finally, I find that the increase in disciplinary referrals on hot days is driven entirely by changes in referrals among students attending schools without air conditioning. In these schools, referrals increase by 7% and 21% on days with temperatures between 80–90°F and above 90°F respectively, relative to days with temperatures between 60–70°F. Results further indicate that the increase increase in disciplinary referrals on hot days primarily affects students who not only lack access to air conditioning at school, but also live in neighborhoods with low levels of residential air conditioning. This finding underscores the importance of accounting for the potential for adaptive behavior and the barriers to accessing adaptive technology when considering the effect of adverse environmental conditions on well-being and inequality (Deschênes and Greenstone, 2011; Kahn, 2016; Graff Zivin and Neidell, 2014; Park *et al.*, 2021).

To my knowledge, this paper presents the first evidence that reported behavioral issues in schools are sensitive to temperature. A couple of papers studying the effect of annual shocks in pollution have documented an increased likelihood of being suspended in more polluted schools (Heissel *et al.*, 2019; Persico and Venator, 2021). In contrast to these papers, I focus on the short-term effect of environmental shocks, suggesting that the temperature-behavior relationship I observe is not the result of longer-term changes in related outcomes, like learning, in response to temperature. Detailed disciplinary data also allow me to examine the broad range of behaviors that result in a disciplinary referral, including minor behavioral issues. These referrals capture real disruptions to learning, productivity, and interpersonal relationships, but are rarely recorded in non-school settings, where misbehavior is typically only recorded if it is deemed to be serious (e.g., crime).

The observed heat-induced increase in disciplinary referrals may stem from several possible channels. First, a physiological response to heat may lead students, teachers, and parents to feel hostile, irritable, and angry (Anderson, 2001, 1989), causing interpersonal interactions to suffer. In adult populations, crime, and violent crime in particular, increases on hot days (Ranson, 2014; Burke *et al.*, 2015; Bondy *et al.*, 2020; Heilmann *et al.*, 2021; Behrer and Bolotnyy, 2022; Mukherjee and Sanders, 2021), and recent contributions to the heat-behavior literature document the effect of heat on negative sentiment expressed online (Baylis, 2020), workplace harassment complaints (Narayan, 2022), and maltreatment of children (Evans *et al.*, 2023). Second, evidence that heat affects academic performance (Park *et al.*, 2020; Park, 2022; Park *et al.*, 2021; Graff Zivin *et al.*, 2018) and performance on cognitive and non-cognitive tasks (Anderson, 1989; Almås *et al.*, 2019) suggest that heat may also impair decision-making and cause students and teachers to be more distracted and frustrated in class. Hot temperatures have been show to adversely affect both physical and mental health (Mullins and White, 2019). Together, these potential channels highlight the challenging learning environment students are likely to face on hot days, where impaired decision-making, volatile interpersonal interactions, and mental and physical stress may contribute to more reported behavioral problems in school.

Results highlight an important way in which warming conditions disproportionately affect students with the lowest access to adaptive technology. They suggest that heat-induced behavioral changes may contribute to the observed negative effect of heat on learning, and they highlight the potential importance that differences in exposure to environmental conditions and access to adaptive technology may have in explaining observed racial and socioeconomic disparities in student behavioral outcomes. In the context of a warming climate and unequal access to residential air conditioning, findings imply that school air conditioning may serve as an effective tool in reducing the unequal effect of climate change on student outcomes.

The remainder of the paper is organized as follows. In section 2, I introduce the institutional setting of the study. I provide additional details about the data in section 3. In section 4, I present key summary statistics. Section 5 outlines my empirical strategies. In section 6, I provide my main results and heterogeneity analysis. In section 7, I apply my estimated models to projections from climate change simulations to predict how climate change will affect adverse behavioral outcomes as well as childhood and later-life well-being. In section 8, I discuss the implications of my results and conclude.

## 2 District setting

The setting of this study is a large urban school district (LUSD), one of the 50 largest K-12 public school districts in the country and the largest in its state. Compared to these other large districts, students enrolled in the LUSD are less likely to graduate from high school, more likely to qualify for free or reduced-price lunch, and more likely to live in poverty (NCES, 2020).

The metropolitan area where the district is located is characterized by a wide range of temperatures, including very hot school days. However, many of the district's schools are not fully air-conditioned, and hot temperatures in non-air-conditioned schools have been a contentious issue among students, parents, educators, and the local community.

Like many districts in the country, the LUSD is actively developing best practices to prioritize new air conditioning installations. For the first six years of the sample period, from 2011/12–2016/17, 55% of the student body attended schools without air conditioning. The school district made no changes to air conditioning in any existing buildings during this period, finding new installations to be prohibitively expensive. In the summer of 2017, the district began using funds from a recently-approved tax package to install air conditioning in the hottest school buildings; over the next two years, school air conditioning was provided to an additional 22% of the student body.

Initial planning prioritized schools for installation based on a 2015 temperature study, which measured the indoor temperatures of non-air-conditioned schools during a hot week of the year. In subsequent years, the district added to its priorities the goals of improving learning environments in "high-need" and high-utilization schools, while also considering "geographic equity."[2] Understanding which students are most vulnerable to heat and who may most benefit from access to school air conditioning may help inform resource-constrained districts, including the LUSD, as they continue to make challenging decisions about which schools to prioritize for new air conditioning installations.

## 3 Data

To create a panel of daily, student-level observations, I link five data sets: (1) daily student-level attendance and discipline data, (2) student demographic and geographic information, (3) student neighborhood characteristics, including residential air conditioning penetration information, (4) school schedules and facility air conditioning information, and (5) daily environmental data.

### 3.1 Daily student-level attendance and discipline data

I use detailed, high-frequency student-level data provided by the LUSD, which include all students enrolled in the district at any time during the 2011/12–2018/19 school years. During these years, the district enrolled an average of about 80,000 K-12 students annually, who attended approximately 200 schools.[3] Unique student identifiers allow me to follow individual students across time.

Daily student-level data include enrolled and absent minutes and student discipline information, which includes every incident in the study period that merited administrative involvement. While some minor forms of misbehavior do not require administrator involvement (e.g., profanity, use of cell phones in class), a large range of incidents and resulting disciplinary outcomes is documented. For each referral, the participant(s), the date and time, and all disciplinary responses to the incident, including whether a student was referred to law enforcement, are noted. I group incidents into eight broad categories based on about 50 incident descriptions: fighting/assault, bullying and harassment, weapons and dangerous

[2] To identify high-need schools, the district relies on a newly-developed "equity index," which is based on the percent of students who are eligible for free or reduced-price lunch, who are English Language Learners, or who have special education needs. It also includes a measure of teacher turnover. Geographic equity is considered to ensure that schools in all regions of the city see some improvements.

[3] All summary statistics and analyses exclude first grade students because of data quality issues particular to that grade.

behavior, theft and destruction, disruptive behavior, alcohol and drugs, recurring offenses, and other incidents (refer to Tables A1 and A2 for descriptions of these categories and the associated disciplinary responses).

### 3.2 Student demographic and geographic data

Student demographic information, which is provided at the annual level, includes student race/ethnicity, English Language Learner status, gender, and grade. The census block of each student's home addresses is also noted.

### 3.3 Student neighborhood characteristics

I assign neighborhood characteristics to each student by matching the census block of their home address to county assessor's office data and American Community Survey (ACS) data.

I construct census block-level estimates of residential air conditioning penetration using air conditioning data from the county assessor's office for the 2022 tax year. These data indicate whether each residential property (e.g., house, apartment building, mixed-use building) has central air conditioning. For multi-unit properties, air conditioning status is reported for each floor of the building, and the number of units on each floor is noted. I construct census block estimates by first geocoding the addresses of each property and then taking an average of the residential air conditioning status of each property in the census block, weighted by the number of units in each property. I categorize census blocks as either "high" or "low" air conditioning neighborhoods, which I define by whether the majority of the housing units in that block have central air conditioning.

I estimate the median age of the housing stock in each census block group using 2011-2015 ACS data. Estimates of the percent of households in each block group that are characterized as low- and moderate-income (LMI) are also constructed from these data (provided by the US Department of Housing and Urban Development). These estimates are used to proxy for student family income because student-level free or reduced-price lunch eligibility data are unavailable.

### 3.4 School and facility data

School and facility data, which I link to students using enrollment data, include information on school schedules and building characteristics. For each school, I use LUSD social media accounts, district calendars, and news articles to identify school vacations and unexpected school disruptions, including power outages, snow days, bomb threats, gas leaks, and other disturbances. I pull school facility information, including building age and air conditioning installation history, from district planning documents.[4]

### 3.5 Daily environmental data

Daily meteorological data come from three main sources. Information on daily maximum temperature and precipitation comes from the 2020 version of the fine-scaled weather data set first described by Schlenker and Roberts (2009). These 2.5 x 2.5 mile gridded data are based on the PRISM Climate Group's gridded re-analysis product, but are constructed in a way that maintains a consistent set of weather stations over time. I construct a daily, district-wide measure of temperature and precipitation from these data using a weighted average of the conditions modeled in each cell where a school is located.[5] Maximum outdoor temperature is chosen as the key measure of temperature (instead of minimum or average temperature), both because students attend school during the middle of the day, and also because this region is characterized by substantial diurnal variation in air temperature. For example, the average minimum temperature on days with a maximum temperature between 80–90°F days is 55°F. Snow data are obtained from the National Oceanic and Atmospheric Administration's Daily Global Historical Climatology Network. Daily fine particulate matter ($PM_{2.5}$) and ground-level ozone ($O_3$) readings are obtained from monitor data provided by the U.S. EPA Air Quality System.[6]

## 4 Descriptive statistics

Table 1 provides descriptive statistics for the K-12 student population between the 2011/12 and 2016/17 school years.[7] As a share of total enrollment, 19% of students are white, 16% are Black, 57% are Hispanic, and 8% are another race/ethnicity. Hispanic and Black students live in neighborhoods where 65% and 59% of households, respectively, are categorized as low- and moderate-income (LMI), relative to 37% of households in neighborhoods where white students live. Most (63%) Hispanic students are enrolled in English Language Learner programs.

[4]Other substantial modifications to facilities during the study period are also noted. A few schools were relocated to new buildings or received major, non-HVAC-related updates during the sample period. These schools were not included in the analysis.

[5]A single daily measure of temperature is used to correspond to available snow and air pollution data. Results are robust to using a simple average of all 2.5 x 2.5 mile cells located in the school district.

[6]These data come from a single monitor in the center of the district. While other monitors are located in the district, only one monitor reported readings for the full sample period (with the exception of part of the 2011/12 school year when o3 readings from another central monitor were used).

[7]Unless otherwise noted, descriptive statistics are provided for school days during the academic years prior to new air conditioning installations, which began in the 2017/18 school year, because the majority of the analysis in this paper focuses on this period.

Table 1. Students, Neighborhoods, and School Air Conditioning.

| | | Gender | | Race/Ethnicity | | | Grade Level | | |
|---|---|---|---|---|---|---|---|---|---|
| | All | Female | Male | White | Black | Hisp. | Elem. | Middle | High |
| **Student and Neighborhood Characteristics** | | | | | | | | | |
| Share of Enrollment (%) | 100 | 48.9 | 51.1 | 19.3 | 15.7 | 57.2 | 47.8 | 23.9 | 28.3 |
| % English Language Learners | 42.4 | 42.6 | 42.2 | 6.3 | 15.1 | 62.8 | 42.3 | 44.6 | 40.7 |
| Average % LMI | 57.7 | 57.6 | 57.7 | 36.7 | 59 | 65.2 | 57.4 | 58.2 | 57.7 |
| Average % Built <1970 | 66.7 | 66.8 | 66.5 | 64.3 | 55.1 | 71.3 | 66.7 | 66 | 67.2 |
| % Neighborhood with AC | 39.9 | 40.1 | 39.7 | 48.1 | 48.7 | 33.5 | 41.2 | 39.6 | 37.6 |
| **School Characteristics** | | | | | | | | | |
| % Schools with AC | 45 | 44.9 | 44.5 | 36.4 | 52.2 | 45.7 | 47.5 | 47.2 | 37.9 |
| % Schools without AC | 55 | 55.1 | 55.5 | 63.6 | 47.8 | 54.3 | 52.5 | 52.8 | 62.1 |
| % Schools Built <1970 | 60 | 59.7 | 60.2 | 66.2 | 52.9 | 59.8 | 55.7 | 57.7 | 69.1 |

*Notes:* The top panel shows, for each gender, race/ethnicity, and grade level, the share of total enrollment, the percent enrolled in English Language Learners programs, the average percent of low- and moderate-income households in students' home census block groups, the average percent of housing units built prior to 1970 in students' home census block groups, and the percent of homes with central air conditioning in students' home census blocks. The second panel shows the percent of each group enrolled in air-conditioned and non-air-conditioned schools and schools built prior to 1970. Descriptive statistics are shown for the 2011/12–2016/17 school years. All enrolled students are included, but statistics in columns 4–6 are only shown for the three largest racial/ethnic groups, which comprise 92% of the student body, on average.

## 4.1 Student and neighborhood characteristics and access to air conditioning

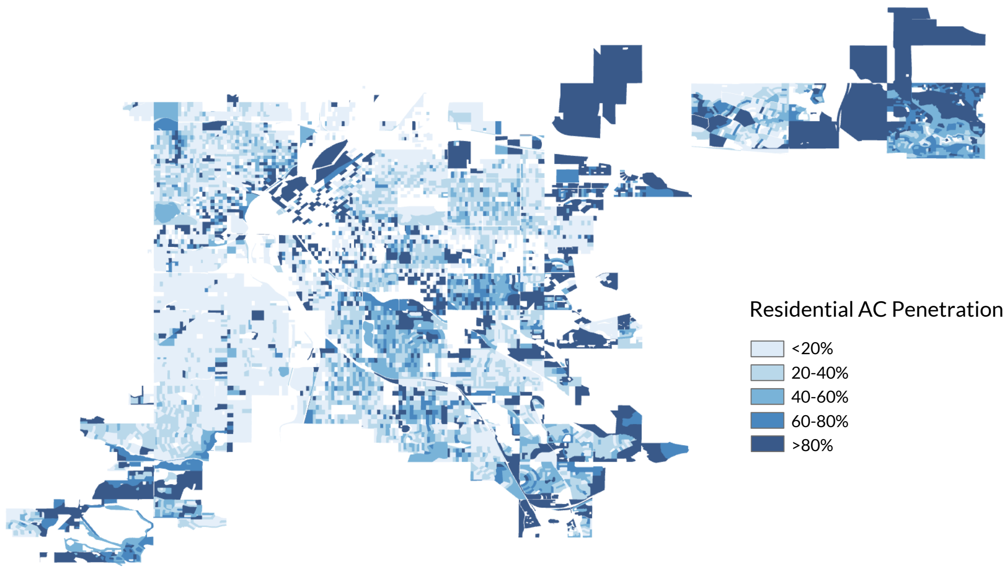
During the 2011/12–2016/17 school years, 45 percent of all students attend air-conditioned schools, which tend to be located in newer buildings and to serve students living in newer neighborhoods.[8] On average, white students are more likely to attend older schools and are less likely to attend air-conditioned schools than Hispanic and Black students, and air conditioning is more common in elementary and middle schools than in high schools.[9]

Access to residential air conditioning, which is measured at the census block level, also differs by race/ethnicity.[10] Relative to their white and Black peers, who live in neighborhoods

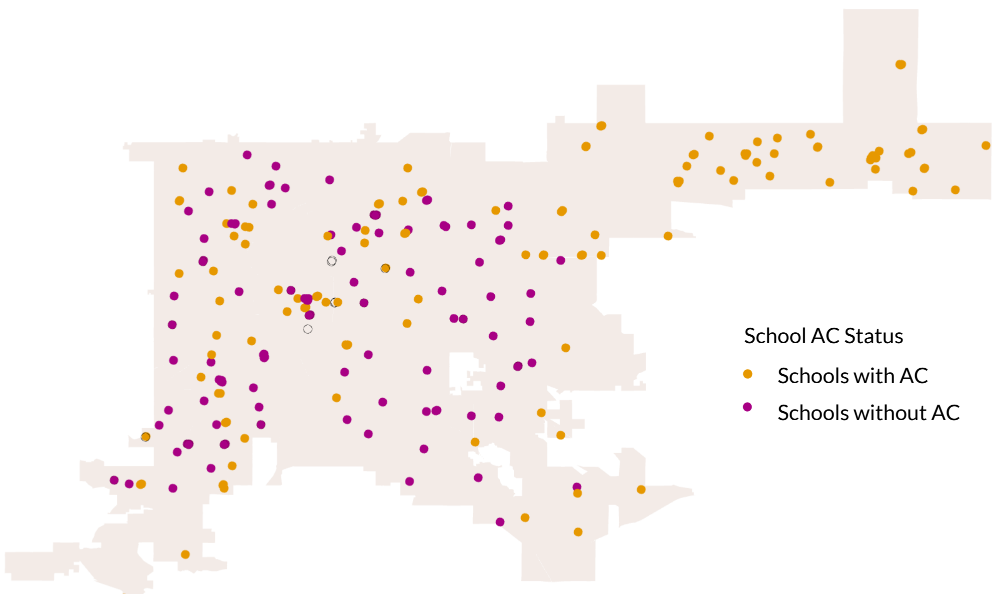
[8]Table A4 provides greater detail on the characteristics of facilities and student body populations by school air conditioning status. Students attending schools without air conditioning live in older (78% of homes built prior to 1970 vs. 53%) and slightly lower-income neighborhoods (58% of households LMI vs. 57%). As illustrated in Figure A1, school building age is highly predictive of air conditioning status; only 1% of school buildings built in 1970 or later lack air conditioning, compared to 86% of school buildings built before 1970.

[9]White and higher-income students do not appear to disproportionately select into air-conditioned schools through the district's school choice program. Among high school students, for example, students "choosing" an air-conditioned school over a non-air-conditioned school (those enrolled in air-conditioned schools whose school or schools to which they could automatically enroll is not air-conditioned) are, on average, less likely to be white and more likely to live in lower-income neighborhoods (11% white, 65% LMI) than those "choosing" a non-air-conditioned school over an air-conditioned school (12% white, 50% LMI), those "choosing" a different non-air-conditioned school (17% white, 63% LMI), or those attending the non-air-conditioned schools to which they are automatically enrolled (24% white, 55% LMI).

[10]While census block estimates of residential air conditioning do not translate perfectly to access to home air conditioning for an individual student, the bimodal nature of the data allows for central air conditioning to




(A) Residential Air Conditioning




(B) School Air Conditioning

Figure 1. School and Residential Air Conditioning

*Notes:* Panel (A) shows census-block level average residential air conditioning penetration levels, taken from 2022 tax year county assessor's office data. White spaces represent areas in which no residential property is reported. Panel (B) shows school locations and air conditioning penetration (constant from 2011/12–2016/17). Multiple schools may share the same campus. Hollow circles represent schools that relocated or had major renovations and were excluded from the sample.

where 48–49% of homes are air-conditioned on average, Hispanic students live in neighborhoods where only 34% of homes are air-conditioned on average. Racial/ethnic differences in residential air conditioning penetration may stem from differences in housing stock age and income. Air conditioning penetration tends to be lower in both older neighborhoods and lower-income neighborhoods (see Figure A2). Compared to other students, white students are substantially less likely to live in lower-income neighborhoods and Black students are substantially less likely to live in older neighborhoods; Hispanic students live in neighborhoods that are, on average, characterized by *both* an aging housing stock and relatively low-income households. In addition to affecting the likelihood of living in a home with central air conditioning, income may also affect unobserved dimensions of heterogeneity in housing quality and access to air conditioning. For example, income may affect central air conditioning use, the purchase and use of alternative cooling technology (e.g., evaporative cooling, window air conditioning units), the quality of insulation within a home, and the likelihood of renting versus owning a home. According to a district representative, an estimated 10-20% of the student population is undocumented; access to home air conditioning among these families may be even further limited due to lack of access to benefits and housing protections.[11]

Figure 1 shows the locations and air conditioning status of schools in the district as well as census-block average residential air conditioning penetration. Students living in neighborhoods with "high" residential air conditioning penetration are more likely to attend air-conditioned schools. However, as the figure illustrates, with the exception of a few areas, such as the far northeast region of the district, schools and neighborhoods with high air conditioning penetration appear to be relatively well-mixed. The fact that substantial variation in school air conditioning status exists among students in both highly air-conditioned and less-well air-conditioned neighborhoods makes heterogeneity analyses of these two dimensions of air conditioning access more feasible (see Table A3).

### 4.2 Absences and disciplinary referrals

Table 2 provides descriptive statistics for student attendance and behavioral referrals, the two behavioral outcomes studied in this paper. As shown in this table, the average number of absences and disciplinary referrals differs by race/ethnicity, grade level, and gender. Hispanic and Black students are more than 30% more likely than white students to be absent from school on any given day. They are also more likely to receive a behavioral referral and to face harsher, exclusionary discipline (suspensions, expulsions, or referrals to fire or law enforcement). This is especially true for Black students, who are six times more likely than

be predicted precisely for many students: 22% of students live in census blocks with 0 or 100% residential air conditioning penetration.

[11] See, for example, Alsan and Yang (2022) for a discussion of factors that may discourage undocumented Hispanic households from enrolling in benefit programs.

white students to receive one of these more severe disciplinary outcomes during a given year. Male students are more likely to receive a behavioral referral than female students, and middle school students are the most likely age group to receive a referral. In an average year, approximately 10% of students receive at least one referral, and 4% of students receive multiple referrals.

TABLE 2. Student Behavioral Outcomes

| | | **Gender** | | **Race/Ethnicity** | | | **Grade Level** | | |
|---|---|---|---|---|---|---|---|---|---|
| | All | Female | Male | White | Black | Hisp. | Elem | Middle | High |
| **Attendance** | | | | | | | | | |
| % Absent on Avg. Day | 6.2 | 6.2 | 6.2 | 4.8 | 6.5 | 6.6 | 5.8 | 5.6 | 7.4 |
| **Behavioral Referrals** | | | | | | | | | |
| % Referred in Avg. Year | 10 | 6.7 | 13.2 | 4.1 | 17.7 | 10.2 | 5.4 | 16.4 | 12.4 |
| % Susp./Law in Avg. Year | 4.6 | 2.9 | 6.2 | 1.5 | 9.2 | 4.5 | 2.1 | 8.3 | 5.6 |
| % Referred $\geq$1 in Avg. Year | 4 | 2.3 | 5.7 | 1.3 | 8.2 | 3.9 | 1.9 | 7.3 | 4.8 |
| Avg. Ann. Ref. $\mid \geq$1 Ref | 2.1 | 1.8 | 2.2 | 1.8 | 2.4 | 2 | 1.9 | 2.4 | 1.9 |
| % Referred on Avg. Day | 0.14 | 0.08 | 0.2 | 0.05 | 0.29 | 0.14 | 0.07 | 0.26 | 0.17 |

*Notes:* This table shows, for each gender, race/ethnicity, and grade level, the percent of students absent on an average day, the percent of students referred in an average day and year, the percent receiving a suspension or a referral to law enforcement/fire department in an average year, the percent receiving more than one referral in an average year, and the average number of referrals received by students who received at least one referral. Descriptive statistics are shown for the 2011/12–2016/17 school years. All enrolled students are included, but statistics in columns (4)-(6) are only shown for the three largest racial/ethnic groups, which comprise 92% of the student body, on average.

Referrals are made in response to a variety of different behaviors and result in disciplinary outcomes ranging from restorative approaches to expulsions (see Figure A3 for a visual representation of the average annual frequency and resulting disciplinary outcomes of each category of referral). The most common category of referral describes "disruptive" or "defiant" behavior. A 2014/2015 change in reporting procedures discouraged teachers and administrators from describing incidents as "disruptive" or "defiant", in part due to the hypothesis that a movement away from these categories may reduce racial bias in incidents; after this change, descriptions in this category became less common.[12]

Both student attendance and behavioral referrals vary throughout a typical academic year (see Figures A4 and A5). Absences follow a general upward trend throughout the year, with relatively small increases in absences on the days on either end of school breaks. In a typical year, the rate of behavioral referrals (per present student) is characterized by a striking pattern around school breaks; referrals appear to "ramp up" at the beginning of the year and to "ramp down" at the end, and this pattern is also present near winter break.

At the beginning of the semester, this "ramping up" period may result from a combination

[12] A comparison of the composition of referrals for each demographic group is shown in Table **??**.

of school policies that give students second chances and the gradual formation of social groups. The fresh start effect, a documented phenomenon where people are more likely to be motivated to achieve goals at salient points of time, like the start of the year, may also influence student and teacher behavior (Dai *et al.*, 2014). Pre-break testing as well as teacher or administrator fatigue in anticipation of a break may contribute to the decline in referrals at the end of the semester. While this trend is not surprising, it highlights the importance of carefully controlling for the time of the school year when estimating the effect of adverse environmental conditions on student outcomes so as not to mistakenly attribute typical trends in behavior throughout an academic year to seasonal patterns in environmental conditions.

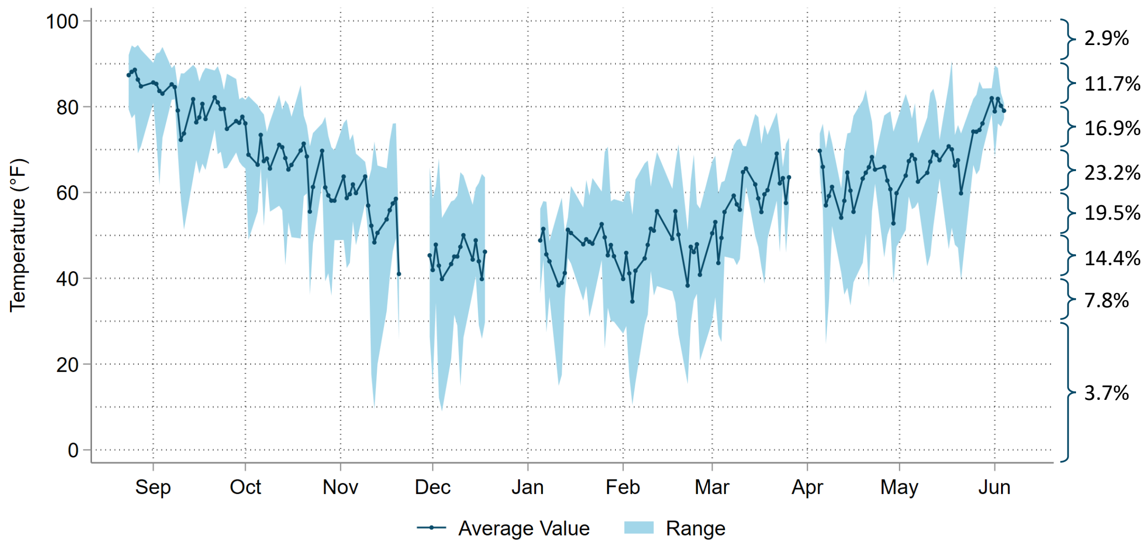



FIGURE 2. Interannual Variation in Maximum Temperature on School Days

*Notes:* This figure shows the average district-wide maximum temperature and the interannual range of temperatures on each school day across the 2011/12–2016/17 school years. In this image, the academic year is shifted to align weekends. Temperature values from the realigned data are displayed for a given day if it corresponds to a school day in at least two academic years. Blank spaces represent school breaks.

Seasonal trends in temperature and interannual variation in temperature at a given time of the year are illustrated in Figure 2. From 2011/12–2016/17, an average of 14.6% of school days exceeded 80°F, 2.9% exceeded 90°F, and 3.7% fell below 30°F. Temperature is correlated with ambient levels of ground-level ozone and fine particulate matter, which I control for in my empirical analysis.[13]

[13]There is a positive correlation of 0.53 between temperature and ambient levels of ozone and a negative correlation of -0.24 between temperature and ambient levels of fine particulate matter.

## 5 Empirical Framework

My identification strategy relies on between-year variation in daily temperature and student behavioral outcomes at a given time of the school year, controlling for student and school characteristics. This strategy avoids attributing patterns in attendance or behavioral referrals *within* an average academic year to corresponding seasonal patterns in environmental conditions. Identification therefore relies only on the assumption that, on a particular day of the school year, variation in temperature is plausibly exogenous with respect to the outcomes of interest, attendance and the receipt of behavioral referrals. This is similar to asking: given the environmental conditions that typically characterize this day of the school year, how does student behavior respond to temperature?

### 5.1 Main estimating equation

In my main specification, I estimate the following linear probability model using daily, student-level data over the first six academic years (2011/12–2016/17) of the sample, during which the air conditioning status of all schools remained constant:

$$Y_{isty} = \sum_{j=1}^{J} \beta_j Temp_{jty} + W'_{ty}\nu + C'_{iy}\sigma + \eta_s + \gamma_y + \delta'_{ty} + \varepsilon_{isty} \tag{1}$$

where $Y_{isty}$ is a binary indicator for whether student $i$ enrolled in school $s$ (1) is absent from school or (2) receives a behavioral referral on day $t$ in academic year $y$. Only present students are included when estimating the latter relationship, but results are robust to the inclusion of absent students as well as to alternative specifications.

The parameters of interest are $\beta_j$, the coefficients on binned maximum outdoor temperature. Additional weather controls, $W'_{ty}$, include the ambient levels of fine particulate matter ($PM_{2.5}$) and ground-level ozone ($O_3$), a linear and quadratic term for rain, and indicators for any snow (>0 inches) and moderate snow (>4 inches).[14] Controls for a set of student demographic characteristics (grade, race/ethnicity, gender, and English Language Learner status), $C'_{iy}$, and school fixed effects, $\eta_s$, are also included. Results are robust to the inclusion of school-by-year or student-by-year fixed effects in place of school and year fixed effects.

Year fixed effects, $\gamma_y$, and a set of daily timing controls, $\delta'_{ty}$, ensure that the model is identified off of variation between academic years, holding the time of the year constant. These daily timing controls include fixed effects for the day of the week and the day before and after a holiday as well as 155 "day of school year" fixed effects, each of which corresponds to a day of the school year (first day of school, second day of school, etc.).[15] These fixed effects

[14] The threshold of 4 inches was selected following Goodman (2014).

[15] To create these fixed effects, I count forward and backward from the summer and winter breaks so that

are estimated separately for the pre- and post-2014/15 reporting policy change years, so a total of 310 "day of school year" fixed effects are included. The last two weeks of the spring semester are excluded from the analysis because many schools have testing during this time, and district-wide enrollment declines substantially over these weeks. Heteroskedasticity-robust standard errors are clustered at the school level because temperature is experienced differently for students living in different neighborhoods and mitigating technology differs at the school level (Abadie *et al.*, 2017).

There are several ways that absences and referrals may affect each other. I discuss these potential interactions at the end of this section.

### 5.2 Heterogeneity by school and residential air conditioning status

To estimate heterogeneity in the temperature-behavior relationships by access to air conditioning, I begin by estimating how the relationship shown in equation (1) varies by school air conditioning status, again focusing on the years prior to the start of new air conditioning installations (2011/12–2016/17). To estimate this relationship, I interact a set of indicators for school air conditioning status, $AC'_s$, with temperature, other environmental controls, year fixed effects, and daily timing controls.

$$\begin{aligned} Y_{isty} = &\sum_{j=1}^{J} \beta_j Temp_{jty} + W'_{ty}\nu + C'_{iy}\sigma + \eta_s + \gamma_y + \delta'_{ty} + \\ &AC'_s \times (\rho + \sum_{j=1}^{J} \alpha_j Temp_{jty} + W'_{ty}\mu + \gamma_y\omega + \delta'_{ty}\psi) + \varepsilon_{isty} \end{aligned} \tag{2}$$

Including interactions with timing controls is necessary to ensure that the variation in behavioral outcomes used to estimate this relationship doesn't include inter-school differences in how these outcomes change throughout a typical school year.[16]

The results from this analysis provide cross-sectional evidence of the causal effect of temperature on student behavioral outcomes, unmitigated by school air conditioning. Results should not be interpreted as estimating the mitigating effect of access to school air conditioning directly because air conditioning status is not randomly assigned. It is worth noting, however, that there is little evidence that non-random assignment has caused students who are more

the beginning and end of school breaks are aligned across school years.

[16]This is necessary in all heterogeneity analyses. For example, if more "chances" are given to certain groups of children before a referral is made, there may be fewer referrals early in the school year for this group, when temperatures are particularly hot. When comparing how sensitive referrals are to hot days between different groups of students, failing to account for how often referrals are typically made at a given time of the year for each group would cause one to confuse differences in sensitivity to differences in leniency/"second chances". Note that these sets of interactions make the result of estimating equation 2 very similar to the result of estimating equation 1 with a sample that is split by the relevant dimension of heterogeneity; this is done in some cases where there are computational constraints.

vulnerable to heat (e.g., because of chronic conditions) to disproportionately attend non-air-conditioned schools in this district. This selection issue may arise if families with more resources select into air-conditioned schools or if these families are more successful in lobbying for new air-conditioning installations. As discussed previously, descriptive statistics, the relationship between school air conditioning and building age, and the exploration of school choice do not support the hypothesis; students attending air-conditioned schools are more likely to be English Language Learners and less likely to be white, and they live in neighborhoods with similar levels of household income as students attending non-air-conditioned schools.

Students attending air-conditioned schools are more likely to live in air-conditioned homes, which is unsurprising given that building age is predictive of school air conditioning status and housing age is predictive of residential air conditioning penetration. Observed heterogeneity by school air conditioning status may therefore capture differences in sensitivity by both school and home air conditioning. To examine these two dimensions of heterogeneity, I estimate the effect of temperature on behavioral referrals separately for each of four groups of students based on access to air conditioning at school and at home.[17]

### 5.3 Heterogeneity by race/ethnicity, income, and the type of behavior

I next examine differences in temperature sensitivity by race/ethnicity and neighborhood measures of household income. For simplicity, in these regressions I define "lower-income" neighborhoods as census block groups with greater than the median percent of low- or moderate-income households (over 60%). When studying these dimensions of heterogeneity, I restrict the sample to non-air-conditioned schools (2011/12–2016/17) and, similarly to equation (2), create interaction terms by each relevant student/neighborhood characteristic.

Finally, I investigate which category of behavioral referrals is most responsive to heat and cold by estimating equation (1) separately for each type of behavior, allowing $Y_{isty}$ to be an indicator for whether student $i$ enrolled in school $s$ receives that category of behavioral referral on day $t$ in academic year $y$. These specifications are run for the sample of years in which referrals were more descriptive. Because this was only true for a limited number of years, all schools and years post-policy change (2014/15-2018/19) are included in these specifications.

## 6 Results

I present results in several steps. I start by describing the effect of temperature on student behavior and how the observed relationships vary by access to air conditioning at school and at home. Then, for students attending non-air-conditioned schools, I explore heterogeneity in

[17] Students are considered to live in "high" residential air conditioning neighborhoods if they live in census blocks where over 50% of housing units have central air conditioning (see Table A3 for descriptive statistics).

the temperature-behavior relationship by race/ethnicity and family income. Next, I discuss which types of disciplinary referrals appear to be particularly sensitive to temperature. Finally, I discuss potential interactions between absences and referrals and how changes in class size and composition may affect the behavior of present students.

### 6.1 Temperature extremes increase absenteeism

The estimated effect of temperature on absences and behavioral referrals within all schools and schools with and without air conditioning is shown in Table 3 and Figure 3.[18] The first three columns of Table 3 illustrate the effect of the specified temperatures (relative to 60-70°F days) on absences and referrals within all schools. Columns 4 and 5 illustrate how this effect varies by access to school air conditioning; the estimated coefficients in column 4 capture the effect of temperature in non-air-conditioned schools, and the sum of column 4 and the temperature-air-conditioning interaction shown in column 5 captures the effect of temperature in air-conditioned schools. Figure 3 illustrates the effect of all temperature ranges in air-conditioned and non-air-conditioned schools.

The estimated coefficients shown in Panel A of Table 3 demonstrate that absences increase on both cold and hot days relative to days with a maximum temperature between 60–70°F. Absences are 34% higher on days below 30°F than on temperate days and are 10% and 16% higher on days between 80–90°F and exceeding 90°F, respectively.[19] Results suggest that extremely cold temperatures and moderately to extremely hot temperatures reduce student attendance. Different mechanisms may drive the increase in absences in these different ranges; for example, the increase in absences observed on 70–80°F days may reflect more discretionary absences in response to pleasant weather, while the increase observed on days exceeding 80°F may be more likely to reflect changes in student comfort or health. I observe a similar relationship between temperature and absences in air-conditioned and non-air-conditioned schools.

### 6.2 Heat increases behavioral referrals in schools without air conditioning

The estimated coefficients in Panel B of Table 3 demonstrate that hot temperatures also affect disciplinary referrals. Columns 1–3 suggest that across all schools, referrals are 4% and 9% higher on days between 80–90°F and exceeding 90°F, respectively, relative to 60–70°F days.

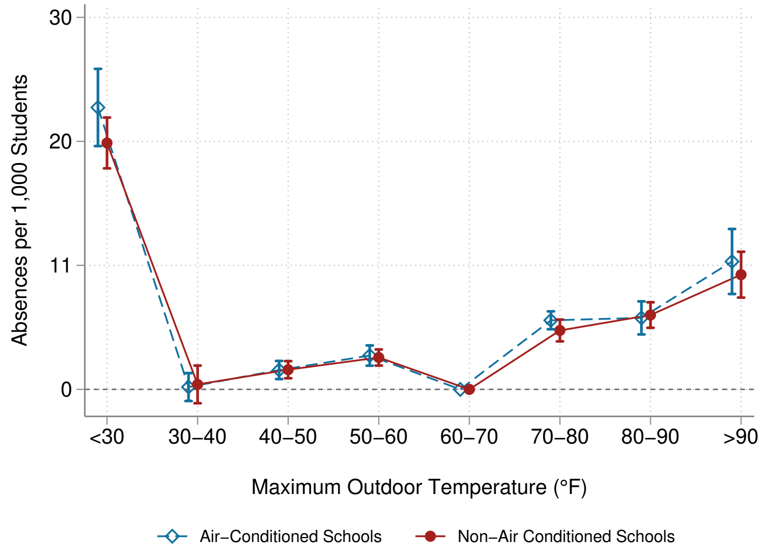
[18] In all tables and figures, I present estimates of temperature-induced changes in rates of absences or referrals per 1,000 students. For simplicity, when discussing results in the text, I refer to percent changes relative to the mean rate of absences or referrals, which is 62 and 1.4, respectively, in the 2011/12–2016/17 period. Note that, as discussed previously, the average rate of absences and referrals varies within a typical school year.

[19] When controls for snowfall are not included, days with a maximum temperature below 30°F have absences that are 44% higher than 60–70°F days. Coefficient estimates of bins below 60°F are also sensitive to the inclusion of snowfall controls.

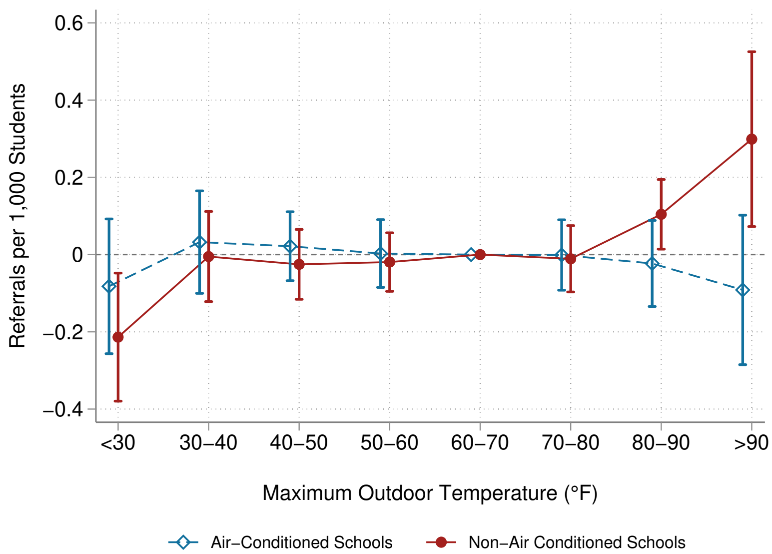
Table 3. Effect of Temperature on Absences and Behavioral Referrals by School AC Status

| | All Schools | | | | AC × Temp. |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | No School AC | Interaction |
| *Panel A:* Absences per 1,000 Enrolled Students (N=60.2 mil.) | | | | | |
| <30F | 21.103*** | 21.076*** | 21.044*** | 19.871*** | 2.863 |
| | (0.911) | (0.910) | (0.914) | (1.040) | (1.891) |
| 80-90F | 5.908*** | 5.818*** | 5.768*** | 5.994*** | -0.230 |
| | (0.415) | (0.414) | (0.404) | (0.523) | (0.855) |
| >90F | 9.667*** | 9.600*** | 8.890*** | 9.250*** | 1.062 |
| | (0.791) | (0.782) | (0.747) | (0.937) | (1.627) |
| *Panel B:* Referrals per 1,000 Present Students (N=56.4 mil.) | | | | | |
| <30F | -0.156** | -0.159*** | -0.160*** | -0.214** | 0.132 |
| | (0.061) | (0.061) | (0.061) | (0.084) | (0.122) |
| 80-90F | 0.049 | 0.046 | 0.056 | 0.104** | -0.127* |
| | (0.036) | (0.036) | (0.036) | (0.046) | (0.073) |
| >90F | 0.130 | 0.137* | 0.132* | 0.299*** | -0.390** |
| | (0.081) | (0.081) | (0.078) | (0.115) | (0.151) |
| School FE | X | | | X | |
| School × Year FE | | X | | | |
| Student × Year FE | | | X | | |

*Notes:* Selected coefficient estimates are from regressions estimating the effect of temperature on absences and behavioral referrals relative to a 60–70°F day. The mean rate of absences and referrals per 1,000 students is 62 and 1.4, respectively in the 2011/12–2016/17 period. Regressions include year, day of school year (fit separately to pre-2013/14), and day before and after vacation fixed effects and controls for rain, snow, $PM_{2.5}$, and $O_3$. Columns 1, 2, and 4-5 include school or school-by-year fixed effects and demographic (grade, race/ethnicity, gender, "English learner") fixed effects. Column 3 includes student-by-year fixed effects. Interactions of indicators for school air conditioning status with all timing and environmental controls are included in the regression represented by columns 4-5. Heteroskedasticity robust standard errors are clustered at the school level. The sample comprises all students enrolled in schools during the 2011/12–2016/17 academic years. Panel B includes students present on a given day. Asterisks indicate coefficient significance level (2-tailed): *** p<.01; ** p<.05; * p<.10. The full set of coefficient estimates are provided in Tables A5 and A6.




(A) Absences




(B) Behavioral Referrals

FIGURE 3. Effect of Temperature on Absences and Behavioral Referrals

*Notes:* This figure shows coefficient estimates and 95% confidence intervals of the effect of each temperature range on (A) absences and (B) behavioral referrals relative to a 60–70°F day. Estimates are taken from regressions of daily, student-level outcomes on indicators for maximum daily temperature ranges. The mean rate of absences and referrals per 1,000 students is 62 and 1.4, respectively, in the 2011/12–2016/17 period. Regressions include school, demographic (grade, race/ethnicity, gender, "English learner"), school year, day of school year (fit separately to pre-2013/14), and day before and after vacation fixed effects and controls for rain, snow, $PM_{2.5}$, and $O_3$. Interactions of indicators for school air conditioning access with all timing and environmental controls are also included. Heteroskedasticity robust standard errors are clustered at the school level. The sample comprises all students enrolled in schools during the 2011/12–2016/17 academic years. In (B), students absent on a given day are excluded. Estimates are taken from column 4 and the sum of columns 4 and 5 of Table 3.

However, as illustrated in columns 4 and 5, these estimated coefficients mask substantial heterogeneity in the temperature-behavior relationship by school air conditioning status; indeed, the increase in behavioral referrals on hot days that is observed across all schools appears to be entirely driven by students attending non-air-conditioned schools. In these schools, referrals are 7% higher on days with a maximum temperature between 80–90°F and 21% higher on days with a maximum temperature exceeding 90°F. The observed increase in referrals on hot days is robust to a variety of alternative specifications, including Poisson specifications and specifications that include absent students (see Table A7).[20]

Disciplinary referrals also appear to be sensitive to cold temperatures; on days below 30°F, behavioral referrals are 11% lower. However, school schedules often change in response to extreme cold, when most elementary schools keep children indoors, so these days are less comparable to days in other temperature ranges than those days are to each other.[21] As I discuss later, it is also possible that this decrease, and the decrease seen on hot days in air-conditioned schools, may stem partly from changes in the size and composition of the present student body on these days.[22]

### 6.3 Heat-induced increases in referrals are largest among students without access to air conditioning at school ***and*** at home

Figure 4 illustrates how behavioral referrals respond to hot conditions (>80°F) among four groups of students: those who don't have access to air conditioning, those who only have air conditioning at school, those who only have air conditioning at home, and those who have access to air conditioning in both places. To explore access to residential air conditioning, I define census blocks as "high" or "low" AC depending on whether the majority of housing units have central air conditioning. For simplicity and to avoid a lack of power, I combine the highest two temperature bins in this analysis, constructing a >80°F bin, and also combine bins representing a maximum temperature between 30 and 80°F.

Results indicate that the heterogeneity in the effect of heat on behavioral referrals by access to school AC does not stem solely from differences in home air conditioning status. The largest difference in coefficient estimates shown in Figure 4 is observed between students

[20] One possible reason for the higher percent increase suggested by Poisson estimates in response to hot temperatures stems from the fact that the average rate of referrals is substantially lower at the beginning of the year. In the first 30 school days, when all >90°F days occur and most 80°F days occur, the referral rate is 1.0 per 1,000 rather than 1.4 per 1,000 (full-year average). For simplicity, when discussing results in the text, I refer to percent changes relative to the average referral rate over all days, but the true percent change may be higher.

[21] According to district representatives, similar protocols for schedule changes on hot days do not exist, with the exception of designated "heat days". On several days in the sample, schools are canceled or released early due to heat. These heat days are not included in the analysis.

[22] It is also possible that teacher absences, which are not observed in this study, increase on very cold or snowy days, disrupting scheduling and reporting practices.

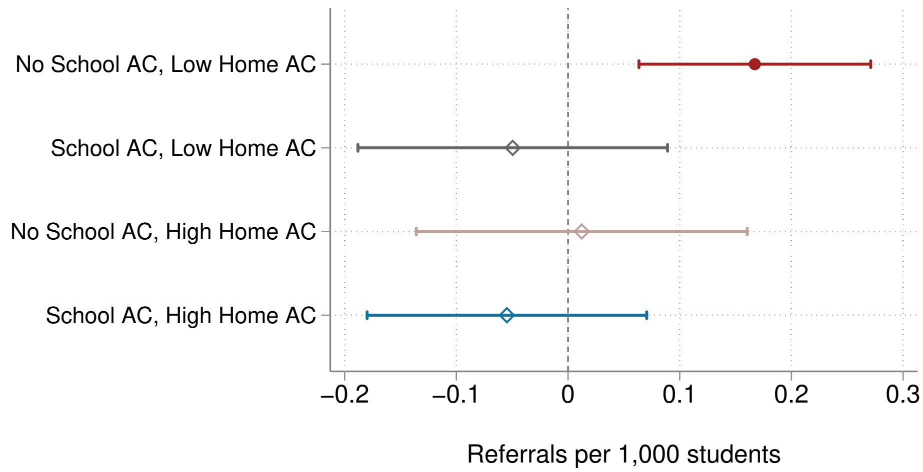



FIGURE 4. Heat, Behavioral Referrals, and Access to Air Conditioning

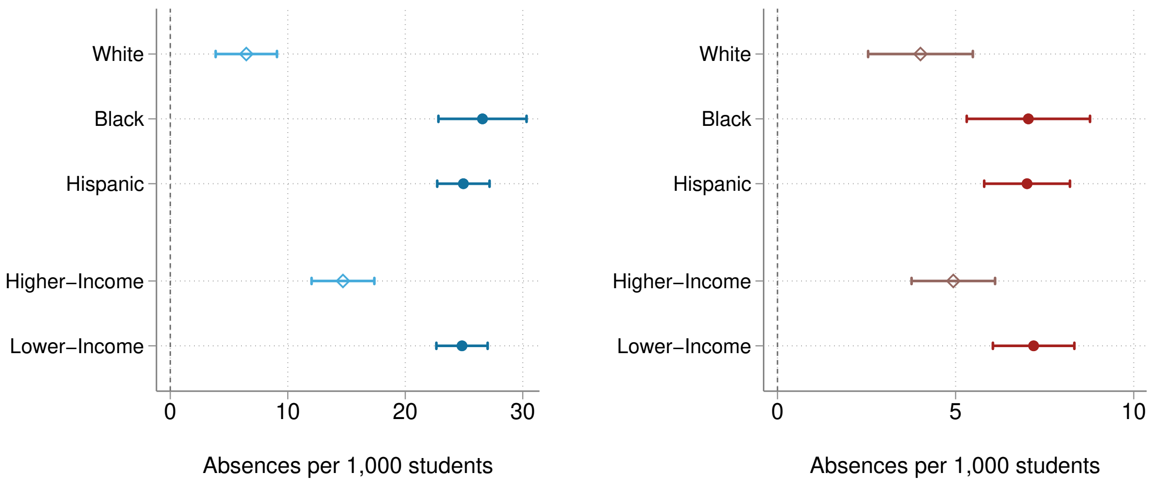
*Notes:* This figures shows coefficient estimates and 95% confidence intervals of the effect of a >80°F day on behavioral referrals relative to a 30-80°F day, taken from regressions of daily, student-level behavioral referrals on indicators for maximum daily temperature ranges. The mean rate of referrals per 1,000 students is 1.4 in the 2011/12–2016/17 period. Regressions include school, demographic (grade, race/ethnicity, gender, "English learner"), school year, day of school year (fit separately to pre-2013/14), and day before and after vacation fixed effects and controls for rain, snow, $PM_{2.5}$, and $O_3$. Interactions of four indicators of air conditioning access with all timing and environmental controls are also included. Each student's home census block is defined as "high" or "low" home AC based on a 50% residential air conditioning penetration threshold. Heteroskedasticity robust standard errors are clustered at the school level. The sample comprises all present students attending schools during the 2011/12–2016/17 academic years.

who have access to air conditioning both at home and at school and students who lack access to air conditioning in both places, but disciplinary referrals of students who have access to air conditioning *either* at home or at school are also less sensitive to heat than those of students who lack access to air conditioning in both places.

A comparison of the temperature sensitivity of absences between these four groups of students suggests that access to air conditioning at home and at school may also be predictive of a lower likelihood of being absent on hot days. However, observed differences in sensitivity are not statistically significant (see Figure A6 for more detail).

### 6.4 The effect of extreme temperature on behavior varies by race, ethnicity, and socioeconomic status

I next explore heterogeneity in the effect of temperature by student and neighborhood characteristics, focusing particularly on students attending schools without air conditioning. Similarly to subsection 6.3, I combine the highest two temperature bins (constructing a >80°F bin) in this analysis, and when estimating disciplinary referrals, I also combine the bins representing a maximum temperature between 30 and 80°F.




(A) Cold Days

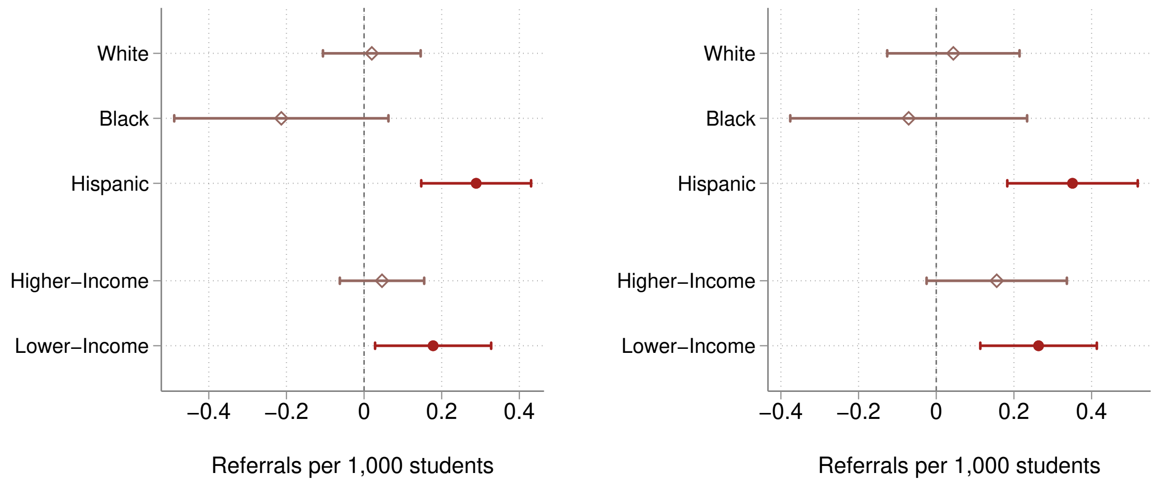
(B) Hot Days

FIGURE 5. Heat, Cold, and Absences: Heterogeneity

*Notes:* This figure shows coefficient estimates and 95% confidence intervals of the effect of a (A) <30°F and (B) >80°F day on absences relative to a 60–70°F day, taken from regressions of daily, student-level absences on indicators for maximum daily temperature ranges. The mean rate of absences per 1,000 students is 62 in the 2011/12–2016/17 period. Regressions include school, demographic (grade, race/ethnicity, gender, "English learner"), school year, day of school year (fit separately to pre-2013/14), and day before and after vacation fixed effects and controls for rain, snow, $PM_{2.5}$, and $O_3$. Interactions of race or income group (split by median household income) with all timing and environmental controls are also included. Heteroskedasticity robust standard errors are clustered at the school level. The sample comprises all students enrolled in non-air-conditioned schools during the 2011/12–2016/17 academic years.

Coefficient estimates of the effect of cold (<30°F) and hot (>80°F) temperatures on absences are illustrated in Figure 5. Although the attendance of students of all races is affected by temperature, results indicate that both Black and Hispanic students are more likely to be absent on particularly cold days (and, to a lesser extent, hot days) than are white students. Absences of students in lower-income neighborhoods, also appear to be more sensitive to temperature. The attendance of Black, Hispanic, and lower-income students is also more sensitive to snow (see Figure A7).

Figure 6 illustrates observed heterogeneity in the effect of hot ( >80°F) temperatures on behavioral referrals in non-air-conditioned schools. Results indicate that referrals of Hispanic students are more responsive to temperature than are referrals of either white or Black students, although referrals of Black students appear to be imprecisely estimated. One possible explanation for the higher sensitivity of behavioral referrals of Hispanic students to




(A) No Home AC Controls

(B) Controlling for Home AC

FIGURE 6. Heat and Behavioral Referrals: Heterogeneity

*Notes:* This figure shows coefficient estimates and 95% confidence intervals of the effect of an >80°F day on behavioral referrals relative to a 30-80°F day, taken from regressions of daily, student-level behavioral referrals on indicators for maximum daily temperature ranges. The mean rate of referrals per 1,000 students is 1.4 in the 2011/12–2016/17 period. Regressions include school, demographic (grade, race/ethnicity, gender, "English learner"), school year, day of school year (fit separately to pre-2013/14), and day before and after vacation fixed effects and controls for rain, snow, $PM_{2.5}$, and $O_3$. Interactions of race or income group (split by median household income) with all timing and environmental controls are also included. Race- or income-specific interactions between home air conditioning penetration and temperature bin are included in the regressions represented in (B), so coefficients reflect the estimated effect of heat on referrals for students with low access to home air conditioning. Students with missing home air conditioning penetration data are excluded from regressions in both figures. Heteroskedasticity robust standard errors are clustered at the school level. The sample comprises all present students attending non-air-conditioned schools during the 2011/12–2016/17 academic years.

heat may stem from differential access to air conditioning at home.[23] However, the observed higher heat sensitivity of referrals among Hispanic students is robust to including race-specific controls for home air conditioning status in Panel B (although these controls somewhat reduce the Black-Hispanic gap). As discussed previously, the Hispanic population of students also has a close overlap with the population of English Language Learner (ELL) students, who may be more likely to be vulnerable to and exposed to temperature.[24] A comparison of

[23] Conditional on attending a non-air-conditioned school, white and Black students are more likely to live in highly air-conditioned neighborhoods than are Hispanic students (see Table A3).

[24] I do not separately estimate the effect of temperature on behavioral outcomes for ELL students, in part because of the correlation with race/ethnicity and family income. When I separate the effect of hot temperatures between non-ELL Hispanic students and ELL Hispanic students, the estimated coefficient on hot temperatures for ELL Hispanic students (0.32 per 1,000 students) is nearly twice as large as the effect among

students by neighborhood income suggests that lower-income students may be more sensitive to temperature, although differences between these groups (those living in above vs. below median %LMI census block groups) are not statistically significant. This gap also continues to be observed after controlling for home air conditioning.

The relationship between temperature and behavior is likely affected by many unobservable factors, some of which may be correlated with race/ethnicity, family income, or access to residential air conditioning. For example, the physiological effect of temperature may be affected by both exposure to temperature and vulnerability to that temperature, which may be affected by factors like health status and access to health care and transportation. As previously discussed, the extent to which changes in student behavior lead to referrals may also be affected by unobserved teacher or administrator bias. Considering potential unobservable factors may be helpful in interpreting the results of this study and considering how the effect of temperature on student behavior may differ in other settings.

### 6.5 Sensitivity to heat varies by category of behavior

Coefficient estimates of the effect of hot temperatures on specific categories of behavioral referrals suggest that the most common category of behavior referrals, "disruptive behavior" is responsive to hot (>80°F) temperatures (see Figure A8). These referrals capture reports of irritability, anger, lack of respect, attention, or obedience. As discussed previously, more subjective referrals, like those for disruptive behavior, may be particularly likely to reflect teacher discretion in responding to behavior, so this result may lend support to the hypothesis that both student and teacher behavior is responsive to heat. Statistical power is limited when examining some categories of behavior, but referrals for bullying/harassment and recurring offenses also appear to increase in response to hot temperatures. Due to the limited number of years in the sample post-policy change (2014/15-2018/19), regressions are estimates using students attending both air-conditioned and non-air-conditioned schools, so coefficient estimates may mask heterogeneity by access to air conditioning.

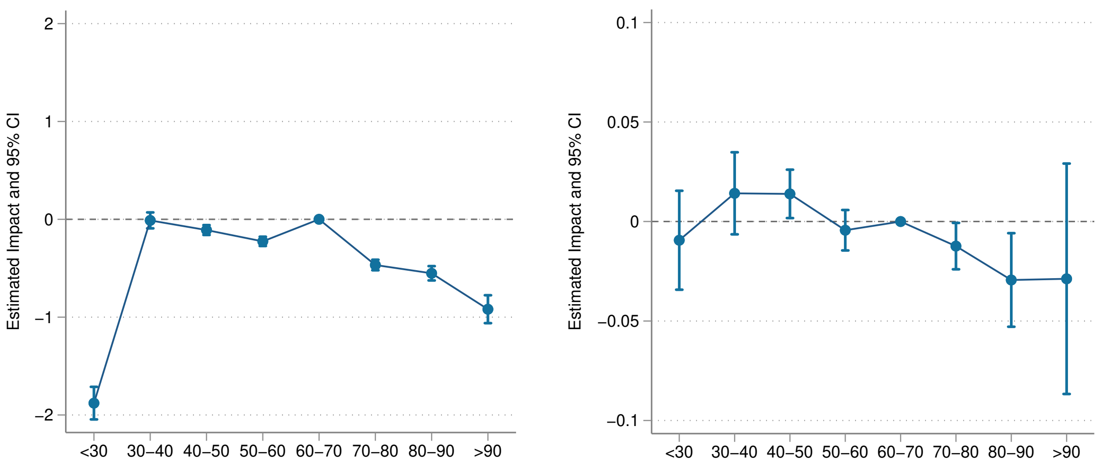
### 6.6 Potential interactions between absences and referrals

When interpreting the results presented in this section, several possible interactions between the two outcomes of interest, student absences and disciplinary referrals, may be valuable to consider. First, the effect of temperature on disciplinary referrals can only be identified from the behavior of present students.[25] If students whose referrals are particularly temperature-

non-ELL Hispanic students (0.16 per 1,000 students).

[25] Students are very unlikely to receive disciplinary referrals when they are absent from school. A few observed exceptions include instances when students were referred prior to the start of the school day or for online behavior.

sensitive are also more (less) likely to be absent on hot and/or cold days, then the estimated effect of temperature on disciplinary referrals will be lower (higher) than if absences did not also vary in response to temperature. Regardless of the case, estimates presented in this section still capture the true effect of temperature on referrals; however, this consideration may be important to note when considering the effect of temperature on interpersonal interactions more broadly (including interactions occurring outside of school) or when applying estimates to other districts where the sensitivity of absences to temperature and heterogeneity in that sensitivity between students may be different.




(A) "Class Size" (B) "Class Risk"

Figure 7. Effect of Temperature on "Class Size" and "Class Risk"

*Notes:* Coefficient estimates are taken from a linear regression modeling the "class size" and "class risk" of present students on indicators for binned temperature. A "class" is defined to include students enrolled in the same grade and school in the same year. A student's class size is the percent of enrolled peers who are present on a given day. A student's class risk is the percent of present peers on a given day who have already or will at some point receive a referral in a given year. In panel (A) and (B), class size and class risk are expressed per 100 students. The mean class size is 94, with a standard deviation of 5, and the mean class risk is 10, with a standard deviation of 10. Regressions include class (school × grade × year), demographic (race/ethnicity, gender, "English learner"), day of school year (fit separately to pre-2013/14), and day before and after vacation fixed effects and controls for rain, snow, $PM_{2.5}$, and $O_3$. Heteroskedasticity robust standard errors are clustered at the school level.

Second, if students' peers are absent, the size and composition of their classes will change, and this may also affect the behavior of present students and their teachers. To understand how the number and composition of students present in class varies by temperature, I construct measures of the "size" and "risk" of each school-by-grade-by-year group, which, in the absence of classroom assignment data, I define as a "class." I define the class size, $\overline{Z}_{icty}$, of present student $i$ in class $c$ on day $t$ in academic year $y$ as the percent of their enrolled peers who are present. I define class risk, $\overline{R}_{icty}$, as the percent of their present peers who receive at least one referral in the given year. Both are constructed as leave-out-means. I then estimate the effect of temperature on these measures of class size and composition by replacing the left-hand side of equation (1) with $\overline{Z}_{icty}$ and $\overline{R}_{icty}$ respectively.

Figure 7 shows the effect of temperature on "class size" and "class risk." Mirroring the results presented earlier in this section, Panel A illustrates that class size is affected by temperature, although the magnitude of the change is not large. On the coldest days, the average school $\times$ grade of 100 students would be missing an additional 2 students. As shown in Panel B, the effect of hot and cold conditions on class risk is negligible.

# 7 Student behavior, long-term outcomes, and climate change

How will climate change affect student behavioral outcomes and childhood and later life well-being and how effective might adaptive measures be in mitigating adverse effects? To explore this thought experiment, I rely on temperature projections, estimates from my modified empirical model, and studies of the effect of student behavioral outcomes on childhood and later-life outcomes.

## 7.1 Projected change in temperatures: 2000-2050

Climate change is expected to result in an increase in the number of school days with moderately and very hot temperatures. To estimate how temperature in a typical year will change in the future, I rely on a series of temperature projections from global circulation models (GCM) provided by Rasmussen *et al.* (2016), which include annual county-level projections of the number of days that fall within each 1°F bin from 1981 to 2100.[26] I draw from models of the Representative Concentration Pathway (RCP) 6.0 scenario, which corresponds to a warming of 3–4°C by 2100 relative to pre-industrial temperatures. This pathway is described as one of two "intermediate scenarios" by the Intergovernmental Panel on Climate Change (IPCC) and is generally considered to be a plausible representation of likely climate change absent more ambitious efforts to cut emissions (IPCC AR6).

In this thought experiment, I focus on the change in temperatures from 2000 to 2050. To minimize noise in my estimates, I assign temperatures to individual school days in each year within 20-year ranges centered around 2000 (1990–2010) and 2050 (2040–2060), assuming that the rank order of days by temperature from 2011–2019 is preserved over time (the hottest day of the year in present years will be the hottest day of the year in future years). While I focus on the change in temperatures from 2000 to 2050, by the year 2000, global temperatures

[26] For each of several Representative Concentration Pathway (RCP) scenarios, they provide data from a set of GCM and model surrogates and corresponding surrogate/model mixed ensemble probability weights that are used to weigh each model output so the resulting distribution of the temperatures matches the distribution of estimated global mean surface temperature responses under each RCP scenario.

had already increased by approximately 0.75°C compared to pre-industrial temperatures (1850–1900) (IPCC AR6).

Estimates from an RCP6.0 scenario suggest that by 2050, which corresponds to a "mid-term" future reference period used by the IPCC, the average school year in the LUSD will be characterized by 64% more school days with a maximum temperature exceeding 80°F than in 2000, and more than twice as many >90°F days. At the same time, cold conditions are expected to become less common, although the LUSD is expected to experience a smaller decrease in cold conditions than a pure mean shift in temperature would suggest; by 2050, the district is expected to experience an 17% decrease in the number of school days with a maximum temperature below 30°F. This lack of symmetry in changes in hot and cold conditions may reflect increased variability in temperature.[27] Changes in precipitation events, air pollution from wildfires, and other forms of extreme weather may also affect student behavior, although these potential changes are not modeled here.

### 7.2 Projected change in behavioral outcomes: 2000-2050

To predict behavioral referrals and absences using modeled temperatures, I estimate equation (1) for the 2011/12–2016/17 school years. I focus on non-air-conditioned schools to better capture the effect of warming conditions on student behavior, unmitigated by school air conditioning. I focus on a "no adaptation" scenario in which no new installations of air conditioning, either at school or in student homes, are made from 2000 to 2050. This is not meant to reflect the most likely outcome; instead, it serves as a thought experiment to study how climate-change-induced changes in temperature may affect the most vulnerable students and how the value of air conditioning may be affected by warming temperatures. While predicting how homes, schools, or school districts will adapt to climate change is outside the scope of this paper, the results of this paper suggest that differences in access to adaptive technology will be important in determining the effect of temperature.

I make two changes to the specification outlined in equation (1). First, I exclude all non-temperature environmental controls when estimating this equation, effectively assuming that whatever environmental conditions typically accompany a day with a certain maximum temperature will continue to do so in the future. Second, due to the challenges and additional assumptions needed to predict the attendance of each *individual* student (predictions provide estimates of fractional absences), I rely on a model predicting the disciplinary referrals of all enrolled students rather than all present students. I use the resulting estimated coefficients

[27] There is evidence that climate variability may increase as a result of climate change, although future changes in variability are less robustly modeled than mean changes and may vary regionally. Rodgers *et al.* (2021) find that "changes in variability, considered broadly in terms of probability distribution, amplitude, frequency, phasing, and patterns, are ubiquitous and span a wide range of physical and ecosystem variables across many spatial and temporal scales."

and the projected temperatures to estimate the number of absences and behavioral referrals for each year from 1990-2010 and 2040-2060. I randomly select an academic year (2016/2017) from which I take all information about the enrolled student body, schools, and academic calendar. I then compare the projected average number of behavioral referrals and absences in the 2040-2060 period to the 1990-2010 period.[28]

My estimates suggest that, relative to 2000, in 2050 there will be approximately 0.8% more behavioral referrals and 0.8% fewer absences in a typical year among students attending schools without air conditioning. It is important to note that absences are highly responsive to snow, so the response of attendance to future climate is dependent on how snowfall responds to warming conditions.

The increase in behavioral referrals expected in 2050 relative to 2000 may translate into worse academic and later-life outcomes. While I do not observe these outcomes directly, previous studies may be used to illustrate the potential magnitude of the effect of warming conditions on academic and later-life outcomes. For example, Bacher-Hicks *et al.* (2019) find that students quasi-randomly assigned to a stricter middle school due to a large school catchment area boundary change receive more suspensions and are also less likely to attend a 4-year college and are more likely to be arrested and/or incarcerated in early adulthood. While the effect of a suspension on the marginal student studied in this study and in Bacher-Hicks *et al.* (2019) may differ for several reasons, their estimates nevertheless provide a valuable way to interpret the results of this study.[29]

Estimating equation (1) for middle school students attending non-air-conditioned schools where the outcome variable is a binary indicator for a suspension, and repeating the projection exercise outlined above, I find that in 2050 there will be approximately 1.6% more suspensions of middle school students relative to 2000. Scaling estimates from Bacher-Hicks *et al.* (2019) suggests that relative to 2000, in 2050 students will be 2% less likely to attend 4-year college, 3% more likely to be arrested (leading to 4% more arrests), and 4% more likely to be incarcerated (leading to 5% more incarcerations) in late childhood and early adulthood (ages 16 to 21).[30]

[28]Student behavioral outcomes are estimated using the daily temperature projections for each of the years between 1990-2010 and 2040-2060. These averages are constructed from resulting estimated behavioral outcomes (daily temperature averages are never used).

[29]For example, while teacher and administrator behavior may have important roles in both contexts, school policy is central to the mechanism exploited by Bacher-Hicks *et al.* (2019). This suggests that in their setting, changes in *student* behavior may play a smaller role than discipline itself in driving the observed changes in student outcomes, especially if stricter disciplinary procedures act as a deterrent to students. In my setting, student disruptions to the classroom setting may accompany the increase in suspensions I observe, which may cause the heat-induced suspensions I observe to be more harmful to students and their peers. However, marginal suspensions received at particularly strict schools may be perceived as unfairly harsh, which may also affect student outcomes.

[30]Bacher-Hicks *et al.* (2019) estimate how school assignment affects the number of days that a given student is suspended annually and the likelihood of receiving at least one suspension in a given year. I use the latter measure to scale my estimates because the number of days suspended may reflect more or longer suspension periods. If the increase in the number of suspensions conditional on receiving at least one suspension in a given

Warming-induced decreases in absences may reduce disruptions to learning, but the decrease in absences I estimate is dependent on the snowfall-temperature relationship, and the positive effect of increased attendance on student outcomes is likely far outweighed by the negative effect of the increase in disciplinary referrals.[31]

These estimates capture only the effect of temperature changes during middle school on the measured behavioral outcomes. Students will experience hotter temperatures in-utero, as young children, and during elementary and high school. These estimates do not capture the effect of potential disciplinary referrals during those years or the direct effect of heat on learning and other student (e.g., test scores) and non-student outcomes (e.g., health, crime).[32]

These estimates suggest that global warming-induced increases in behavioral referrals may contribute to economically meaningful disruptions to human capital accumulation and increases in arrests and incarcerations, particularly for those students who are more exposed to hot temperatures due to a lack access to air conditioning at school and at home.[33] They also suggest that warming conditions will cause the benefit of school air conditioning, or other adaptive or protective measures, like shifting the school year or canceling school more frequently in response to hot temperatures, to increase.[34]

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year is greater (smaller) than the increase in the likelihood of having at least one suspension, these results may be overestimated (underestimated). I focus on out-of-school suspensions because I expect them to be more comparable across school districts; estimates that include both in- and out-of-school school suspensions project a 0.9% increase over this period. I also include more serious disciplinary outcomes (expulsion hearings, etc.), in part because it is sometimes unclear whether a suspension was also given.

[31] Goodman (2014) finds that one moderate snow day-induced absence reduces student mathematics scores by 0.05 standard deviations, about 6% of the achievement gap between poor and non-poor students (measured by FRPL eligibility). I project approximately 0.1 fewer absent days per student per year in 2040-2060 relative to 1990-2010, a decrease expected to be concentrated among Black, Hispanic, and lower-income students.

[32] Heat-induced increases in disciplinary referrals may explain some of the heat-induced changes in academic outcomes, but it is unlikely to explain all of this effect, particularly because the short-term effect of heat on cognitive performance has been observed both in the laboratory (Seppanen *et al.*, 2005; Mackworth, 1946) and in schools (Park, 2022).

[33] While I did not focus on residential air conditioning in this thought experiment, the projected increase in suspensions for middle school students with low access to air conditioning at school and at home is larger than for the average student attending a non-air-conditioned school (2.0% vs. 1.6%).

[34] A back-of-the-envelope estimate of the effect of air conditioning suggests that school air-conditioning installations would result in a 2% reduction in middle school suspensions if those installations occurred in 2000 and a 3% reduction if those installations occurred in 2050. These estimates are made by predicting student outcomes in schools that currently lack air conditioning using estimated coefficients from my empirical model, but treating these schools as air-conditioned on $\geq$80°F days (by adding the estimated coefficient on the $AC \times Temperature$ interaction variables). Air conditioning may have longer-term effects on student behavior (perhaps affecting school fixed effects) or may change the effect of other environmental conditions, like pollution and precipitation, on student outcomes. Here, I focus just on the effects of temperatures in the range that air conditioning is most likely to be used. For the sake of this thought experiment, I assume that the relationship observed in my cross-sectional analysis captures the causal effect of air conditioning.

## 8 Discussion and conclusion

This paper explores the impact of extreme temperatures on student absences and disciplinary referrals, two components of student behavior which may be disruptive to learning and affect later life well-being. To study this question, I link a data set of daily student-level behavioral outcomes from a large urban school district with environmental data and school and residential air conditioning information. I then leverage this data set to estimate the short-term response of student behavioral outcomes to temperature. My empirical strategy exploits between-year variation in temperature, while controlling for the exact day of the school year as well as time-invariant student and school characteristics. This research design as well as the rich data set of student, school, and neighborhood characteristics, allows for a nuanced exploration of heterogeneity in this relationship.

I find that both hot and cold temperatures have a causal, statistically significant impact on student attendance. The attendance of both minority and lower-income students is more affected by cold, and, to a lesser extent, by heat. Results indicate that, relative to temperate days with an outdoor maximum temperature between 60–70°F, days with a temperature between 80–90°F and exceeding 90°F result in an estimated 10% and 16% increase in absences, respectively. Very cold conditions, those with temperatures below 30°F, result in a 34% increase in absences.

I further find that behavioral referrals increase in response to heat. This response is driven by students attending schools that lack air conditioning and is largest among lower-income and Hispanic students and those who have limited access to air conditioning at home. In schools without air conditioning, behavioral referrals are 7% and 21% higher on days with a temperature between 80–90°F and exceeding 90°F, respectively.

While existing literature on the effect of heat in schools has largely focused on academic performance, the potential long-term consequences of involvement in the school discipline system as well as the large racial/ethnic and socioeconomic disparities that characterize this system make understanding the factors that contribute to behavioral problems in schools especially important. The observed effect of heat on behavioral referrals may also be a result of and contribute to other effects of heat on student outcomes, including the effect of heat on learning. For example, behavioral issues may arise if students exposed to hot temperatures have difficulty learning, which causes them to become distracted or frustrated; conversely, students may have more difficulty learning if they or their peers have a heat-induced behavioral problem in class. In addition to highlighting the potential detrimental effect of temperature on behavioral referrals, the results of this study also demonstrate a possible benefit of improving school infrastructure; there is no observed heat-induced increase in referrals in air-conditioned schools, including among students with low access to air conditioning at home.

Results have important implications in the context of a rapidly changing climate. Many schools lack air conditioning, and school closures on “heat days” are becoming more common. Climate change is expected to increase temperatures and the variability in the climate system, exposing students to hotter temperatures more frequently. Students who are more vulnerable and those who have fewer options to adapt to these conditions may be disproportionately affected. Across the United States, existing racial/ethnic and socioeconomic differences in access to adaptive technology at home and at school suggest that warming conditions may exacerbate disparities in the school discipline system, leading to more inequality in educational and later-life outcomes.

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# A Appendix

## A.1 Additional figures

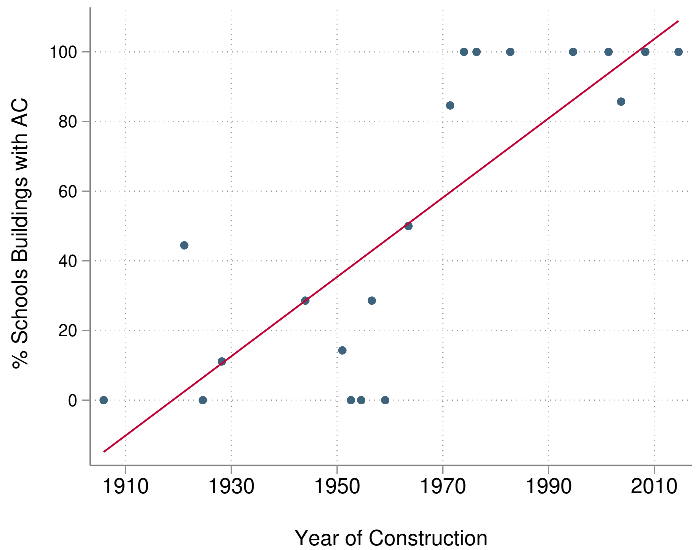
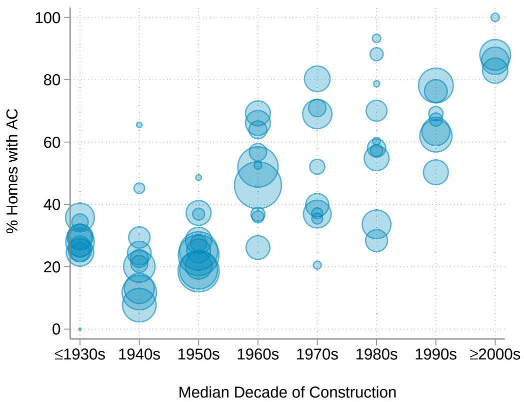
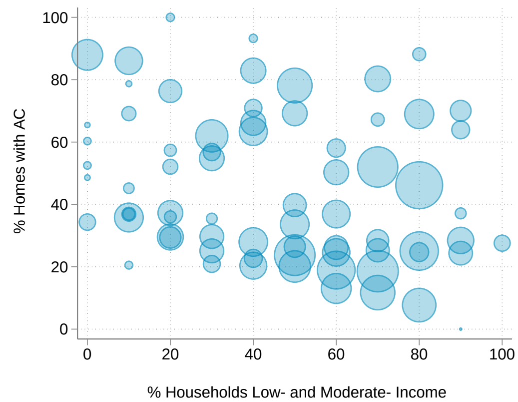



FIGURE A1. School Air Conditioning and Building Age

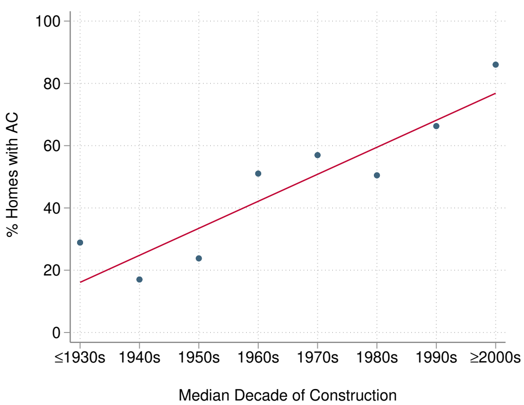
*Notes:* The binned scatter plot illustrates the correlation between school air conditioning penetration and the year of construction of the school building.



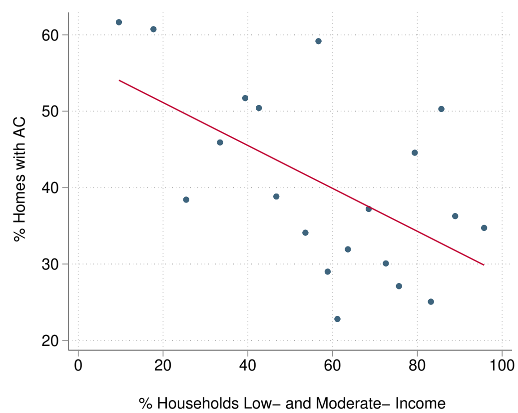

(A) Home AC by Neighborhood Age




(B) Home AC by Neighborhood Income



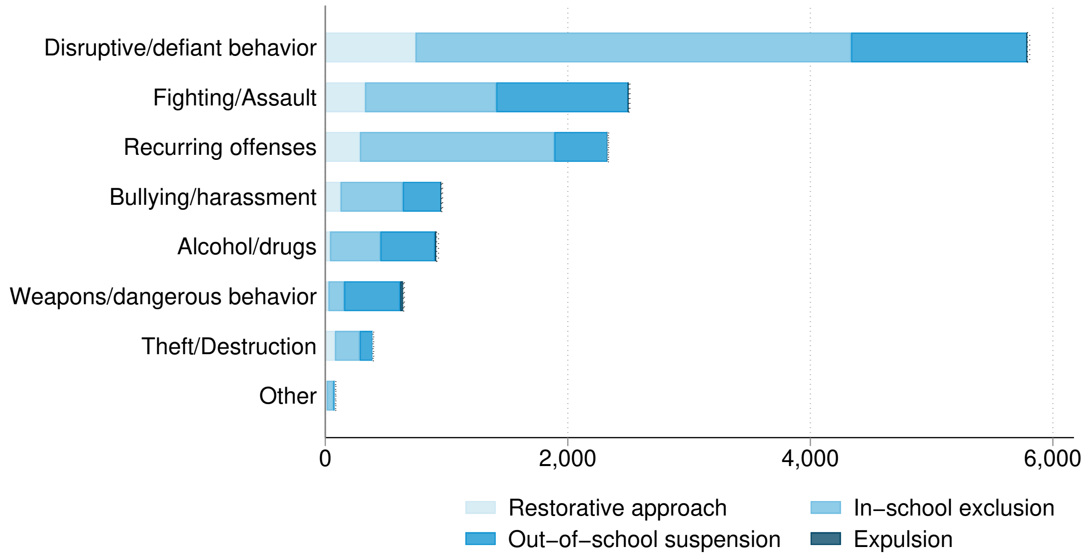

(C) Home AC by Neighborhood Age



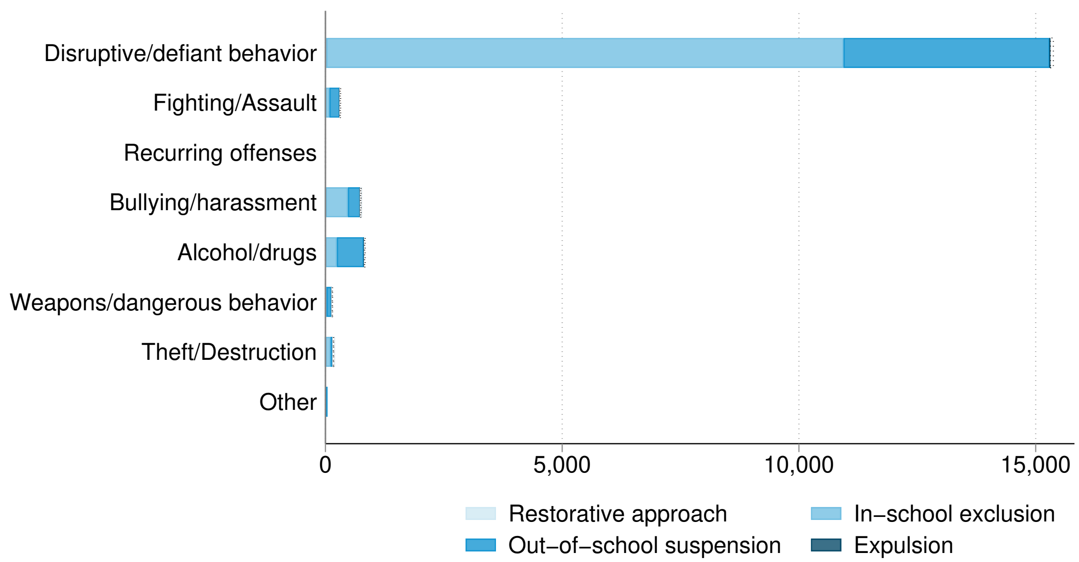

(D) Home AC by Neighborhood Income

Figure A2. Air Conditioning, Housing Stock Age and Household Income

*Notes:* Scatter plots illustrate the correlation between home air conditioning penetration in each census block group and the (A) housing stock age and (B) percent of households who are low- and moderate-income in those census block groups. "Home air conditioning" is defined as central air conditioning. Each point on the scatter plots represents a census block group. The size of the bubble is scaled in proportion to the number of enrolled students living in that census block group. Plots (C) and (D) are binned scatter plots representing the same relationships.




(A) Referrals and Discipline: 2014/15–2018/19




(B) Referrals and Discipline: 2011/12–2013/14

FIGURE A3. Behavioral Referrals by Category and Disciplinary Outcome

*Notes:* This figure shows behavioral referrals in an average year, by category and disciplinary outcomes, for (A) the 2014/15-2018/19 school years and (B) the 2011/12–2013/14 school years. Details about the categorization of referrals by behavior and discipline can be found in Tables A1 and A2 respectively. This figure shows only school-level discipline; referrals to law enforcement (police or fire) are not displayed here.

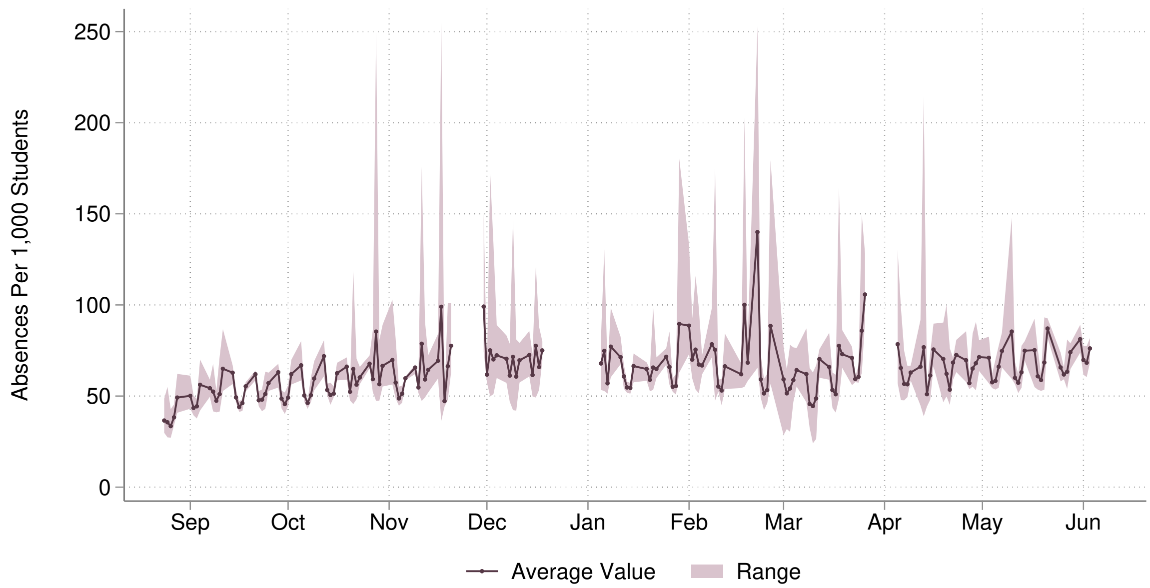



Figure A4. Interannual Variation in Absences per 1,000 Students

*Notes:* Shown above is the average number of absences per 1,000 students and the range of absences per 1,000 students across all years (2011/12–2016/17) on each school day. In this image, the academic school year is shifted to align weekends. The absence rates from the realigned data are displayed for a given day if it corresponds to a school day in at least two academic years. Blank spaces represent school breaks.

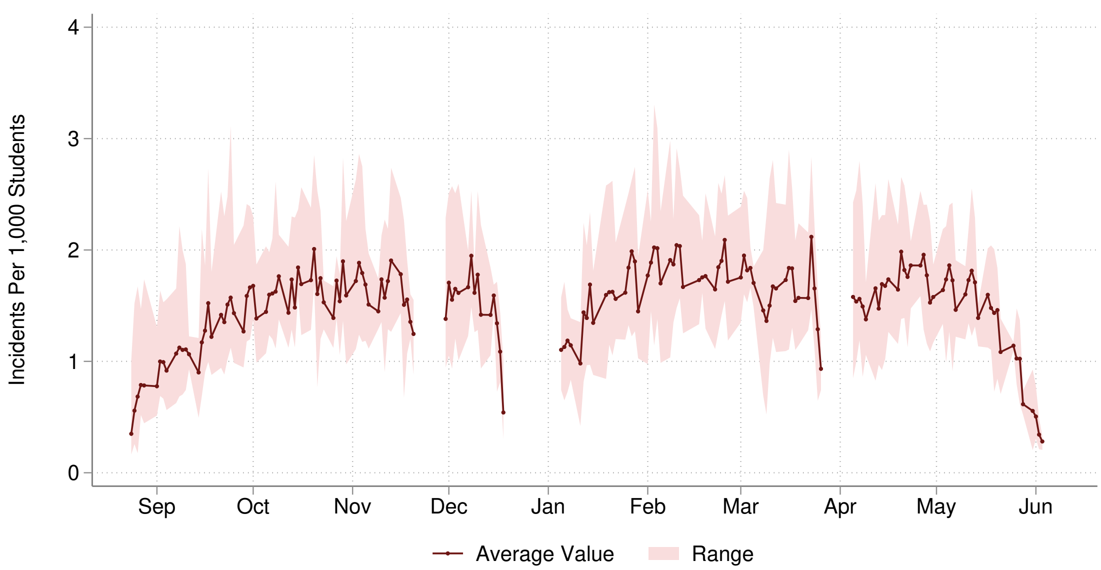



Figure A5. Interannual Variation in Referrals per 1,000 Present Students

*Notes:* Shown above is the average number of behavioral incidents per 1,000 present students and the range of incidents per 1,000 present students across all years (2011/12–2016/17) on each school day. In this image, the academic school year is shifted to align weekends. The referral rates from the realigned data are displayed for a given day if it corresponds to a school day in at least two academic years. Blank spaces represent school breaks.

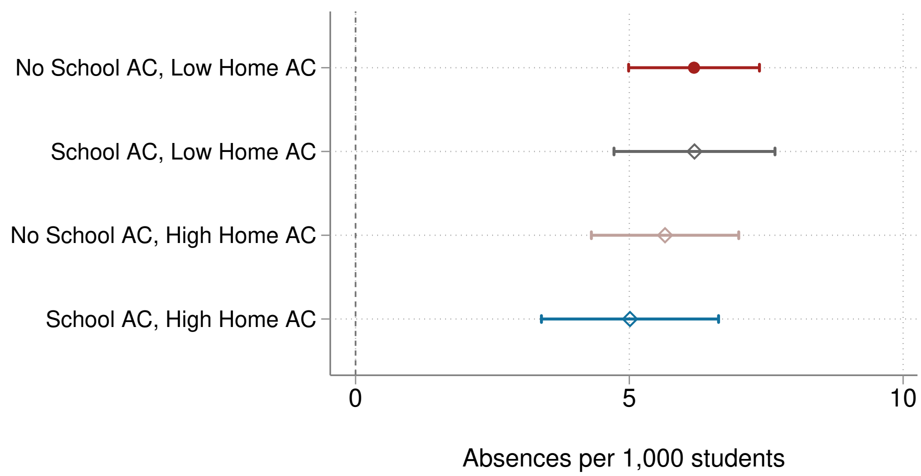



Figure A6. Heat, Absences, and Access to Air Conditioning

*Notes:* This figures shows coefficient estimates and 95% confidence intervals of the effect of a >80°F day on absences relative to a 60–70°F day, taken from regressions of daily, student-level absences on indicators for maximum daily temperature ranges. The mean rate of absences per 1,000 students is 62 in the 2011/12–2016/17 period. Regressions include school, demographic (grade, race/ethnicity, gender, "English learner"), school year, day of school year (fit separately to pre-2013/14), and day before and after vacation fixed effects and controls for rain, snow, $PM_{2.5}$, and $O_3$. Interactions of four indicators of air conditioning access with all timing and environmental controls are also included. Each student's home census block is defined as "high" or "low" home AC based on a 50% residential air conditioning penetration threshold. Heteroskedasticity robust standard errors are clustered at the school level. The sample comprises all present students attending schools during the 2011/12–2016/17 academic years.

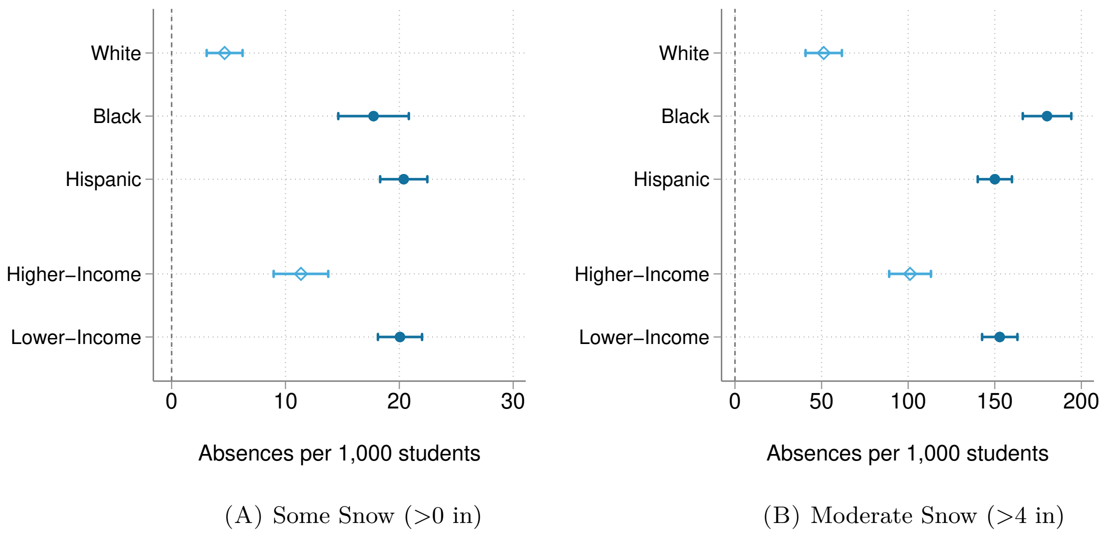



Figure A7. Snow and Absences: Heterogeneity

*Notes:* Shown above are coefficient estimates and 95% confidence intervals of the effect of a (A) somewhat snowy ($>0$ in) and (B) moderately snowy (>4 in) day on absences relative to a 60–70°F day without snow, taken from regressions of daily, student-level absences on indicators for somewhat and moderately snowy conditions. The mean rate of absences per 1,000 students is 62 in the 2011/12–2016/17 period. Regressions include indicators for maximum daily temperature ranges, school, demographic (grade, race/ethnicity, gender, "English learner"), school year, day of school year (fit separately to pre-2013/14), and day before and after vacation fixed effects and controls for rain, $PM_{2.5}$, and $O_3$. Interactions of race or income group (split by median household income) with all timing and environmental controls are also included. Heteroskedasticity robust standard errors are clustered at the school level. The sample comprises all students enrolled in non-air-conditioned schools during the 2011/12–2016/17 academic years.

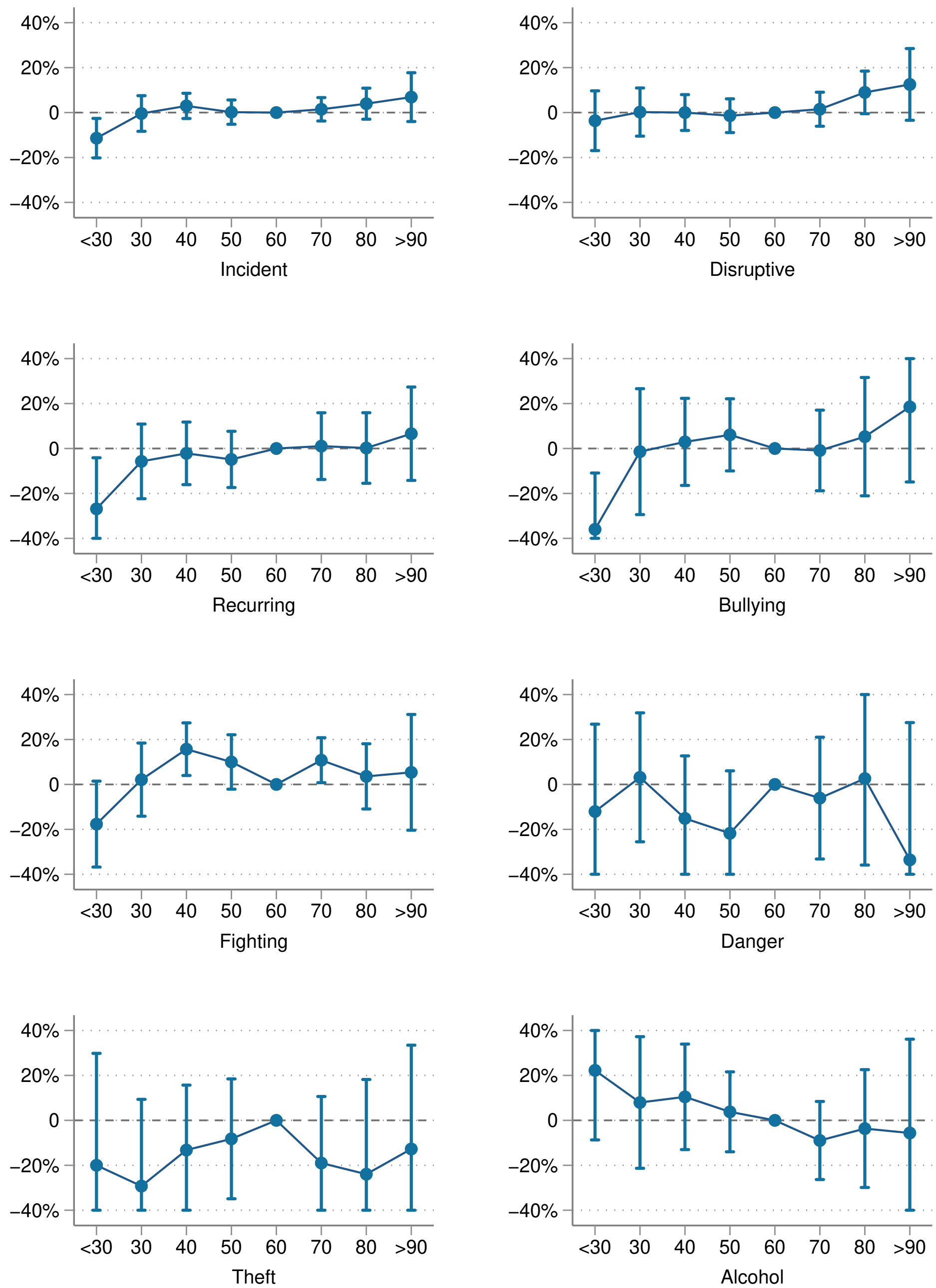



FIGURE A8. Temperature and Referrals (by Type)

*Notes:* Coefficient estimates and 95% confidence intervals are taken from linear regressions modeling daily, student-level behavioral referrals in all schools on indicators for binned temperature for the 2015/16-2018/19 academic years. All estimates are expressed as a percent of the mean daily rate of behavioral referrals of that type. Regressions include school, demographic (grade, race/ethnicity, gender, "English learner"), school year, day of school year (fit separately to pre-2013/14), and day before and after vacation fixed effects and controls for rain, snow, $PM_{2.5}$, and $O_3$. Some large confidence intervals are truncated. Heteroskedasticity robust standard errors are clustered at the school level.

## A.2 Additional tables

Table A1. Incident Categorization

| Incident Category | Count | Incident Category | Count |
|---|---|---|---|
| Fighting/Assault (Total) | 13,519 | Other school based misconduct that substantially disrupts the school environment | 7,823 |
| Fighting, level I | 11,106 | Other violations of code of conduct | 7,723 |
| Fighting, level II | 1,168 | Severe defiance of authority/disobedience | 7,067 |
| Assault III, disorderly conduct | 643 | Theft/Destruction (Total) | 2,505 |
| Unlawful sexual behavior or contact, and indecent exposure | 537 | Theft from an individual (under $500) | 1,258 |
| Assault I or II, vehicular assault, or sexual assault | 65 | Destruction or theft of school property | 845 |
| Bullying/harassment (Total) | 7,089 | Theft from an individual ($500 -$5000) | 214 |
| Bullying | 2,089 | Destruction or theft of school property ($500-$5000) | 155 |
| Bullying, level I | 1,720 | Willfully causing damage to the property of a school employee | 25 |
| Sexual harassment, level I | 801 | Theft from an individual (over $5000) | 7 |
| Bullying, level II | 796 | Destruction or theft of school property (over $5000) | 1 |
| Harassment (race, ethnicity, sexual orientation, gender identity, disability, or religion) | 629 | Alcohol/drugs (Total) | 7,182 |
| Assault, harassment, or false allegation of abuse against a school employee | 531 | Drug violation | 2,115 |
| Sexual harassment, level II | 299 | Under the influence of drugs or alcohol | 1,816 |
| Robbery | 150 | Possession of illegal drugs | 1,765 |
| Witness intimidation or retaliation | 74 | Possession of alcohol or unauthorized, (but legal) drugs | 945 |
| Weapons/dangerous behavior (Total) | 3,705 | Alcohol violation | 225 |
| Other student behavior presenting an active or ongoing danger to the welfare or safety of school occupants | 2,749 | Tobacco | 176 |
| Carrying, bringing, using, or possessing a knife or dangerous weapon | 719 | Sale or distribution of, or intent to sell, unauthorized drugs or controlled substance | 140 |
| Arson | 113 | Recurring offenses (Total) | 11,684 |
| Hazing activities | 41 | Recurring type I offenses | 8,557 |
| Firearm | 37 | Recurring type II offenses | 2,132 |
| Other felonies | 33 | Recurring type III offenses | 637 |
| Possession of an explosive | 12 | Habitually disruptive | 358 |
| Child abuse | 1 | Other (Total) | 548 |
| Disruptive/defiant behavior (Total) | 75,162 | Consensual, but inappropriate, physical contact | 182 |
| Detrimental behavior | 20,146 | Trespassing | 128 |
| Disobedient/defiant, repeated interference | 18,250 | Gang affiliation | 114 |
| Other school based misconduct that disrupts the school environment | 14,153 | Possession of fireworks/firecrackers | 74 |
| | | False activation fire alarm | 50 |
| | | Total | 121,394 |

*Notes:* This table includes all referrals that occurred during school days during the 2011/12-2018/19 school years. Very similar event descriptions are combined in this table.

Table A2. Resolution Categorization

| Resolution Category | Count |
|---|---|
| No Action Taken (Total) | 281 |
| Restorative (Total) | 22,222 |
| Restorative Approach | 18,621 |
| Behavior Contract | 2,868 |
| Behavior Plan-General Education | 554 |
| FBA/BIP Student with disability | 179 |
| In-School Exclusion (Total) | 80,104 |
| Referral | 37,700 |
| In School Suspension | 36,425 |
| In School Intervention Room - ISIR | 3,825 |
| Classroom Suspension/Teacher Removal | 1,311 |
| Bus Referral | 843 |
| Out-of-School Suspension (Total) | 41,065 |
| Out of School Suspension | 38,318 |
| Extended Suspension Requested/Approved/Denied | 824 |
| Expulsion Hearing Requested/Approved/Denied | 1,330 |
| Extended Suspension Requested/Approved/Denied | 408 |
| Declared Habitually Disruptive | 99 |
| Expulsion Denied | 70 |
| Withdraw In Lieu of Expulsion Hearing | 16 |
| Expulsion (Total) | 411 |
| Law Enforcement/Fire Department Referral (Total) | 4,549 |
| Referred to Law Enforcement | 4,434 |
| Referral to Fire Department | 115 |
| Other (Total) | 1,779 |
| Reinstate w/Conditions | 1,571 |
| Habitual Incident | 182 |
| Transferred or Other Cause of Removal | 23 |
| Unilateral Removal by School Personnel | 3 |

*Notes:* This table includes all referrals that occurred during school days during the 2011/12-2018/19 school years. Very similar event descriptions are combined in this table. Note that a single behavioral incident may result in multiple outcomes, so the total of this table and Table A1 are not equal.

Table A3. Student Characteristics by Home and School Air Conditioning Status

| | High AC Neighborhoods | | | Low AC Neighborhoods | | |
|---|---|---|---|---|---|---|
| | All | School AC | No School AC | All | School AC | No School AC |
| **Student Characteristics** | | | | | | |
| Share of Enrollment (%) | 34 | 19 | 15 | 66 | 25 | 41 |
| % with School AC | 56 | – | – | 37 | – | – |
| % English Language Learners | 40 | 43 | 38 | 44 | 50 | 41 |
| Average % LMI | 54 | 52 | 57 | 60 | 62 | 58 |
| Average % Homes Built <1970 | 47 | 35 | 62 | 79 | 68 | 86 |
| **Race/Ethnicity** | | | | | | |
| White(%) | 23 | 21 | 26 | 17 | 11 | 21 |
| Black(%) | 20 | 21 | 18 | 13 | 16 | 11 |
| Hispanic(%) | 47 | 47 | 46 | 63 | 67 | 60 |
| **Grade Level** | | | | | | |
| Elementary(%) | 52 | 59 | 43 | 48 | 48 | 48 |
| Middle(%) | 24 | 23 | 24 | 24 | 27 | 22 |
| High (%) | 24 | 18 | 32 | 28 | 25 | 30 |

*Notes:* The top panel shows student characteristics by air conditioning status. Characteristics are shown just for 2011/12–2016/2017 school years. "High" and "Low" AC neighborhoods are defined as census blocks where the majority and minority of housing units have central air conditioning, respectfully.

Table A4. Student and Facility Characteristics by School Air Conditioning Status.

| | Air-Conditioned | Non-Air-Conditioned |
|---|---|---|
| **Student Characteristics** | | |
| Share of Enrollment (%) | 45 | 55 |
| % English Language Learners | 45.8 | 39.6 |
| Average % VLI or LMI | 57.2 | 58.1 |
| Average % Homes Built <1970 | 53 | 77.6 |
| **Facility Characteristics** | | |
| Number of Schools | 116 | 103 |
| Number of Buildings | 82 | 78 |
| Average Year Constructed | 1984 | 1943 |

*Notes:* The top panel shows student characteristics by school air conditioning status. The bottom panel shows facility characteristics by air conditioning status. Characteristics are shown for the 2011/12–2016/17 school years. All enrolled students are included.

Table A5. Effect of Temperature on Absences by School AC Status

| | All Schools | | | | AC × Temp. |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | No School AC | Interaction |
| **Max Temp.** | | | | | |
| <30F | 21.103*** | 21.076*** | 21.044*** | 19.871*** | 2.863 |
| | (0.911) | (0.910) | (0.914) | (1.040) | (1.891) |
| 30-40F | 0.300 | 0.299 | 0.368 | 0.401 | -0.213 |
| | (0.501) | (0.501) | (0.499) | (0.771) | (0.959) |
| 40-50F | 1.541*** | 1.523*** | 1.538*** | 1.587*** | -0.026 |
| | (0.255) | (0.253) | (0.253) | (0.351) | (0.511) |
| 50-60F | 2.624*** | 2.603*** | 2.603*** | 2.570*** | 0.157 |
| | (0.259) | (0.261) | (0.263) | (0.330) | (0.529) |
| 60-70F | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | (.) | (.) | (.) | (.) | (.) |
| 70-80F | 5.090*** | 5.057*** | 5.085*** | 4.751*** | 0.820 |
| | (0.309) | (0.305) | (0.309) | (0.446) | (0.577) |
| 80-90F | 5.908*** | 5.818*** | 5.768*** | 5.994*** | -0.230 |
| | (0.415) | (0.414) | (0.404) | (0.523) | (0.855) |
| >90F | 9.667*** | 9.600*** | 8.890*** | 9.250*** | 1.062 |
| | (0.791) | (0.782) | (0.747) | (0.937) | (1.627) |
| Obs. (millions) | 60.2 | 60.2 | 60.2 | 60.2 | |
| School FE | X | | | X | |
| School × Year FE | | X | | | |
| Student × Year FE | | | X | | |

*Notes:* Coefficient estimates are from regressions estimating the effect of temperature on absences per 1,000 students relative to a 60–70°F day. The mean rate of absences per 1,000 students is 62 in the 2011/12–2016/17 period. Regressions include year, day of school year (fit separately to pre-2013/14), and day before and after vacation fixed effects and controls for rain, snow, $PM_{2.5}$, and $O_3$. Columns 1, 2, and 4-5 include school or school-by-year fixed effects and demographic (grade, race/ethnicity, gender, "English learner") fixed effects. Column 3 includes student-by-year fixed effects. Interactions of indicators for school air conditioning status with all timing and environmental controls are included in the regression represented by columns 4-5. Heteroskedasticity robust standard errors are clustered at the school level. The sample comprises all students enrolled in schools during the 2011/12–2016/17 academic years. Asterisks indicate coefficient significance level (2-tailed): *** p<.01; ** p<.05; * p<.10.

Table A6. Effect of Temperature on Behavioral Referrals by School AC Status

| | All Schools | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | No School AC | AC × Temp. Interaction |
| **Max Temp.** | | | | | |
| <30F | -0.156** | -0.159*** | -0.160*** | -0.214** | 0.132 |
| | (0.061) | (0.061) | (0.061) | (0.084) | (0.122) |
| 30.temp | 0.010 | 0.017 | 0.009 | -0.005 | 0.037 |
| | (0.044) | (0.044) | (0.043) | (0.059) | (0.090) |
| 40-50F | -0.006 | -0.003 | -0.007 | -0.025 | 0.047 |
| | (0.033) | (0.033) | (0.033) | (0.046) | (0.064) |
| 50-60F | -0.009 | -0.008 | -0.006 | -0.019 | 0.022 |
| | (0.029) | (0.029) | (0.029) | (0.038) | (0.059) |
| 60-70F | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | (.) | (.) | (.) | (.) | (.) |
| 70-80F | -0.007 | -0.008 | -0.003 | -0.011 | 0.010 |
| | (0.032) | (0.032) | (0.032) | (0.044) | (0.064) |
| 80-90F | 0.049 | 0.046 | 0.056 | 0.104** | -0.127* |
| | (0.036) | (0.036) | (0.036) | (0.046) | (0.073) |
| >90F | 0.130 | 0.137* | 0.132* | 0.299*** | -0.390** |
| | (0.081) | (0.081) | (0.078) | (0.115) | (0.151) |
| Obs. (millions) | 56.5 | 56.5 | 56.5 | 56.5 | |
| School FE | X | | | X | |
| School × Year FE | | X | | | |
| Student × Year FE | | | X | | |

*Notes:* Coefficient estimates are from regressions estimating the effect of temperature on behavioral referrals per 1,000 present students relative to a 60–70°F day. The mean rate of referrals per 1,000 present students is 1.4 in the 2011/12–2016/17 period. Regressions include year, day of school year (fit separately to pre-2013/14), and day before and after vacation fixed effects and controls for rain, snow, $PM_{2.5}$, and $O_3$. Columns 1, 2, and 4-5 include school or school-by-year fixed effects and demographic (grade, race/ethnicity, gender, "English learner") fixed effects. Column 3 includes student-by-year fixed effects. Interactions of indicators for school air conditioning status with all timing and environmental controls are included in the regression represented by columns 4-5. Heteroskedasticity robust standard errors are clustered at the school level. The sample comprises all present students attending schools during the 2011/12–2016/17 academic years. Asterisks indicate coefficient significance level (2-tailed): *** p<.01; ** p<.05; * p<.10.

Table A7. Alternative Specifications: Absences and Referrals

| | All Schools | | | | AC × Temp. | | AC × Temp. |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | No School AC | Interaction | No School AC | Interaction |
| **Max Temp.** | | | | | | | |
| <30F | 0.253*** | -0.237*** | -0.121*** | -0.165*** | 0.107 | -0.289*** | 0.118 |
| | (0.010) | (0.064) | (0.046) | (0.062) | (0.093) | (0.082) | (0.130) |
| 30-40F | -0.001 | 0.003 | 0.002 | -0.020 | 0.052 | -0.014 | 0.041 |
| | (0.008) | (0.045) | (0.031) | (0.040) | (0.065) | (0.057) | (0.092) |
| 40-50F | 0.031*** | -0.032 | -0.002 | -0.023 | 0.050 | -0.042 | 0.028 |
| | (0.004) | (0.032) | (0.024) | (0.032) | (0.048) | (0.045) | (0.063) |
| 50-60F | 0.045*** | -0.025 | -0.000 | -0.006 | 0.013 | -0.044 | 0.042 |
| | (0.004) | (0.030) | (0.022) | (0.027) | (0.045) | (0.038) | (0.062) |
| 60-70F | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | (.) | (.) | (.) | (.) | (.) | (.) | (.) |
| 70-80F | 0.072*** | -0.024 | 0.001 | -0.005 | 0.016 | -0.033 | 0.023 |
| | (0.005) | (0.033) | (0.025) | (0.031) | (0.051) | (0.045) | (0.065) |
| 80-90F | 0.090*** | 0.059 | 0.040 | 0.083** | -0.110* | 0.112** | -0.124 |
| | (0.007) | (0.038) | (0.030) | (0.037) | (0.063) | (0.048) | (0.076) |
| >90F | 0.136*** | 0.124 | 0.202** | 0.361** | -0.402** | 0.311*** | -0.432*** |
| | (0.015) | (0.086) | (0.103) | (0.148) | (0.191) | (0.117) | (0.161) |
| Obs. (millions) | 56.0 | 60.2 | 5.8 | 4.7 | | 60.2 | |
| Outcome | Absences | Referrals | Referrals | Referrals | | Referrals | |
| Method | Poisson | Linear | Poisson | Poisson | | Linear | |
| All Enrolled | X | X | | | | X | |
| School FE | | X | | | | X | |
| Student × Year FE | X | | X | X | | | |

*Notes:* Coefficient estimates are from regressions estimating the effect of temperature on absences and behavioral referrals relative to a 60–70°F day. The mean rate of absences and referrals per 1,000 students is 62 and 1.4, respectively, in the 2011/12–2016/17 period. Estimates in column 1 are expressed per 1,000 enrolled students. Estimates from Poisson regressions are unchanged. Regressions include year, day of school year (fit separately to pre-2013/14), and day before and after vacation fixed effects and controls for rain, snow, $PM_{2.5}$, and $O_3$. Column 1 includes school or school-by-year fixed effects and demographic (grade, race/ethnicity, gender, "English learner") fixed effects. Columns 2-5 include student-by-year fixed effects. The effective sample size changes when using a Poisson pseudo-maximum likelihood estimator and many (e.g. student × year) fixed effects because the estimator drops separated observations. Interactions of indicators for school air conditioning status with all timing and environmental controls are included in the regression represented by columns 4-5. Heteroskedasticity robust standard errors are clustered at the school level. The sample comprises all students enrolled in schools during the 2011/12–2016/17 academic years. Asterisks indicate coefficient significance level (2-tailed): *** p<.01; ** p<.05; * p<.10.