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

Kristen McCormack*
Harvard University

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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 and Hispanic students. Hot conditions also increase the likelihood that a student will receive a disciplinary referral, a result driven by students attending schools without air conditioning. Results offer a potential mechanism through which academic outcomes are affected by hot temperatures and suggest that unequal access to air conditioning, both at home and at school, may exacerbate racial, ethnic, and socioeconomic disparities in school.

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[1]Clicking on this link will direct you to `https://kristen-mccormack.com/files/mccormack_jmp.pdf`

1 Introduction

How does student behavior respond to extreme temperatures, and who is most affected? 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).[1] Although both school absences and disciplinary referrals are disruptive to learning and predictive of worse academic and later life outcomes, little is known about how they are affected by extreme temperatures.[2] Understanding these relationships may offer valuable information about the benefits of school infrastructure investments. In the United States, many schools are facing a record number of hot days, a trend that is expected to continue in a rapidly changing climate. At the same time, many school districts have deteriorating or outdated HVAC systems that are expensive to update.[3] Black, Hispanic, and low-income students tend to live in hotter areas and to have less access to air conditioning at school and at home (Park et al., 2020; Hsu et al., 2021). This contributes to concerns that climate change will exacerbate existing inequality in student outcomes as well as childhood and later life-well-being.

To estimate the causal impact of extreme temperatures on student absenteeism and disciplinary referrals, I link local weather data to a panel of daily, student-level data for approximately 70,000 K-12 students enrolled in a large urban school district from 2011 to 2019. I also construct measures of school and residential air conditioning penetration, which I match to each student. The resulting data set provides a detailed 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, 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 which might affect behavior are rarely made in response to environmental conditions, and when changes are made (e.g., snow days), those responses are easily observed. Second, attendance data allow me to observe which students

[1] Heissel et al. (2019); Persico and Venator (2021); Gilraine and Zheng (2022) and Duque and Gilraine (2022) explore the effect of pollution on student achievement.

[2] Several papers study the relationship between student outcomes and absenteeism (Aucejo and Romano, 2016; Goodman, 2014; Gottfried, 2010; Gershenson et al., 2017) as well as the relationship between student outcomes and disciplinary referrals (Craig and Martin, 2019; Bacher-Hicks et al., 2019; Morris and Perry, 2016; Lacoe and Steinberg, 2019; Noltemeyer et al., 2015).

[3] Approximately a quarter of the 50 largest US school districts lack full air conditioning (Barnum, 2017), and 41% of districts report that heating, ventilation, and air conditioning (HVAC) systems in at least half of their schools need to be updated or replaced (GAO, 2020).

are absent and therefore not engaging in observable social interactions.[4]

I present three primary findings about the effect of extreme temperatures on student behavior. First, extreme temperatures exacerbate absenteeism, especially for minority and low-income students. Relative to school days with temperatures in the 60s (°F), students are 34% more likely to be absent on days with temperatures below 30°F. Moderately to extremely hot temperatures also result in an increase in absenteeism. 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. 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. Low-income students are also more sensitive to both heat and cold, although the differences, as measured by neighborhood family income, are smaller than differences by race/ethnicity. Consistent with Goodman (2014), I find that absences also increase in response to snow, particularly for Black, Hispanic, and low-income students.[5] On average, Black and Hispanic students are more than 30% more likely to be absent on a given day than white students, representing a substantial disparity in instructional time (more than 2.5 days over a typical school year). Results suggest that both hot and cold conditions exacerbate existing racial and socioeconomic disparities in absences, reducing instructional time for the most disadvantaged students.

My second key finding is that disciplinary referrals increase in response to heat. On days with temperatures in the 80s (°F) and exceeding 90°F, students are 4% and 9% more likely to receive a disciplinary referral than on school days with temperatures in the 60s (°F). To my knowledge, this paper presents the first evidence that reported behavioral issues in schools are sensitive to temperature.[6] Hot conditions might be expected to exacerbate disciplinary problems if either students or their teachers experience a physiological response to heat that leads to irritability and anger, a mechanism hypothesized by a broad set of papers to explain evidence of heat-induced behavioral changes in adult populations (Anderson, 2001).

With the exception of a few papers examining negative sentiment expressed online (Baylis, 2020) and workplace harassment complaints (Narayan, 2022), most of the work studying behavioral responses to heat has focused on adult crime, and evidence points to a heat-induced

[4] Observing the temperature-behavior relationship outside of the laboratory is often made challenging by the endogeneity of the observability and number of social interactions to temperature. Mukherjee and Sanders (2021) discuss these challenges and highlight the advantage of greater observability and schedule consistency in their study of heat and misbehavior in prisons.

[5] Absences also increase in response to higher levels of air pollution (Currie et al., 2009; Chen et al., 2018).

[6] A couple of papers provide evidence of the effect of annual shocks in pollution on suspensions. Heissel et al. (2019) find that attending a high school that is downwind (vs. upwind) of a highway results in a 4.1 percentage point increase in behavioral incidents (>95% of which result in suspensions). Persico and Venator (2021) find that close proximity of a school to an operating Toxic Release Inventory site is associated with a 1.6 percentage point increase in the likelihood of being suspended.

increase in violent crime in particular (Ranson, 2014; Burke et al., 2015; Bondy et al., 2018; Heilmann et al., 2021; Behrer and Bolotnyy, 2022). By contrast, in this study, I 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. I find that the increase in behavioral referrals on hot days is composed largely of behavior the district categorizes as "disruptive", "defiant", or "disobedient", the descriptions of which include words like irritability, anger, and lack of respect. It is important to note that referrals may reflect student behavior, teacher discretion in responding to behavior, or a combination of the two. Referrals for defiant, disobedient, or disruptive behavior may be more subjective both because they often result from teacher-student interactions and also because they are understood to be more affected by teacher bias (Okonofua and Eberhardt, 2015; Morris, 2007; Nolan, 2011).

Finally, I find the increase in disciplinary referrals on hot days to be driven entirely by students attending schools without air conditioning. In these schools, referrals increase by 7% on days with temperatures in the 80s (°F) relative to days with temperatures in the 60s (°F), and days above 90°F see a 21% increase in referrals. I further find that the increase in disciplinary referrals on hot days is observed mainly among students who not only lack access to air conditioning at school, but also live in neighborhoods with low levels of residential air conditioning. The highest sensitivity is observed among Hispanic students, who, in this district, live in older, lower-income neighborhoods with the lowest levels of residential air conditioning penetration. These findings highlight the potential importance of the environment and access to adaptive technology in explaining racial and socioeconomic disparities in student behavioral outcomes and suggest that heat-induced behavioral changes may contribute to the observed negative effect of heat on learning.

The remainder of the paper is organized as follows. In Section 2, I introduce the institutional setting of the study. I provide additional details on 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. In Section 8, I discuss the implications of my results and conclude.

2 District Setting

The setting of my study is a large urban school district (LUSD), which is one of the 50 largest K-12 public school districts in the country and the largest in its state. Compared to other large districts, students enrolled in the LUSD are less likely to graduate from high school, more likely to qualify for free and reduced price lunch, and more likely to live in poverty (NCES, 2020). The metropolitan area where the district is located is characterized by very cold and very hot school days.

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. For the first six years of the sample period, 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, an additional 19% of the student body was provided with access to school air conditioning.[7]

Like many districts in the country, the LUSD is actively developing best practices to prioritize new air conditioning installations. 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. However, the district now prioritizes improving learning environments in "high-need" schools, while also considering building utilization and measures of "geographic equity."[8] Understanding which students are most vulnerable to heat and who can most benefit from access to school air conditioning will be helpful in informing decisions about which schools should be prioritized for new installations.

3 Data

I link four primary sets of data: (1) student demographics and daily attendance and disciplinary outcomes, (2) school schedules and facility air conditioning information, (3) daily environmental data, and (4) student neighborhood characteristics, including residential air conditioning penetration.

[7]In addition to new air conditioning installations, funds were earmarked to be spent on installing automated nighttime air exchange systems in the buildings that didn't have them and to repair broken cooling systems.

[8]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.

3.1 Student-Level Data

I use detailed, high-frequency student-level and facility-level data provided by the LUSD. Longitudinal student-level administrative data include all students enrolled in the district at any time during the sample period (2011/12 - 2018/19). During these years, the district enrolled an average of about 70,000 K-12 students, who attended approximately 200 schools.[9] Unique student identifiers allow me to follow individual students across time. Daily student-level data include enrolled and absent minutes and student disciplinary referral information. Demographic information, which is provided at the annual level, includes student race/ethnicity, English Language Learner status, gender, and grade, and the census block of each student's home residence, which is reported at an annual level.

Student disciplinary referral data include 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, etc.), the range of documented incidents and their disciplinary outcomes is large. For each referral, 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 behavior, theft and destruction, disruptive behavior, alcohol and drugs, recurring offenses, and other incidents (refer to Tables B1 and B2 for descriptions of these categories and the associated disciplinary responses).

3.2 School Facility-Level Data

I link students to schools using enrollment data. For each school, I compile information using the 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 to students' school days. I also construct school facility information, including building age and air conditioning installation history, from district planning documents.[10]

[9]Enrollment increased during the study period. All summary statistics and analysis exclude first grade students because of data quality issues particular to that grade.

[10]Other substantial modifications to facilities or 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.

3.3 Daily Environmental Data

Daily meteorological data come from three main sources. Information on daily maximum temperature and precipitation come 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.[11] Maximum outdoor temperature is chosen as the key measure of temperature (vs. minimum or average temperature), both because students attend schools 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 come 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 come from monitor data provided by the U.S. EPA Air Quality System.[12]

3.4 Neighborhood-Level Data

To better characterize students and their neighborhoods, several variables are estimated at the census region level and matched to student home locations. The median age of the housing stock in each census block group is estimated using 2011-2015 American Community Survey (ACS) data. Estimates of the percent of households in each block group that are characterized as very low income (VLI) or low- and moderate-income (LMI) are also constructed from these data (provided by HUD). These estimates are used to proxy for student family income because free and reduced price lunch eligibility is only available as school-level averages.

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 units on each floor is noted. I construct census block estimates by first geocoding the addresses of each property and then taking

[11] 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.

[12] These data come from a single monitor in the center of the district. While other monitors are located in the district, only one reported readings for the full sample period.

a weighted average of the residential air conditioning status of each property in the census block, weighted by the number of units in each property. I then 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.

To compare the typical outdoor temperatures that might be experienced in different parts of the district on a hot day, I create census-block level estimates of land surface temperature from Landsat8 30x30m satellite imagery taken on a non-cloudy summer day.[13]

4 Descriptive Statistics

Table 1 provides descriptive statistics of the K-12 student population between 2011/12 and 2018/19. As a share of total enrollment, 20% of students are white, 16% are Black, 57% are Hispanic and 8% are another race. 43% of students are enrolled in English Language Learner programs, the majority of whom are Hispanic and speak Spanish as their first language.

4.1 Student and Neighborhood Characteristics and Access to Air Conditioning

Prior to the fall of 2017, approximately half of all students attended schools with complete air conditioning. Compared to non-white students, and especially Black students, white students were less likely to attend air-conditioned schools. Air conditioning was also more common in elementary and middle schools than high schools. Table B4 provides greater detail about the characteristics of facilities and the student population by school air conditioning status. Schools that had air conditioning for the full sample period tended to be in newer buildings and to serve students living in newer neighborhoods.[14]

Access to residential air conditioning also differs by race/ethnicity. Relative to their white and Black peers, who live in neighborhoods (census block groups) 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 home air conditioning penetration may reflect differences in housing stock age and income, both of which are

[13]This imagery captures the temperature of the land surface, which is highly correlated with air temperature outside of tropical climates (Good et al., 2017). All complete infrared images of the region taken by the Landsat8 satellite from May to October were downloaded, and images were excluded if cloud cover exceeded 10% of the image. Images were then selected based on the location of low quality pixels (largely clouds). Two images with low cloud cover were selected from this process, both of which occurred on days with maximum temperatures exceeding 80°F. The highest quality image was used to estimate the area-weighted average land surface temperature in each census block. The blocks containing low quality pixels in the first image were then assigned the value of their closest percentile rank block as defined by the second image.

[14]Building age as of 2017 is highly predictive of air conditioning status; only 3% of schools built in the 50 years prior to the 2016/2017 school year lacked air conditioning, compared to 85% and 100% of schools built 50 to 100 and over 100 years prior to 2017, respectively.

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

	All	Gender: Female	Gender: Male	Race/Ethnicity: White	Race/Ethnicity: Black	Race/Ethnicity: Hisp.	Grade Level: Elem	Grade Level: Middle	Grade Level: High
Student and Neighborhood Characteristics									
Share of Enrollment (%)	100	49	51	20	16	57	48	24	28
% English Language Learners	42.5	42.7	42.3	6.3	15.1	63	42.3	44.8	40.8
Average % LMI	57.6	57.5	57.6	36.7	58.9	65.1	57.3	58.1	57.6
Average % Built <1950	41.3	41.4	41.1	43.3	27.7	44.8	41.3	40.6	41.7
% Living in Hottest 25th Pct of Neighborhoods	25	25.1	24.9	18.8	30.1	25.9	25.9	25.7	22.9
% Neighborhood with AC	40	40.1	39.8	48.1	48.8	33.6	41.3	39.7	37.7
Share of Enrollment by Access to School AC (%)									
Always AC (108 schs.)	45	45	45	36	52	46	48	47	38
Never AC (67 schs.)	34	34	34	43	26	34	44	33	19
AC starts 2017/18 (18 schs.)	13	13	13	9	11	15	5	16	24
AC starts 2018/19 (7 schs.)	8	8	8	11	5	12	4	4	19

Notes: The top panel shows, for each gender, race/ethnicity, and grade level, the share of enrollment, percent of English Language Learners, the average percent of very low income or low- or moderate-income households in students' home census block groups, the average percent of houses built prior to 1950 in students' census block group, and the percent of students living in the hottest 25th percentile of census blocks. The second panel shows the portion each group that attended schools that always had air conditioning, never had air conditioning, or received air conditioning installations that were completed in 2017/18 or 2018/19 respectively. Descriptive statistics are shown for the 2011/12-2018/19 school years. All enrolled students are included, but statistics are only broken down by the three largest racial/ethnic groups, which comprise 92% of the student body, on average.

predictive of access to residential air conditioning.[15]

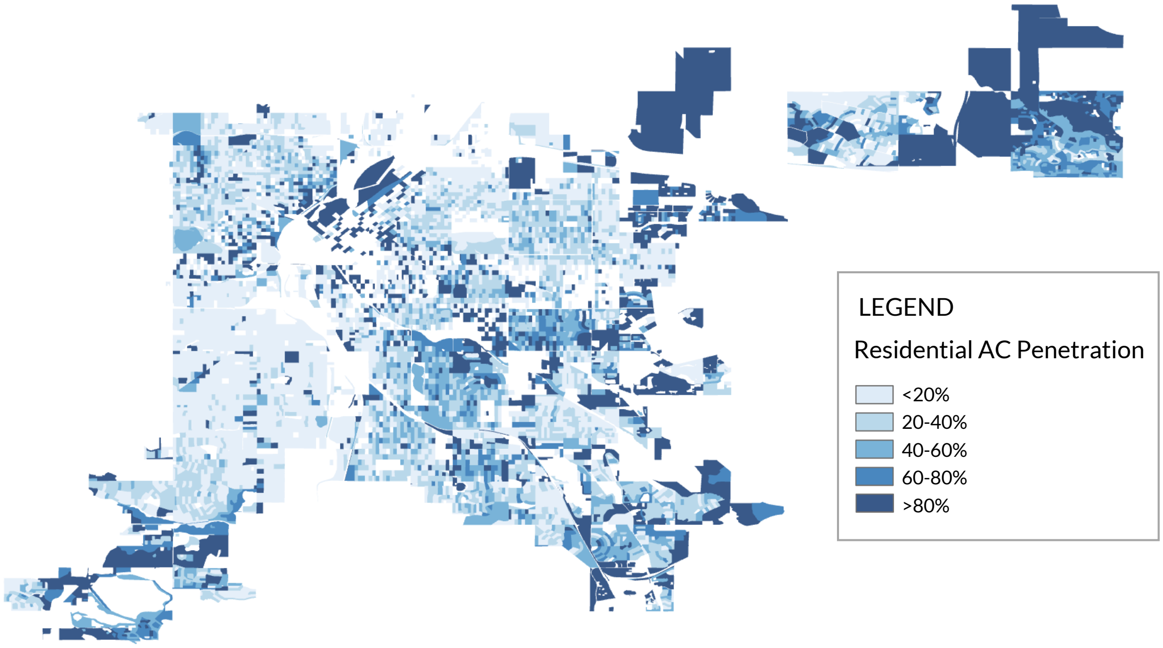
Air conditioning penetration tends to be lower in both older neighborhoods and lower income neighborhoods (see Figure A1).[16] Both white and Black students have greater access to residential air conditioning than Hispanic students, but examining the characteristics of their neighborhoods suggests separate reasons for these differences. 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.[17] By contrast, Hispanic students tend to live in neighborhoods that are characterized by *both* an aging housing stock and relatively low-income households. The relationship between housing stock age, neighborhood income, race/ethnicity, and residential air conditioning penetration is described in greater detail in Appendix C.

It is important to note that neighborhood income also affects additional unobserved

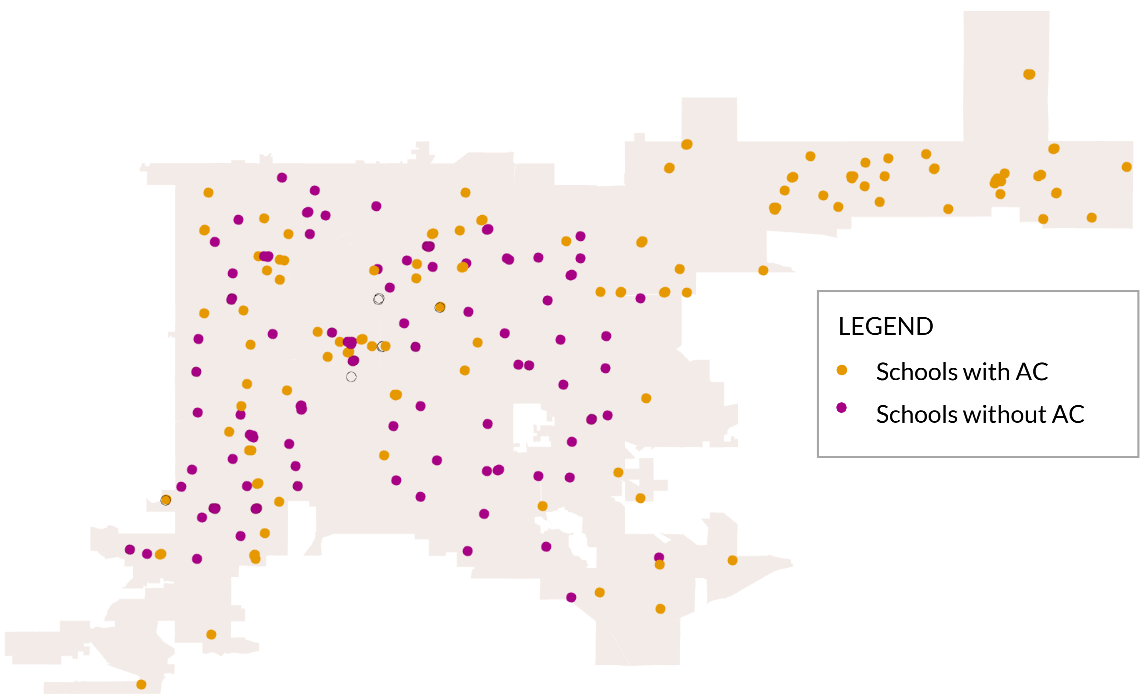
[15]Davis and Gertler (2015) find that adoption of air conditioning depends both on climate and household income, and interaction of the two is the most predictive of adoption.

[16]Note, however, that substantial variation within income groups remains.

[17]Black and Hispanic students are also substantially more likely than white students to live in neighborhoods with a higher average land surface temperature.



(A) Residential Air Conditioning



(B) School Air Conditioning

Figure 1. School and Residential Air Conditioning

Notes: Census-block level averages of residential air conditioning penetration, taken from 2022 tax year assessor data, are illustrated in Panel (A). White spaces represent areas in which no residential property is reported. School locations and air conditioning penetration (constant from 2011/12-2016/17) are shown in Panel (B). Multiple schools may share the same campus. All schools excluded from the sample because of moves or major renovations are represented as hollow circles.

dimensions of heterogeneity in housing quality and access to air conditioning. For example, income may affect not only the likelihood of living in a home where central air conditioning is installed, but also the ability to pay for air conditioning use and/or to purchase and use alternative cooling technology (e.g., evaporative cooling, window air conditioning units). Income may also affect other dimensions of housing quality, like insulation, as well as the likelihood of being a renter, and therefore having fewer options for housing improvements. In addition, according to a district representative, an estimated 20% of the student population is undocumented; the rate of home air conditioning among these families may be even further depressed due to lack of access to benefits and housing protections.[18]

While school air conditioning and home air conditioning are positively correlated (correlation of 0.17), substantial variation in residential air conditioning exists among students who attend both air conditioned and non-air-conditioned schools, suggesting that heterogeneity analysis of these two dimensions of air conditioning access may be possible. Within neighborhoods with "high" and "low" air conditioning penetration, school and home air conditioning are even less correlated (correlation of 0.02 and 0.06 respectively).[19] While census block estimates of residential air conditioning do not translate perfectly to access to home air conditioning for an individual student, the strongly bimodal nature of the data allows for central air conditioning to be predicted precisely for many students: 22% of students live in census block groups with 0 or 100% residential air conditioning penetration.

Figure 1 illustrates the locations and air conditioning penetration of schools in the district and census block averages of residential air conditioning penetration. The map illustrates that, with the exception of the far northeast region of the district, schools and neighborhoods with high air conditioning penetration appear to be relatively well-mixed.

4.2 Absences and Disciplinary Referrals

The average number of absences and disciplinary referrals differ by race/ethnicity, as well as by age and gender, as shown in Table 2. Hispanic and Black students are over 30% more likely than white students to be absent from school. They are also more likely to receive a behavioral referral and are more likely 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 white students to receive a severe penalty during a given year. Male students are more often involved in reported incidents than female students, and middle school students are the most likely age group to be referred for an incident. In an

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

[19]These categorizations are defined as above or below 50% air conditioning penetration.

Table 2. Student behavioral outcomes

		Gender		Race/Ethnicity			Grade Level		
	All	Female	Male	White	Black	Hisp.	Elem	Middle	High
Attendance									
% Absent on Avg. Day	6.1	6.1	6.1	4.8	6.3	6.5	5.7	5.5	7.2
Behavioral Referrals									
% Referred in Avg. Year	9.8	6.5	12.9	4.1	17.4	10	5.3	16.2	12
% Susp./Law in Avg. Year	4.4	2.8	6	1.5	9	4.3	2.1	8.1	5.4
% Referred $\geq$1 in Avg. Year	3.9	2.2	5.5	1.3	8	3.8	1.9	7.1	4.6
Avg Ann. Ref. $\mid \geq$1 Ref.	2.1	1.8	2.2	1.8	2.3	2	1.9	2.3	1.9
% Referred on Avg. Day	0.14	0.08	0.19	0.05	0.28	0.14	0.07	0.25	0.16

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 on 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 for a student who has received at least one referral. Descriptive statistics are shown for the 2011/12-2016/17 school years, which are the focus of the empirical analysis. All enrolled students are included, but statistics are only broken down by the three largest racial/ethnic groups, which comprise 92% of the student body, on average.

average year, approximately 10% of students receive at least one referral, and 4% of students receive multiple referrals.

Referrals are made in response to a variety of different behaviors. The average annual frequency and resulting disciplinary outcomes of each category of referral, from 2014/15-2018/19, is illustrated in Figure A5. A similar figure illustrating these categories in previous years (2011/12-2013/14), when incident descriptions were often not recorded at the same level of detail, is provided in Figure A6. A 2014/2015 reporting procedure change 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.

A comparison of the composition of referrals for each demographic group suggests that Black students receive more referrals for fighting and disruptive behavior, while white students are more likely to be referred for bullying and harassment; Hispanic students fall between these groups. Fighting, bullying, and disruptive behavior are more common in younger students; older students are more likely to receive referrals for alcohol or drug-related behavior (see Table C1).

Both student attendance and behavioral referrals vary substantially throughout a typical academic year. Attendance follows a general downward trend throughout the year, with relatively small drops 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

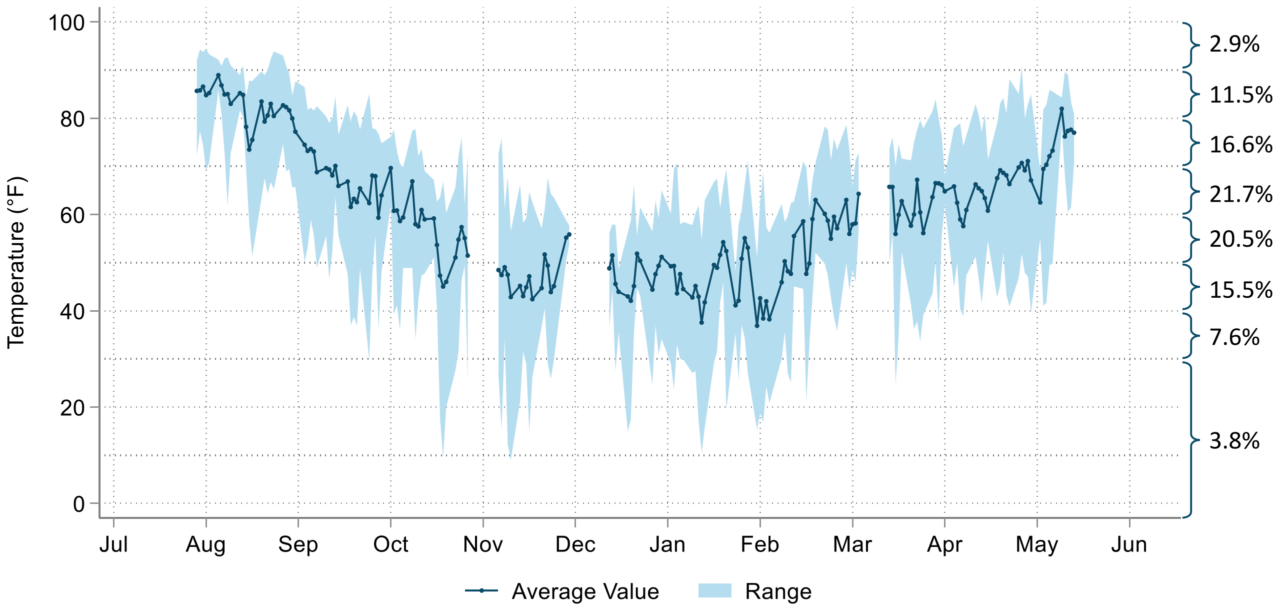


Figure 2. Interannual Variation in Maximum Temperature on School Days

Notes: Shown above are the average district-wide maximum temperature for each school day and the range of temperatures across all years (2011/12-2018/19) on each particular school day. In this image, the academic school 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.

down" at the end, and this pattern is also present near winter break. These patterns are illustrated in Figures A2 and A3.

At the beginning of the semester, this "ramping up" period is likely due to a combination of school policies that give students second chances and the gradual formation of social groups.[20] 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 conflate academic year trends with seasonal patterns in environmental conditions.

During the sample period, an average of 14.4% of school days exceeded 80°F, 2.9% exceeded 90°F, and 3.8% fell below 30°F. Seasonal trends in temperature are correlated with both ambient levels of ground-level ozone and fine particulate matter (seasonal trends in

[20]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).

temperature and pollution are provided in Figures 2 and A4). Ozone production accelerates at hot temperatures, leading to a positive correlation of 0.53 between temperature and ozone. In this region of the country, temperature inversions, which prevent atmospheric convection and can lead to high concentrations of air pollutants, are more common on colder days, leading to a negative correlation between fine particulate matter and temperature of -0.24.

5 Empirical Framework

My identification strategy relies on between-year variation in daily temperature and student behavior, 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:

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

where Y_{isty} is a binary indicator for whether student i enrolled in school s is (1) 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.[21]

The parameters of interest are β_j, the coefficients on binned maximum outdoor temperature. Additional weather controls, W'_{ty}, account for ambient levels of fine particulate matter, $PM_{2.5}$, and ground-level ozone, O_3, as well as snow and rain. A linear and quadratic term for rain and indicators for any snow (>0 inches) and moderate snow (>4 inches) are included.[22] Controls for a set of student demographic characteristics (grade, race/ethnicity, gender, and

[21] Estimating equation (1) using a fixed effects Poisson model yields similar results (see Table B8).
[22] The threshold of 4 inches was selected following Goodman (2014).

English Language Learner status), C'_{iy}, and school fixed effects, η_s, and are also included. Results are robust to including student- or student-by-year fixed effects in place of school and student demographic controls.

Year fixed effects, γ_y, and a set of daily timing controls, δ'_{ty}, are included to 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.).[23] These fixed effects are estimated separately for a pre- and post-2014/15 reporting policy change, so a total of 310 "day of school year" fixed effects are included.[24] The last two weeks of the spring semester are excluded because many schools have testing during this time, and 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.

To investigate which category of behavioral referrals is most responsive to heat and cold, I estimate 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.

The two outcomes of interest, student absences and disciplinary referrals, interact in several notable ways. First, students are very unlikely to receive disciplinary referrals when they are absent from school.[25] The effect of temperature on disciplinary referrals can therefore only be identified off of present students. If students whose referrals are particularly temperature-sensitive are also particularly likely to be absent on hot and/or cold days, then the estimated effect of temperature on disciplinary referrals will be lower than if absences did not also vary in response to temperature.[26] Students may also differ by their "baseline likelihood" of receiving a referral, either because of differences in student behavior or because

[23]To create these fixed effects, I counted forwards and backwards from major school breaks so the beginning and end of school breaks are aligned across school years.

[24]In this policy change, the district discouraged teachers and administrators from describing incidents using broad, "catch-all" descriptions, like "disruptive behavior".

[25]A few observed exceptions include instances when students were referred prior to the start of the school day or for online behavior (harassment).

[26]In this case estimates would still capture the true effect of temperature on referrals in this district but may underestimate the sensitivity of referrals to temperature in settings (e.g., possibly other districts) where absences are less responsive to temperature.

teachers respond to behavior of certain students differently. Temperature-induced changes in the attendance of high "baseline likelihood" students may cause the baseline likelihood of an average present student to receive a referral to vary by temperature. Student fixed effects, or student-by-year fixed effects, which are included in some specifications, may capture daily changes in this baseline likelihood.

The behavioral referrals of present students may be affected by the number and composition of their peers. 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 equation (1) where the outcome variable is $\overline{Z_{icty}}$ or $\overline{R_{icty}}$. The inclusion of $\overline{Z_{icty}}$ and $\overline{R_{icty}}$ in equation (1) when estimating the effect of temperature on behavioral referrals does not substantially change the coefficient estimates on binned temperature.[27]

5.2 Heterogeneity by school and residential air conditioning status

The relationships estimated by equation (1) may mask heterogeneity in the temperature-behavior relationship by the characteristics of schools, students, and neighborhoods. The effect of temperature on behavior, unmitigated by school air conditioning, is of particular interest, so in addition to estimating equation (1) with the full set of schools, I also estimate how this relationship 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 explore heterogeneity in these relationships between temperature and behavior by school air conditioning status, I interact a set of indicators for school air conditioning status, D'_s, with temperature, other environmental controls, and year and day-of-school-year fixed effects. Including interactions with timing controls is necessary to avoid attributing different patterns in behavioral referrals within each school year to correlated environmental

[27]Precisely estimating the extent to which changes in class size and composition affects the observed relationship between temperature and behavioral referrals is complicated by the fact that direct effects of temperature on behavior may be highly correlated with and driven by similar mechanisms as temperature-induced changes in class size and composition.

conditions.[28]

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

The results from this analysis provide cross-sectional evidence of the causal effect of temperature extremes on student behavioral outcomes, unmitigated by school air conditioning. However, they should not be interpreted as estimating the mitigating effect of access to school air conditioning directly on the temperature-behavior relationship because air conditioning status is not randomly assigned.[29]

Given the non-random assignment of school AC, two key potential confounding effects should be noted when interpreting this relationship. First, if students are able to select into air-conditioned schools or if families with more resources are more successful in lobbying for air conditioning to be installed in their local schools, it may be the case that students who are less exposed or vulnerable to heat (e.g., have fewer chronic conditions, live in neighborhoods with more trees, etc.) are more likely to attend schools with air conditioning. The descriptive statistics discussed earlier and provided in Tables 1 and B4 do not lend support to this hypothesis, at least in this district. Students attending air-conditioned schools are, on average, more likely to live in low-income neighborhoods and hot neighborhoods, more likely to be English Language Learners, and less likely to be white.

However, because building age is predictive of school air conditioning status and the housing age is predictive of residential air conditioning penetration, students attending schools with air conditioning are more likely to live in homes with air conditioning. 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 separately, I divide the sample into four groups of students, which are described in Table B3:

[28] This is necessary in all heterogeneity analyses. For example, if more "chances" are given to certain groups of children (e.g., younger 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 older and younger children, 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".

[29] The additional air conditioning installations made by the school district in 2017/18-2018/19 provide variation that might be used in future work for causal identification. However, the post-period for these installations is less than 2 years and some projects involved multiple years of construction, so statistical power to identify the causal effect of these installations is limited. Analysis of these new installations using a triple-difference estimator yields estimates that are in line with cross-sectional results but lack statistical significance.

students with access to air conditioning at home and at school, students without air conditioning in either place, and students who have access to air conditioning just at home, or just at school.[30]

5.3 Heterogeneity by race/ethnicity and income

In addition to studying heterogeneity by air conditioning penetration, I also examine differences in temperature sensitivity by race/ethnicity and neighborhood measures of household income. When studying these dimensions of heterogeneity, I restrict the sample to non-air-conditioned schools (2011/12-2016/17), and create interaction terms by each student/neighborhood characteristic, following equation (2).[31] I show that the heat-behavioral referral relationship is sensitive to access to air conditioning, so when examining heterogeneity in this relationship, I include race/ethnicity-specific or income group-specific controls for residential air conditioning penetration. This offers evidence as to whether differences in access to residential air conditioning explain any observed heterogeneity in the temperature-disciplinary referral relationship by race/ethnicity and income.

6 Results

I present results in several sections. I start by describing the effect of extreme temperatures on the behavior of students attending all schools as well as those attending schools with and without air-conditioning. I discuss how changes in class size and composition may affect the behavior of present students. I then explore heterogeneity in the temperature-behavior relationship by access to residential air conditioning, race/ethnicity, and neighborhood income. Finally, I discuss which types of disciplinary referrals appear to be particularly sensitive to heat.[32]

6.1 Hot and cold conditions increase absenteeism

Panel A of Table 3 shows that absences are higher on both cold and hot days relative to a day 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

[30]Students are considered to have access to air conditioning at home if they live in "high" air conditioning neighborhoods, census blocks where over 50% of housing units have central air conditioning.

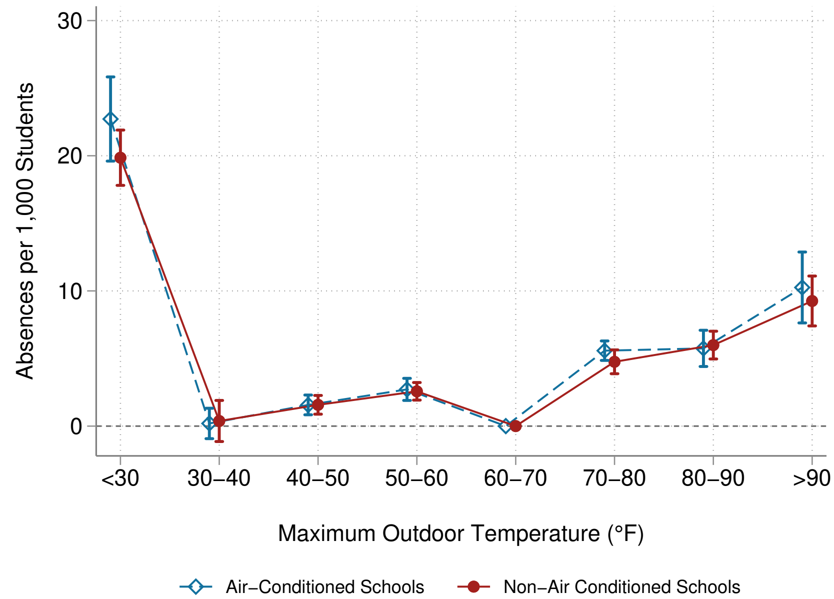
[31]Note that splitting the sample results in very similar coefficient estimates to those that result from including a variety of interaction terms in each specification, as is done in equation (2).

[32]In all tables and figures, I present estimates of temperature-induced changes as a rate 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 61 and 1.4, respectively, in the 2011/12-2017/18 period. As discussed previously, the average rate of absences and referrals varies seasonally.

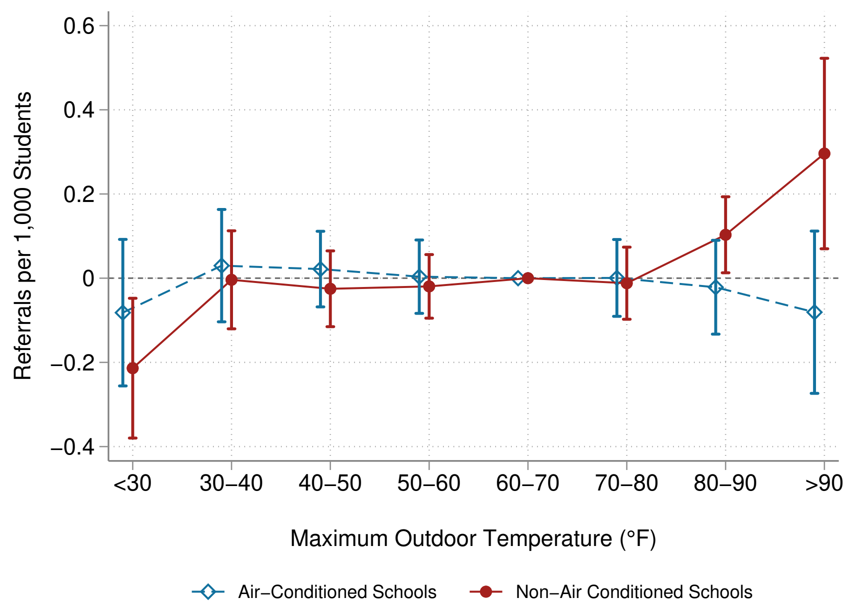
Table 3. Effect of Temperature on Absences and Behavioral Referrals

	All Schools (1)	(2)	(3)	No School AC	AC × Temp. Interaction
Panel A: Absences per 1,000 Enrolled Students (N=60.2 mil.)					
<30F	21.088***	21.059***	21.037***	19.855***	2.864
	(0.910)	(0.909)	(0.914)	(1.038)	(1.890)
80-90F	5.900***	5.809***	5.762***	5.993***	-0.244
	(0.415)	(0.415)	(0.405)	(0.521)	(0.856)
>90F	9.646***	9.576***	8.877***	9.255***	1.000
	(0.791)	(0.782)	(0.748)	(0.936)	(1.627)
Panel B: Referrals per 1,000 Present Students (N=56.4 mil.)					
<30F	-0.156**	-0.158**	-0.161***	-0.214**	0.132
	(0.061)	(0.061)	(0.061)	(0.084)	(0.122)
80-90F	0.049	0.046	0.056	0.103**	-0.125*
	(0.036)	(0.036)	(0.036)	(0.046)	(0.073)
>90F	0.133	0.140*	0.134*	0.296**	-0.377**
	(0.081)	(0.080)	(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 61 and 1.4, respectively in the 2011/12-2017/18 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 B6 and B7.



(A) Absences



(B) Behavioral Referrals

Figure 3. Effect of Temperature on Absences and Behavioral Referrals

Notes: Shown above are coefficient estimates and 95% confidence intervals of the effect of each specified range of temperatures on behavioral referrals relative to a 60-70°F day, taken from regressions of daily, student-level behavioral referrals on indicators for maximum daily temperature ranges. The mean rate of absences and referrals per 1,000 students is 61 and 1.4, respectively in the 2011/12-2017/18 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 Panel B, students absent on a given day are excluded. Estimates are taken from column 4 and the sum of column 4 and 5 of Table 3.

exceeding 90°F, respectively.[33] Coefficient estimates on all temperature bins for both air conditioned and non-air-conditioned schools are illustrated in Panel A of Figure 3. Results indicate that extremely cold temperatures and even moderately hot temperatures reduce student attendance and that this finding is not sensitive to access to school air conditioning.

6.2 Heat increases behavioral referrals in schools without air conditioning

Behavioral referrals are also affected by both hot and cold temperatures. As shown in Panel B of Table 3, referrals are 4% and 9% higher on 80-90°F and >90°F days, respectively, compared with 60-70°F days. However, this effect is not statistically significant when estimated for all schools.

The inclusion of school air conditioning status interaction terms in columns 4 and 5 of Table 3 suggests that the estimated coefficients on hot temperatures in specifications that include all schools mask substantial heterogeneity in this relationship by school air conditioning status. The comparison between air conditioned and non air-conditioned schools, illustrated Figure 3, suggests that the increase in behavioral referrals on hot days is entirely driven by students attending schools without air conditioning. In schools without air conditioning, referrals are 7% higher on days with a maximum temperature between 80-90°F. On days with a temperature exceeding 90°F, this increase jumps to 19%.[34] The difference between temperature-induced referrals by school air conditioning penetration is also observed when estimating this relationship with a Poisson specification (see Table B8).[35]

Disciplinary referrals also appear to be sensitive to cold temperatures; on days below 30°F, behavioral referrals are 11% lower. It is possible that this decrease, and the decrease seen on hot days in air-conditioned schools, may stem partly from the size and composition of the present student body.[36] As noted previously, the probability of a student receiving a behavioral referral on a given day may be affected both by whether that individual student

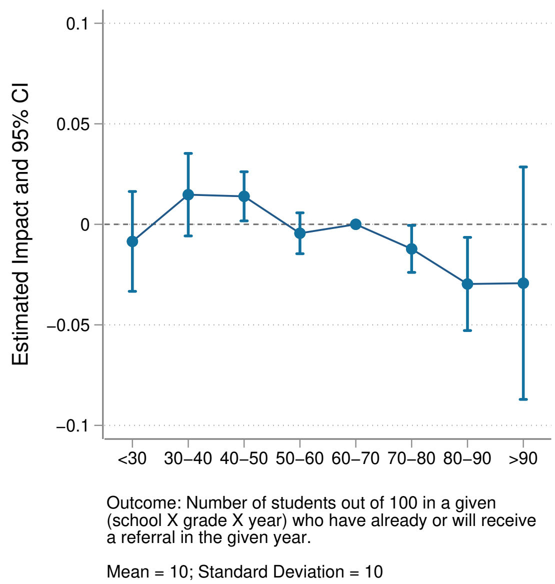
[33]Even moderately hot temperatures appear to increase absences, but more temperate days appear to be generally more similar to each other than days characterized by more extreme temperatures. When controls for snowfall are not included, days with a maximum temperature below 30°F have absences that are 44% higher than 60-70°F days. Coefficient estimates of bins below 60°F are also sensitive to the inclusion of snowfall controls.

[34]This result is robust to the exclusion of schools in the northeast-most part of the district.

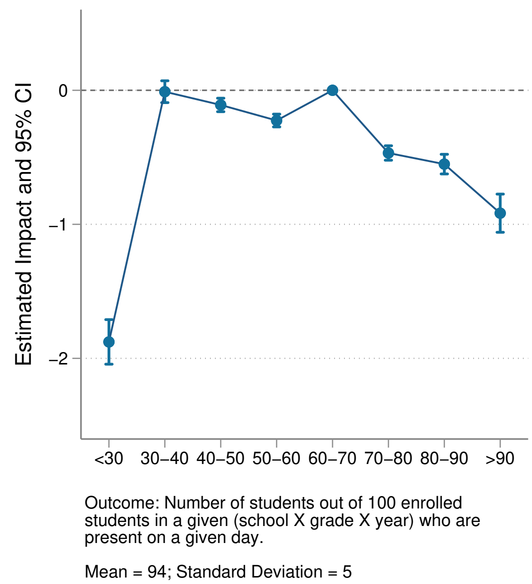
[35]One possible reason for the higher percent increase suggested by Poisson estimates in response to hot temperatures stems from the fact that the average rate of referrals is substantially lower at the beginning of the year. In the first 30 school days, when all >90°F days occur and most 80°F days occur, the referral rate is 1.1 per 1,000 rather than 1.4 per 1,000 (full year average). For simplicity, I present results in the main body of the paper as a percent change from the average referral rate over all days, but the true percent change may be higher.

[36]School scheduling changes on extremely cold days, when most elementary schools keep children indoors. 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.

is present and also by the number and composition of other students present in their class. The high rate of absences on cold days, and to a lesser extent, hot days, raises the possibility that aspects of the school experience, like class size and composition, may differ on these days. Figure 4 shows the effect of temperature on “class risk” and “class size”. The effect of hot and cold conditions on class risk is very small; results suggest that on a >90°F day, 0.03 fewer students with a high-propensity to receive a referral would be present in a school x grade of 100 students. Class size is more affected, although the magnitude of the change does not appear to be large. On the coldest days, the average school x grade of 100 students would be missing an additional 2 students.



(A) “Class Risk”



(B) “Class Size”

FIGURE 4. EFFECT OF TEMPERATURE ON “CLASS RISK” AND “CLASS SIZE”.

Notes: Coefficient estimates are taken from a linear regression modeling class risk and class size on indicators for binned temperature. Regressions include class (school x grade x 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.

The inclusion of these measures of class size and composition in the main temperature-behavioral referral regression does not substantially affect results. While observed changes in student composition are relatively small, changes in class size, particularly on cold days, may be large enough to affect behavior, especially if these changes are concentrated in certain classrooms. For elementary school students, school schedules also change on particularly cold days, when students are kept indoors during recess. According to district representatives, similar protocols for schedule changes on hot days do not exist, with the exception of designated "heat days".[37]

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

School air conditioning status is not randomly assigned, so results illustrated in Figure 3 should not be interpreted as capturing the causal effect of school air conditioning on behavior. Schools in newer neighborhoods are more likely to be air conditioned, and new neighborhoods also have higher rates of residential air conditioning penetration (correlation of 0.17). Using census block-level estimates of residential air conditioning penetration, I identify "high residential AC" neighborhoods as those where the majority of housing units have central air conditioning. I then use this measure to compare how behavioral referrals respond to hot conditions among four groups of students: those who don't have access to AC, 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. For simplicity and to avoid a lack of power, I combine the highest two temperature bins in this analysis, constructing a >80°F bin. I also combine bins representing a maximum temperature between 30 and 80°F. The coefficient estimates on the >80°F bin are shown in Figure 5.

Results indicate that the difference in sensitivity of behavioral referrals to heat illustrated in Figure 3 do not stem solely from differences in home air conditioning status. The largest difference in coefficient estimates is between students who have access to air conditioning both at home and at school and students who lack access to air conditioning in both places, but the disciplinary referrals of students who have access to air conditioning *either* at home or at school are also less sensitive to heat than students who lack access to air conditioning in both places.

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 the students who attend schools without 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. I also combine the bins representing a maximum temperature between 30 and 80°F when estimating disciplinary referrals.

[37] On several days in the sample, schools are canceled or released early due to heat. These heat days are not included in the analysis.

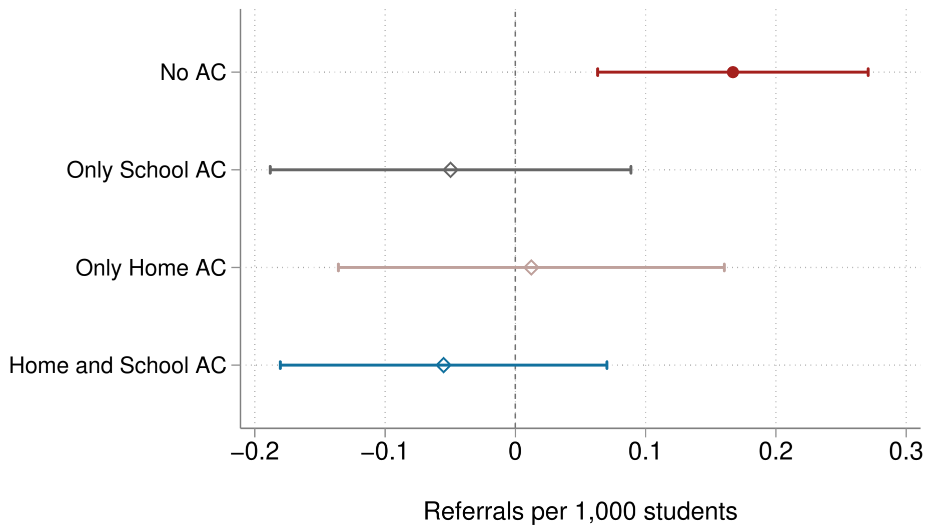


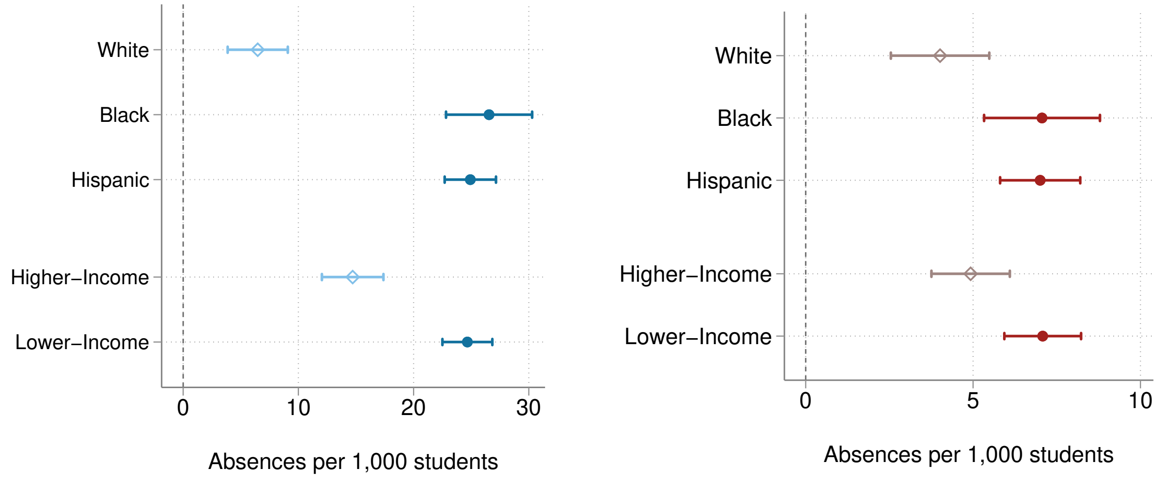
Figure 5. Heat, Behavioral Referrals, and Access to Air Conditioning

Notes: Shown above are 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 2011/12-2017/18 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 (no AC, AC just at home, AC just at school, AC in both places) with all timing and environmental controls are also included. 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.

Coefficient estimates of the effect of <30°F and >80°F temperatures on absences are illustrated in Figure 6. Results indicate that although the attendance of students of all races is affected by temperature, both Black and Hispanic students are more likely to be absent on particularly cold days (and, to a lesser extent, hotter days) than are white students. Absences of students in lower income neighborhoods, defined as having greater than the median percent of low- or moderate-income households (over 60%) also appear to be more sensitive to temperature. The attendance of Black, Hispanic, and low-income students is also more sensitive to snow, as illustrated in Figure A7.

Coefficient estimates of the effect of >80°F temperatures on behavioral referrals are illustrated in the Figure 7. Results indicate that referrals of Hispanic students are more responsive to temperature than referrals of either white or Black students.[38] One possible explanation for the higher sensitivity of behavioral referrals of Hispanic students to heat, at least compared to their white peers, may stem from differential access to air conditioning at

[38] Referrals of Black students are imprecisely estimated for all temperature bins.



(A) Cold Days

(B) Hot Days

FIGURE 6. HEAT, COLD, AND ABSENCES: HETEROGENEITY

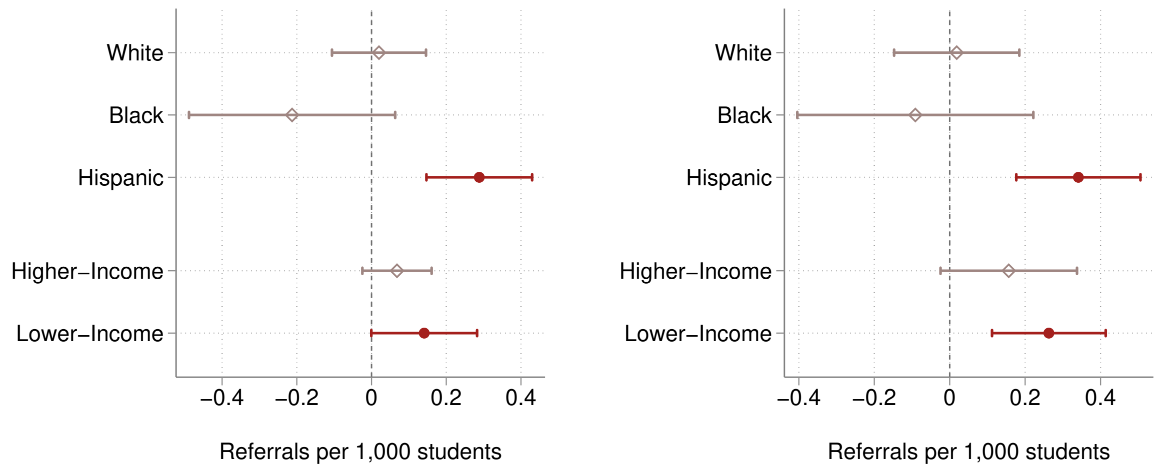
Notes: Shown above are coefficient estimates and 95% confidence intervals of the effect of a (A) <30°F and (B) >80°F day on absences relative to a 60-70°F day, taken from regressions of daily, student-level absences on indicators for maximum daily temperature ranges. The mean rate of absences per 1,000 students is 61 in the 2011/12-2017/18 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. The full set of coefficient estimates from race-specific regressions is illustrated in Figure A10.

home. Including race-specific controls for home air conditioning status reduces the Black-Hispanic gap shown here. While differences are not statistically significant, a comparison of students by neighborhood income suggests that lower-income students may be more sensitive to temperature. This gap remains after controlling for home air conditioning.

6.5 Sensitivity to heat varies by category of behavior

"Disruptive behavior" appears to be the category of referrals that is the most responsive to hot (>80°F) temperatures.[39] 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

[39]Statistical power is limited when examining some categories of behavior. Referrals for bullying/harassment and recurring offenses also appear to increase with temperature.



(A) No Home AC Controls

(B) Controlling for Home AC

Figure 7. Heat and Behavioral Referrals: Heterogeneity

Notes: Shown above are 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 2011/12-2017/18 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 without home air conditioning. 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.

behavior is responsive to heat. See Figures A8 and A9 for more detail.

7 Student Behavior and Climate Change

How will climate change affect student behavioral outcomes? Climate change is expected to result in an increase in the number of school days with moderately and very hot temperatures. To estimate the impact of these changes on student behavioral outcomes in the future, I rely on estimates from my empirical models and a series of temperature projections from global circulation models (GCP) 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.[40] I

[40] 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

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 and is generally considered to be a plausible representation of likely climate change absent more ambitious efforts to cut emissions. This pathway is described as one of two "intermediate scenarios" by the IPCC (IPCC AR6).

I construct two 20-year averages centered around the year 2000 (1990-2010) and the year 2050 (2040-2016), the latter of which corresponds to a "mid-term" future reference period used by the IPCC. It is important to note that by the year 2000, global temperatures had already increased by approximately 0.75°C compared to pre-industrial temperatures (1850-1900). Estimates from an RCP6.0 scenario suggest that by 2050, the average school year in the LUSD will be characterized by 60% more days with a maximum temperature exceeding 80°F than in 2000, and 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 18% decrease in the number of 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.[41] Changes in precipitation events, air pollution from wildfires, and other forms of extreme weather may also affect student behavior, although modeling these directly is challenging.

To predict behavioral referrals and absences using modeled temperature, I estimate equation (1) for the 2011/12-2017/18 school years. I focus on non-air-conditioned schools to better capture the unmitigated effect of warming conditions on student behavior. For simplicity, I make two changes to the specification. 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 of predicting the attendance of each *individual* student (predictions provide estimates of fractional absences, which are not easily translated to binary estimates), I rely on a model predicting the disciplinary referrals of all enrolled students, rather than all present students.

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. I assign temperatures to individual school days in each year assuming that the rank order of temperatures present from 2011-2019 will be preserved (the hottest day in present years will be the hottest day in future years).

[41] 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."

I use the resulting estimated coefficients and the projected temperature data 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 average rate of behavioral referrals and absences for the 1990-2010 period to the 2040-2060 period.

My estimates suggest that relative to 1990-2010, behavioral referrals in the the first 30 days of the school year will increase by 3% in 2040-2060, which represents a nearly doubling of the number of temperature-induced incidents during this period (from 3.7% to 6.2%). Over the full school year (excluding the last two weeks of school), there are expected to be 70% more temperature induced incidents in 2050 relative to 2000.[42]

Absences are highly responsive to both cold temperatures and snow, so the response of attendance to future climate is highly dependent on how snowfall responds to warming conditions. Preserving the current temperature-snowfall relationship implies that while temperature-induced absences rise slightly (4%) in the first 30 days of the school year, about 1% fewer absences can be expected over the full school year, which translates to a 10% decrease in temperature-induced absences.[43]

8 Discussion and Conclusion

This paper explores the impact of extreme temperatures on student attendance 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 my 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

[42]"Temperature-induced" behavioral referrals are calculated as the difference between the number of behavioral referrals in a given year compared with a hypothetical "temperate" year in which all days are 70-80°F. Defining the "temperate" year as a year in which all days are 60-70°F produces similar results: a 3% increase in behavioral referrals, which in this case leads to a tripling of temperature-induced incidents (from 1.3% to 3.8%). The difference between these two choices stems from the increase in absences on 70-80°F days, which results in a decrease in referrals relative to 60-70°F days. The latter definition is used when interpreting attendance results.

[43]When moderately snowy days (days with >4 inches of snowfall) are excluded from this prediction, this decrease is cut in half.

on student attendance. The attendance of both minority and low-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. 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 low-income and Hispanic students, who are the least likely to have 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.

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 the variability in the climate system, exposing students to atypical temperatures more frequently, which may widen disparities in attendance and disciplinary referrals for those who can less easily adapt to temperature extremes. Heat-induced increases in behavioral referrals offer a channel for the observed relationship between heat and worse academic outcomes and highlight a possible benefit of improving school infrastructure. Existing access to adaptive technology at home and at school is characterized by racial/ethnic and socioeconomic differences, suggesting that warming conditions may exacerbate disparities in educational and later-life outcomes.

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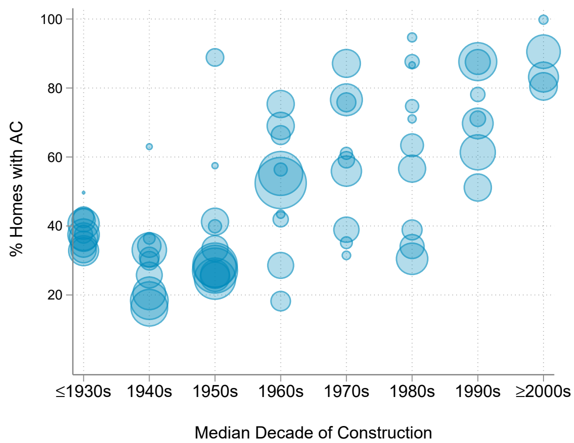
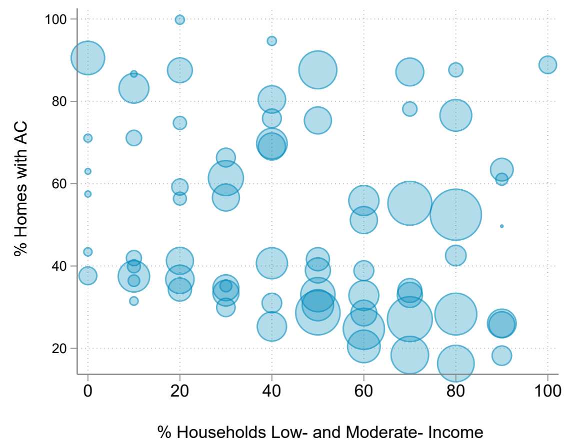
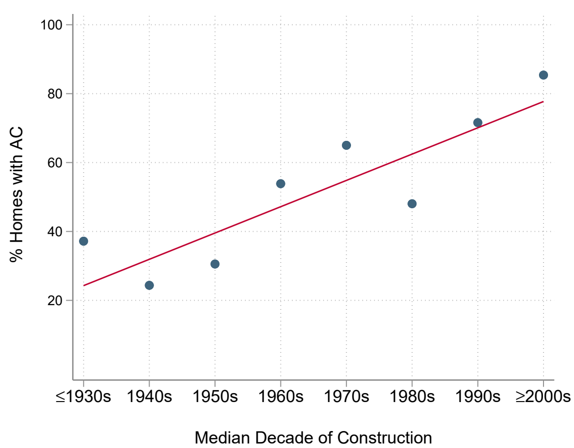
Appendix A: Additional Figures



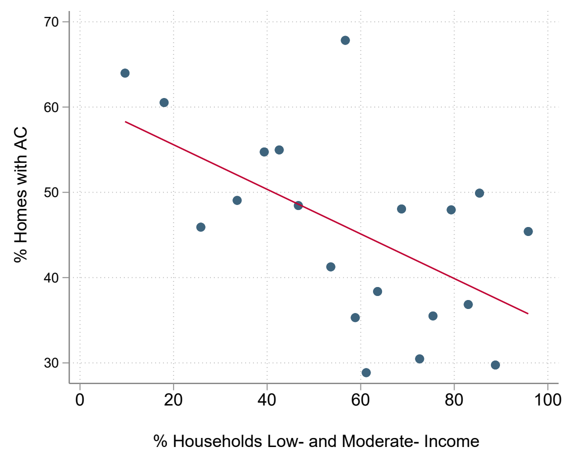
(A) Home AC by Neighborhood Age



(B) Home AC by Neighborhood Income



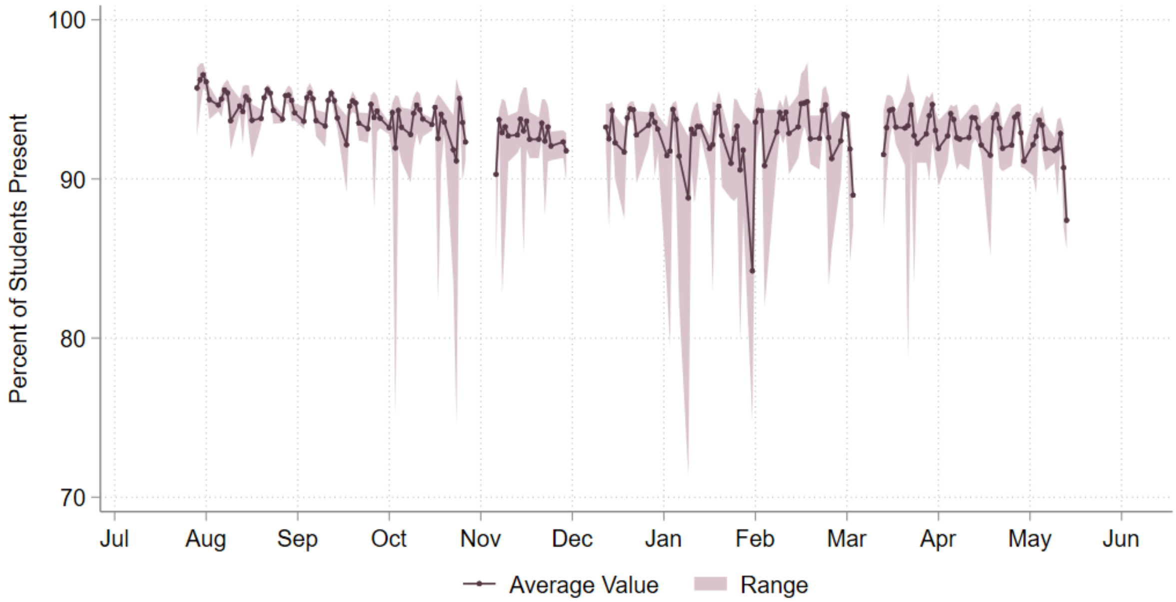
(C) Home AC by Neighborhood Age



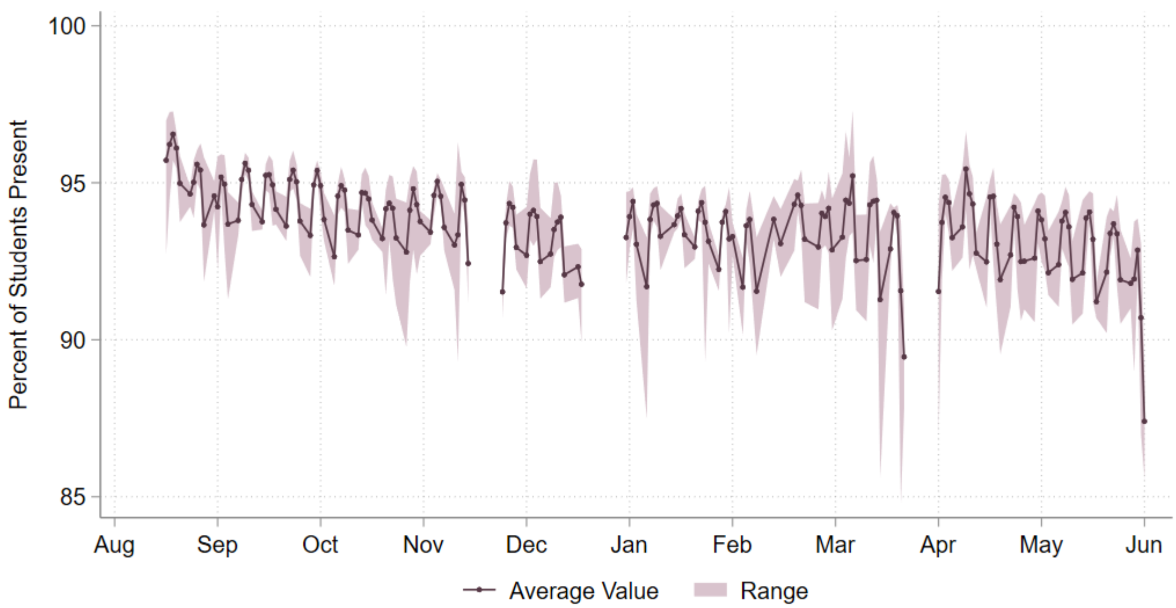
(D) Home AC by Neighborhood Income

FIGURE A1. Association between home air conditioning penetration and (A, C) neighborhood housing stock age and (B, D) percent low or moderate income.

Notes: Scatterplots 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 scatterplots 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 scatterplots representing the same relationships.



(A) All School Days



(B) All School Days, Excluding Known Anomalies

Figure A2. Percent of student body present, grades K-12, 2011/12-2018/19.

Notes: For the purpose of this image, the annual school year is shifted so that weekends are aligned. Blank spaces represent school breaks. In Panel B, days were excluded when absences were high due snowfall or an identifiable, non-environment related reason (Super Bowl parade, the "Day Without Immigrants" protest, etc.)

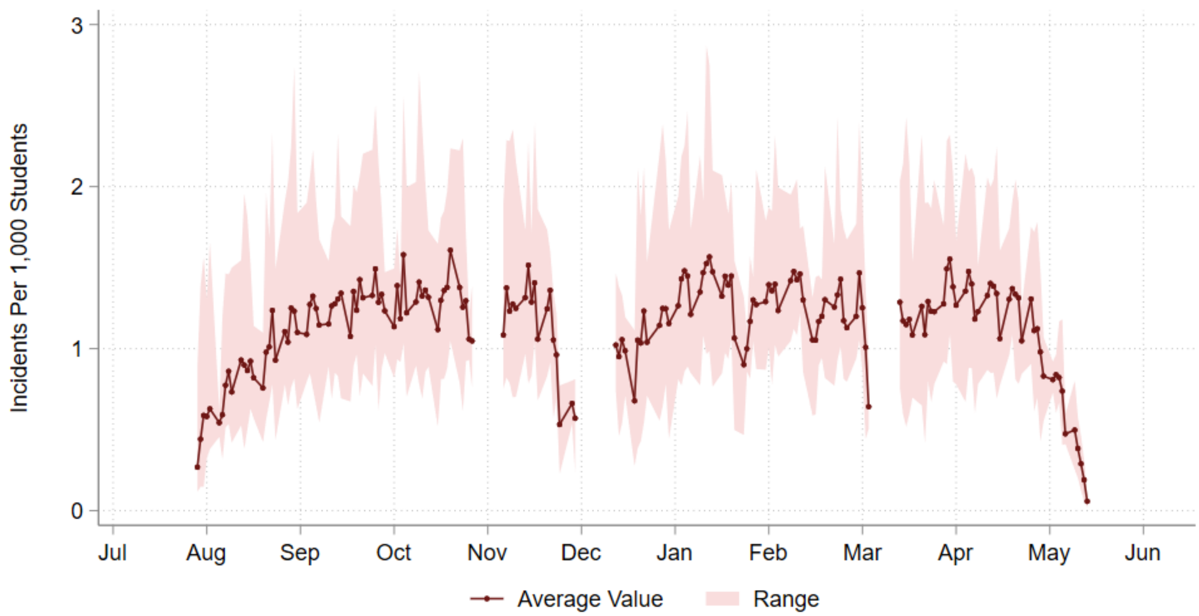
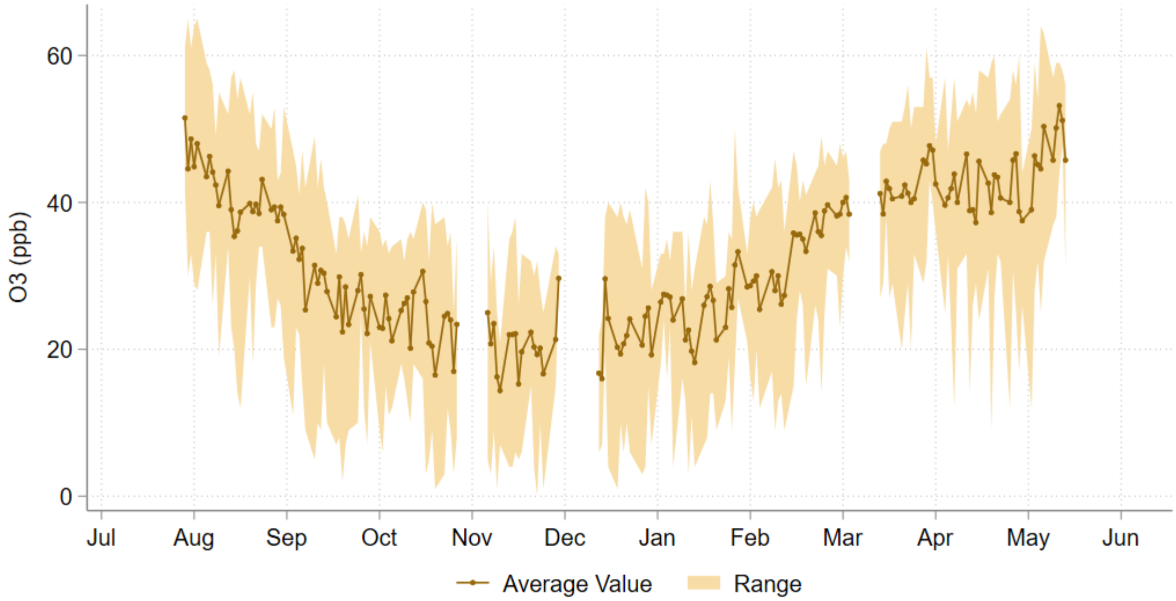
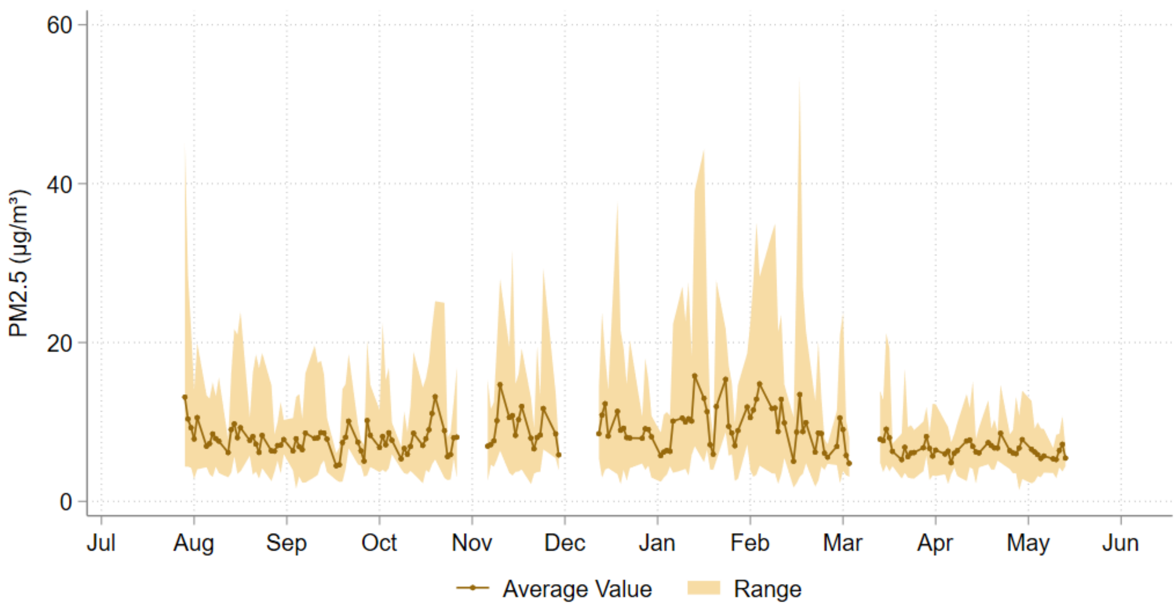


FIGURE A3. Within-year trends in referrals per 1,000 present students (2011/12-2018/19).

Notes: In this image, the academic school 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. Disciplinary referrals are presented per 1,000 present students.



(A) Ambient Levels of Ground Level Ozone (O_3)



(B) Ambient Levels of Fine Particulate Matter ($PM_{2.5}$)

FIGURE A4. District-wide seasonal trends in (a) O_3 and (b) $PM_{2.5}$ over the academic year.

Notes: In this image, the academic school year is shifted to align weekends. Pollution 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.

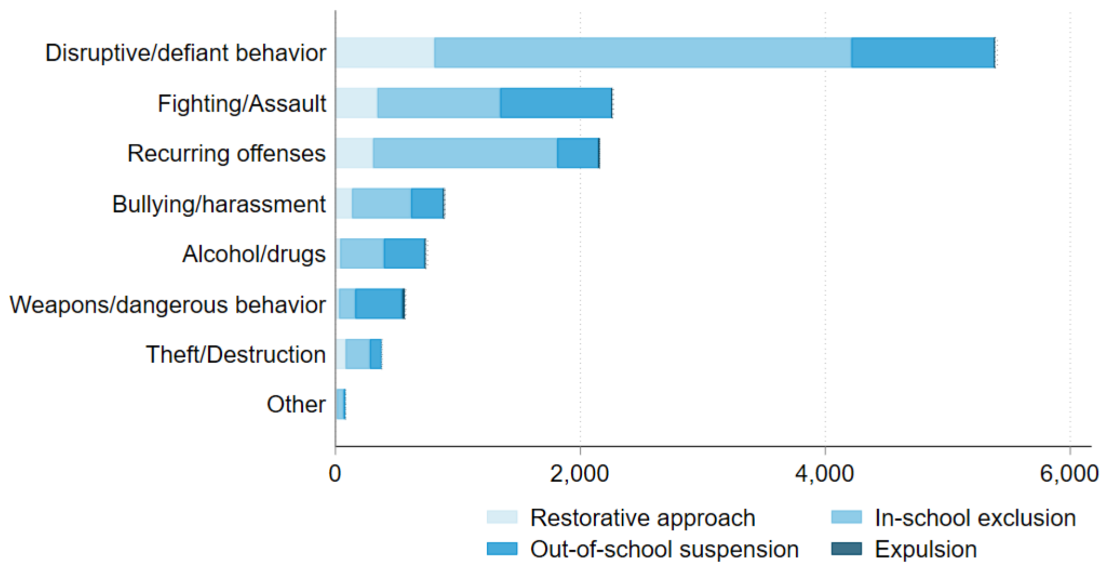


FIGURE A5. Behavioral referrals in an average year, by category and disciplinary outcome (2014/15-2018/19).

Notes: Referrals made on school days for all students during the 2014/15-2018/19 schools years are included. Details about categorization of referrals by behavior and discipline can be found in Tables B1 and B2 respectively. This figure shows only school-level discipline; referrals to law enforcement (police or fire) are not displayed here.

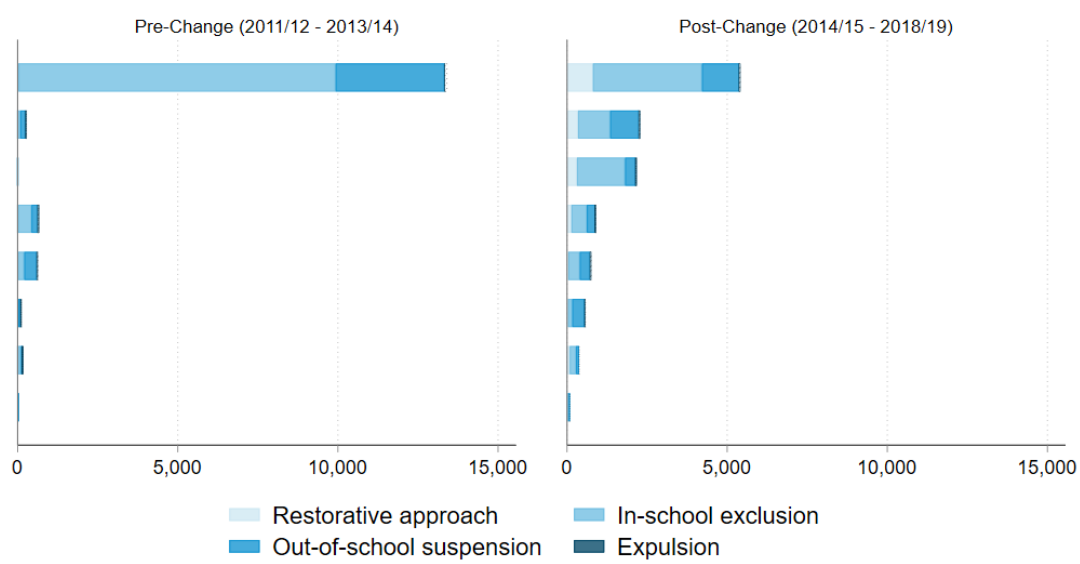
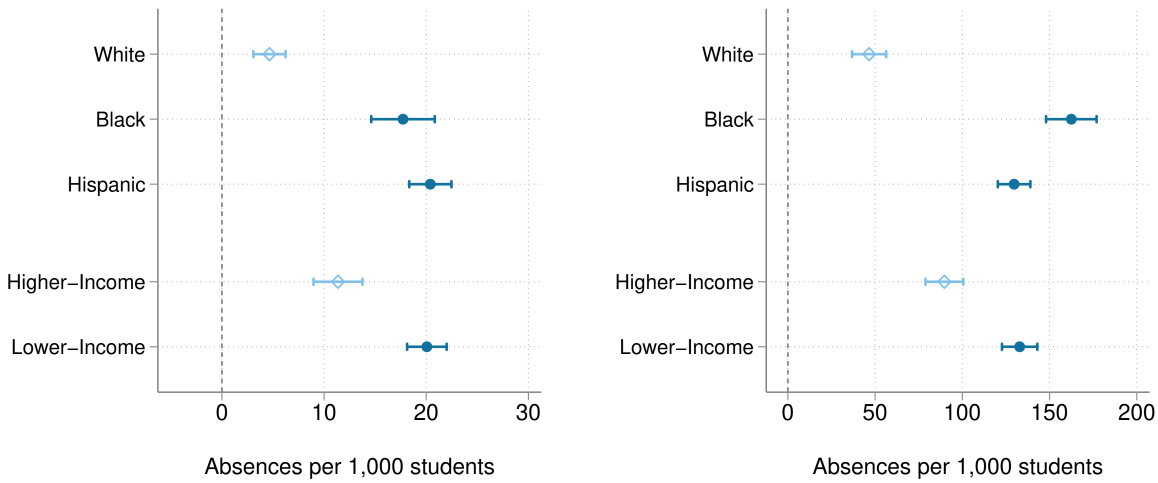


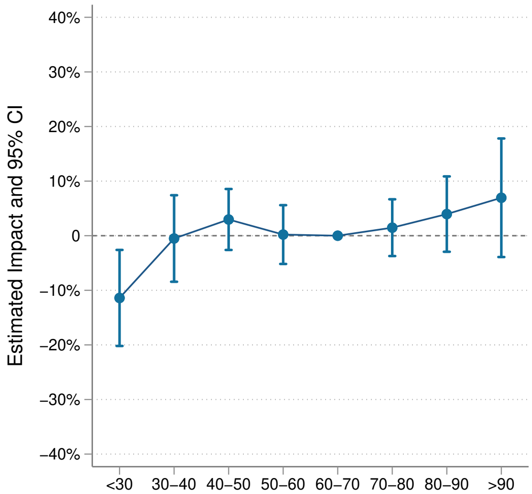
FIGURE A6. Behavioral incidents in an average year before and after reporting policy change, by category and disciplinary outcome.



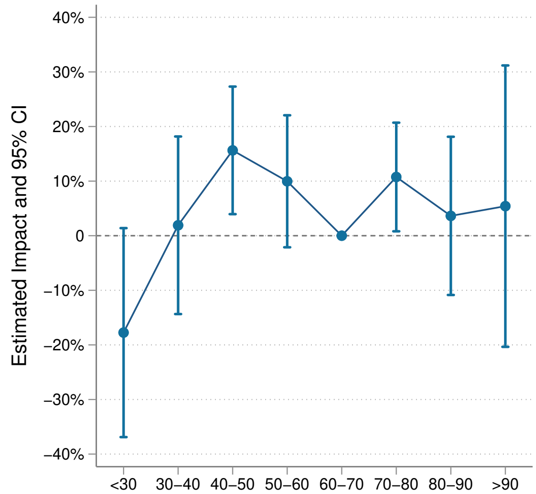
(A) Some Snow (>0 in) (B) Moderate Snow (>4 in)

Figure A7. Snow and Absences: Heterogeneity

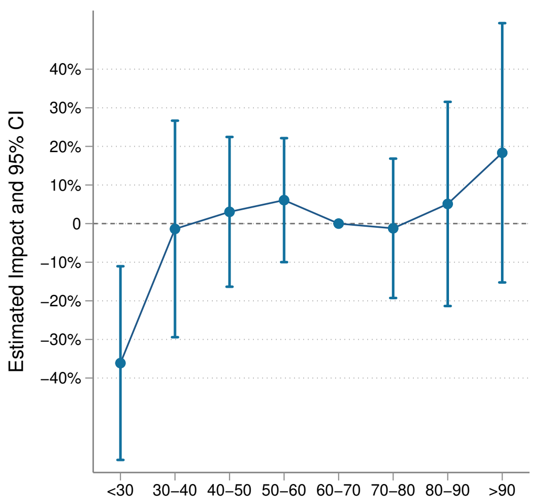
Notes: Shown above are coefficient estimates and 95% confidence intervals of the effect of a (A) somewhat snowy (> 0 in) and (B) moderately snowy (>4 in) day on absences relative to a 60-70°F day without snow, taken from regressions of daily, student-level absences on indicators for maximum daily temperature ranges. The mean rate of absences per 1,000 students is 61 in the 2011/12-2017/18 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, $PM_{2.5}$, 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.



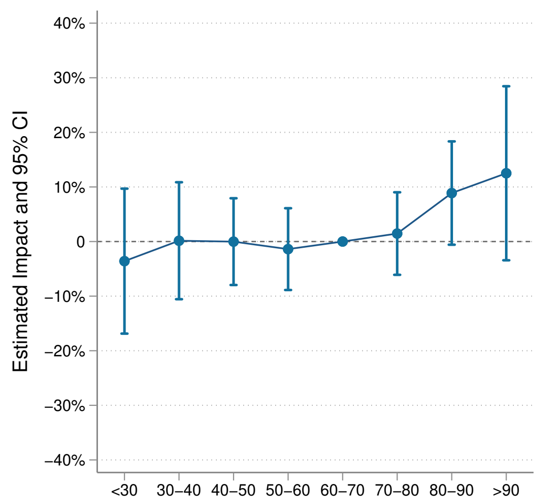
(A) All Types (2014/15-2018/19)



(B) Fighting/Assault



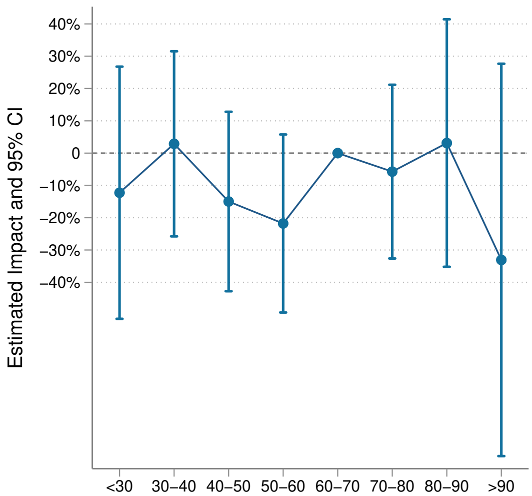
(C) Bullying/Harassment



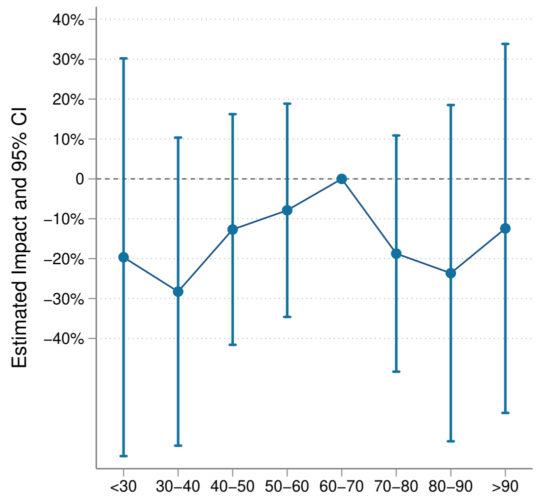
(D) Disruptive/Defiant Behavior

FIGURE A8. Effect of temperature on referrals (separated by type of incident) relative to a day with a maximum temperature between 60-70°F.

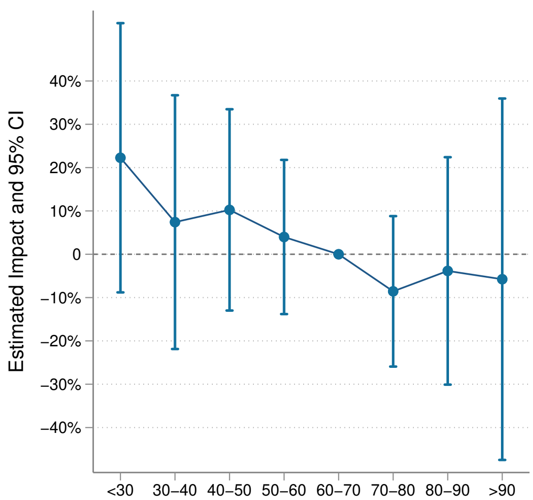
Notes: Coefficient estimates are taken from linear regressions modeling daily, student-level behavioral referrals on indicators for binned temperature for the 2015/16-2018/19 academic years. All estimates are expressed as a percent of the mean daily rate of behavioral referrals of that type. Regressions 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. Heteroskedasticity robust standard errors are clustered at the school level.



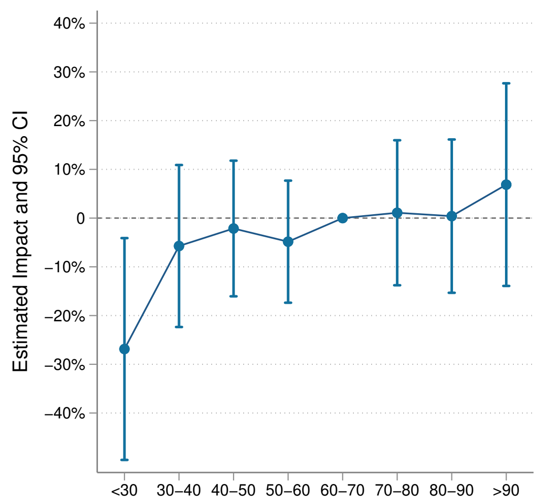
(A) Weapons/Danger



(B) Theft/Destruction



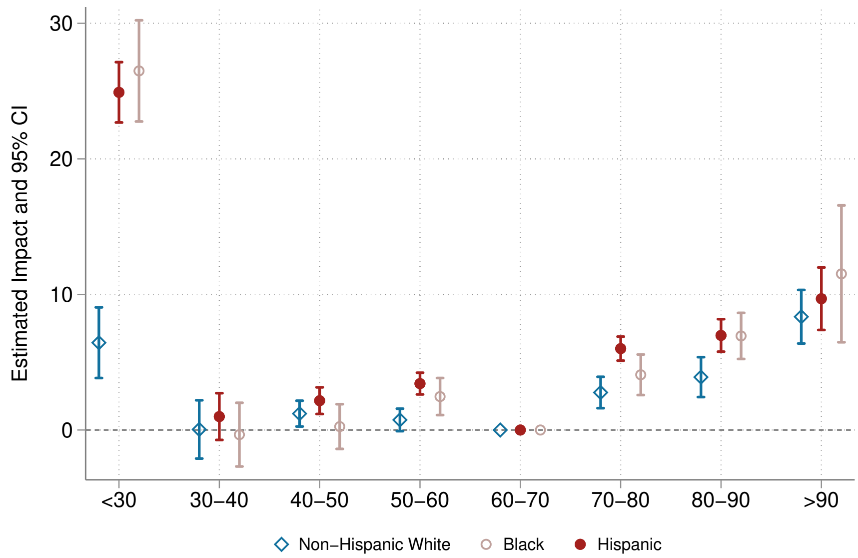
(C) Alcohol/Drugs



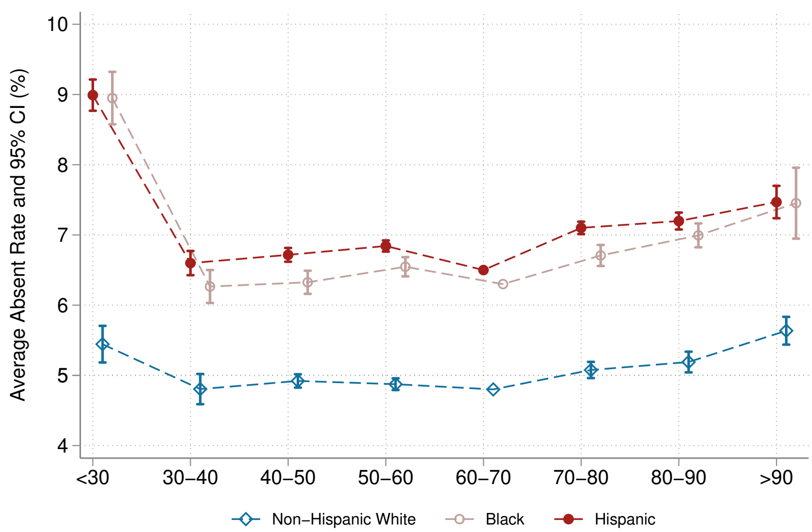
(D) Recurring Offenses

FIGURE A9. Effect of temperature on referrals (separated by type of incident) relative to a day with a maximum temperature between 60-70°F.

Notes: Coefficient estimates are taken from linear regressions modeling daily, student-level behavioral referrals 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. Heteroskedasticity robust standard errors are clustered at the school level.



(A) Estimated Coefficients



(B) Estimated Coefficients + Race-Specific Means

Figure A10. Temperature and Absences: Heterogeneity

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 61 in the 2011/12-2017/18 period. for students attending schools without AC. Estimates in Panel (A) are expressed as absences per 1,000 students. Panel (B) shows the changes in the percent of students absent by temperature, which is calculated as the sum sum of estimates in Panel (A) and race-specific average absent rates. 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. 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 year

Appendix B: Additional Tables

TABLE B1. INCIDENT CATEGORIZATION

Incident Category	Count
Fighting/Assault (Total)	13,993
Fighting, level I	11,571
Fighting, level II	1,188
Assault III, disorderly conduct	621
Unlawful sexual behavior or contact, and indecent exposure	546
Assault I or II, vehicular assault, or sexual assault	67
Bullying/harassment (Total)	7,170
Bullying	1,947
Bullying, level I	1,780
Bullying, level II	848
Sexual harassment, level I	838
Harassment (race, ethnicity, sexual orientation, gender identity, disability, or religion)	637
Assault, harassment, or false allegation of abuse against a school employee	604
Sexual harassment, level II	298
Robbery	147
Witness intimidation or retaliation	71
Weapons/dangerous behavior (Total)	3,876
Other student behavior presenting an active or ongoing danger to the welfare or safety of school occupants	2,915
Carrying, bringing, using, or possessing a knife or dangerous weapon	722
Arson	117
Hazing activities	42
Firearm	40
Other felonies	26
Possession of an explosive	12
Child abuse	2
Disruptive/defiant behavior (Total)	75,092
Detrimental behavior	19,560
Disobedient/defiant, repeated interference	17,517
Other school based misconduct that disrupts the school environment	14,987
Other school based misconduct that substantially disrupts the school environment	8,312
Other violations of code of conduct	7,402
Severe defiance of authority/disobedience	7,314
Theft/Destruction (Total)	2,614
Theft from an individual (under $500)	889
Destruction or theft of school property	1,305
Theft from an individual ($500 -$5000)	218
Destruction or theft of school property ($500-$5000)	165
Willfully causing damage to the property of a school employee	28
Theft from an individual (over $5000)	8
Destruction or theft of school property (over $5000)	1
Alcohol/drugs (Total)	7,269
Drug violation	2,104
Under the influence of drugs or alcohol	1,841
Possession of illegal drugs	1,818
Possession of alcohol or unauthorized, (but legal) drugs	952
Alcohol violation	232
Tobacco	178
Sale or distribution of, or intent to sell, unauthorized drugs or controlled substance	144
Recurring offenses (Total)	12,076
Recurring type I offenses	8,864
Recurring type II offenses	2,176
Recurring type III offenses	659
Habitually disruptive	377
Other (Total)	590
Consensual, but inappropriate, physical contact	196
Trespassing	131
Gang affiliation	120
Possession of fireworks/firecrackers	91
False activation fire alarm	52
Total	122,680

Notes: This table includes all incidents that occurred during school days (when at least 50% of students were present) from 2011/12-2018/19. Some very similar event descriptions are combined in this table.

Table B2. Resolution Categorization

Resolution Category	Count
No Action Taken (Total)	285
Restorative (Total)	21,169
Restorative Approach	18,028
Behavior Contract	2,343
Behavior Plan-General Education	592
FBA/BIP Student with disability	206
In-School Exclusion (Total)	70,174
Referral	36,201
In School Suspension	29,290
In School Intervention Room - ISIR	3,737
Classroom Suspension/Teacher Removal	144
Bus Referral	802
Out-of-School Suspension (Total)	31,522
Out of School Suspension	29,388
Extended Suspension Requested/Approved/Denied	645
Expulsion Hearing Requested/Approved/Denied	1,032
Extended Suspension Requested/Approved/Denied	314
Declared Habitually Disruptive	68
Expulsion Denied	65
Withdraw In Lieu of Expulsion Hearing	10
Expulsion (Total)	306
Law Enforcement/Fire Department Referral (Total)	3,676
Referred to Law Enforcement	3,578
Referral to Fire Department	98
Other (Total)	1,204
Reinstate w/Conditions	1,077
Habitual Incident	111
Transferred or Other Cause of Removal	13
Unilateral Removal by School Personnel	3

Notes: This table includes all incidents that occurred during school days (when at least 50% of students were present)

Table B3. Student Characteristics by Home 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	65	24	41
% with School AC	55	–	–	37	–	–
% English Language Learners	40	43	38	44	50	41
Average % VLI or LMI	54	52	57	60	62	58
Average % Built <1950	19	10	29	56	40	66
% Living in Hottest 25th Pct of Neighborhoods	36	42	28	19	29	13
Race/Ethnicity						
Black (%)	20	21	18	13	16	11
White (%)	23	21	26	17	11	21
Hispanic (%)	47	47	46	63	67	60
Grade Level						
Elementary (%)	52	59	43	48	49	48
Middle (%)	24	23	24	24	27	22
High School (%)	24	18	32	28	24	30

[1]"High air-conditioned neighborhoods" are defined as census block groups where the majority of housing units have central air conditioning.
Notes: The top panel shows student characteristics by air conditioning status. Characteristics are shown just for 2011/12-2017/2018 school years.

Table B4. Student and Facility Characteristics by Air Conditioning Status.

	Always	Never	2017/18-	2018/19-
Student Characteristics				
Share of Enrollment (%)	47	33	12	7
% English Language Learners	45.9	38.4	46.8	33
Average % VLI or LMI	56.6	56.3	62.8	54.2
Average % Built <1950	25.4	52.8	52.4	53.71
% Living in Hottest 25th Pct of Neighborhoods	34.6	16.1	19	18.9
Facility Characteristics				
Number of Schools	107	70	19	7
Number of Buildings	80	59	12	7
Average Building Age (As of 2017)	35	75	72	78

Notes: The top panel shows student characteristics by air conditioning status. Characteristics are shown just for 2016/2017 school year, which is the year prior to the start of new construction and installations. The bottom panel shows facility characteristics by air conditioning status.

Table B5. Incident Categories by Student Demographic Characteristics.

		Gender		Race/Ethnicity				Grade Level		
	All	Female	Male	Black	Hisp.	White	Other	Elem	Middle	High
Incident Type (% of total)										
Full Sample (2011/12-2018/19)										
Fighting/Assault	11.2	13.1	10.4	13.1	10.5	10.2	9.7	14.3	12.1	7.6
Bullying/harassment	5.9	5.4	6.1	5.6	6	6.5	5.9	9	6.7	2.6
Weapons/danger	3.1	2.8	3.3	3.3	3	3.2	3.9	2.6	3	3.7
Theft/Destruction	2.1	1.8	2.2	2.2	2	2.3	2	2.5	2.1	1.7
Disruptive Behavior	62.3	61.3	62.7	63.7	61.8	60.4	61.3	63.3	62.4	61.4
Alcohol/Drugs	6	6.9	5.7	4.1	6.8	7.7	7	.7	4.2	12.6
Recurring Offenses	9.5	8.7	9.9	8.4	10	9.7	10.6	8	9.8	10.2
Other	.5	.4	.5	.4	.5	.5	.5	.2	.5	.6
Post Change (2014/15-)										
Fighting/Assault	18.5	22.1	17.1	21.8	17.6	15.5	15.2	23.6	19.5	13
Bullying/harassment	7.2	6.2	7.5	7	7.1	8.1	7.4	9.8	8.2	3.5
Weapons/danger	4.9	4.8	5	5.3	4.6	4.6	5.8	3.7	4.5	6.5
Theft/Destruction	3	2.6	3.1	3.2	2.8	3	2.7	3.7	2.9	2.6
Disruptive Behavior	42.7	40.4	43.6	43.2	41.9	45.2	44.4	44.9	43.5	39.6
Alcohol/Drugs	6.9	8.4	6.3	4.6	8	7.7	7.2	.8	4.9	15
Recurring Offenses	17	15.6	17.6	15.3	18	15.9	17.9	14.2	16.8	19.7
Other	.7	.7	.6	.6	.7	.8	.7	.4	.8	.7

Notes: This table reflects the population of students who were enrolled in school on at least one "school day" during the sample period. The composition of behavioral referrals by category is provided for gender, race/ethnicity, and grade level, both for the full sample period (2011/12-2018/19) and for the years following a reporting change that caused fewer incidents to be described as "disruptive" and corresponded with a decline in behavioral incidents, particularly for Black students.

Table B6. Effect of Temperature on Absences

	All Schools				AC × Temp.
	(1)	(2)	(3)	No School AC	Interaction
Max Temp.					
<30F	21.088***	21.059***	21.037***	19.855***	2.864
	(0.910)	(0.909)	(0.914)	(1.038)	(1.890)
30-40F	0.291	0.289	0.366	0.379	-0.182
	(0.501)	(0.501)	(0.499)	(0.771)	(0.960)
40-50F	1.537***	1.518***	1.537***	1.575***	-0.007
	(0.255)	(0.253)	(0.253)	(0.351)	(0.511)
50-60F	2.621***	2.600***	2.605***	2.573***	0.144
	(0.259)	(0.261)	(0.263)	(0.330)	(0.530)
60-70F	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
70-80F	5.098***	5.065***	5.090***	4.757***	0.823
	(0.309)	(0.305)	(0.310)	(0.447)	(0.578)
80-90F	5.900***	5.809***	5.762***	5.993***	-0.244
	(0.415)	(0.415)	(0.405)	(0.521)	(0.856)
>90F	9.646***	9.576***	8.877***	9.255***	1.000
	(0.791)	(0.782)	(0.748)	(0.936)	(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 61 in the 2011/12-2017/18 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 B7. Effect of Temperature on Behavioral Referrals

	All Schools				AC × Temp.
	(1)	(2)	(3)	No School AC	Interaction
Max Temp.					
<30F	-0.156**	-0.158**	-0.161***	-0.214**	0.132
	(0.061)	(0.061)	(0.061)	(0.084)	(0.122)
30-40F	0.010	0.016	0.008	-0.004	0.034
	(0.045)	(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)	(0.065)
50-60F	-0.009	-0.008	-0.006	-0.019	0.023
	(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	-0.002	-0.012	0.013
	(0.032)	(0.032)	(0.032)	(0.043)	(0.064)
80-90F	0.049	0.046	0.056	0.103**	-0.125*
	(0.036)	(0.036)	(0.036)	(0.046)	(0.073)
>90F	0.133	0.140*	0.134*	0.296**	-0.377**
	(0.081)	(0.080)	(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 2011/12-2017/18 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.

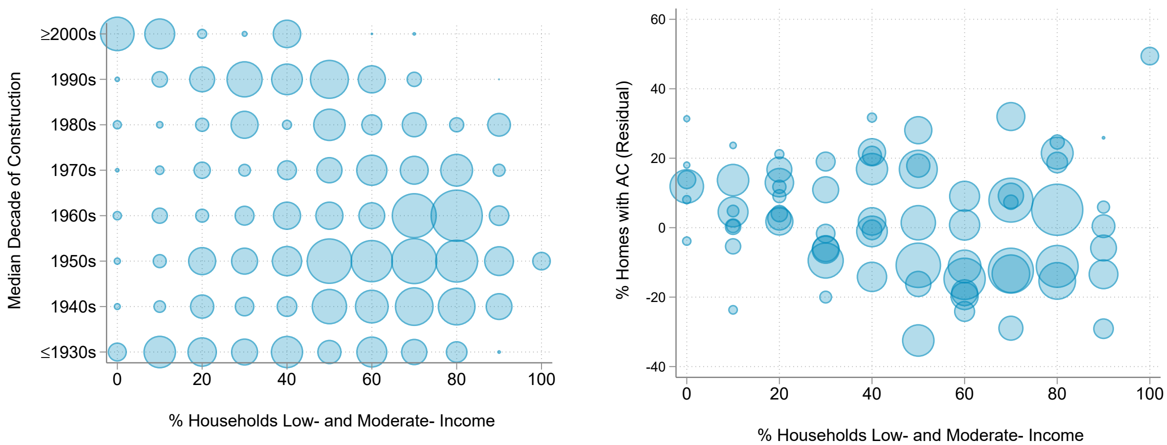
Table B8. Alternative Specifications: Absences and Referrals

	All Schools (1)	(2)	(3)	No School AC	AC × Temp. Interaction
Max Temp.					
<30F	0.253***	-0.238***	-0.165***	-0.165***	0.107
	(0.010)	(0.064)	(0.043)	(0.062)	(0.093)
30-40F	-0.001	0.003	-0.000	-0.019	0.050
	(0.008)	(0.045)	(0.028)	(0.040)	(0.065)
40-50F	0.031***	-0.032	-0.018	-0.023	0.050
	(0.004)	(0.032)	(0.021)	(0.032)	(0.048)
50-60F	0.045***	-0.025	-0.011	-0.006	0.014
	(0.004)	(0.030)	(0.020)	(0.027)	(0.045)
60-70F	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
70-80F	0.072***	-0.025	-0.014	-0.006	0.018
	(0.005)	(0.032)	(0.022)	(0.031)	(0.051)
80-90F	0.089***	0.058	0.040	0.082**	-0.107*
	(0.007)	(0.038)	(0.028)	(0.037)	(0.063)
>90F	0.135***	0.124	0.176*	0.358**	-0.385**
	(0.015)	(0.086)	(0.096)	(0.148)	(0.191)
Obs. (millions)	56.0	60.2	5.8	4.7	
Outcome	Absences	Referrals	Referrals	Referrals	
Method	Poisson	Linear	Poisson	Poisson	
All Enrolled	X	X	X	X	
School FE	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 61 and 1.4, respectively in the 2011/12-2017/18 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. Columns 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.

Appendix C: Predictors of Residential Air Conditioning

As illustrated in Figure C1, housing stock age and income are correlated. Lower-income neighborhoods tend to be older (correlation of 0.2), although this relationship isn't observed for the oldest/most historic neighborhoods (built pre-1940).



(A) Neighborhood Age by Neighborhood Income (B) Home AC by Neighborhood Income (Residual)

Figure C1. Residential Air Conditioning, Income, and Housing Age

Notes: Scatter plots illustrate the correlation between (A) the housing stock age of each census block group and the percent of households who are low- and moderate-income and (B) home air conditioning penetration in each census block group and the percent of households who are low- and moderate-income, after controlling for the age of the housing stock. The size of the bubble is scaled in proportion to the number of enrolled students living in that census block group.

A set of regressions predicting neighborhood residential air conditioning penetration from housing age, income, and race/ethnicity, the results of which are shown in Table C1, suggest that both income and housing age may be independently important predictors of home air conditioning. A ten year increase in the median age of the housing stock is associated with a 7% decrease in average air conditioning penetration, and a 10% increase in the percent of households that are low or moderate income is associated with a 1.4% decrease in average AC penetration. While white and Black students live in neighborhoods with approximately the same level of residential air conditioning penetration, Black students tend to live in neighborhoods with 5 percentage points lower air conditioning penetration than white students after controlling for building age. After controlling for building age, Hispanic children live in neighborhoods with 13 percentage points lower air conditioning penetration than white students. The coefficient estimate on income is sensitive to the inclusion of housing age and, to a greater extent, race/ethnicity.

Table C1. Predictors of Residential Air-Conditioning Penetration (%)

	(1)	(2)	(3)	(4)	(5)	(6)
Median Housing Age (Decades)	-7.600***		-7.300***		-7.378***	-7.280***
	(0.697)		(0.655)		(0.625)	(0.626)
LMI (%)		-0.264***	-0.146**			-0.051
		(0.101)	(0.062)			(0.067)
Black				-0.068	-5.525***	-4.251**
				(3.875)	(1.881)	(1.752)
White				0.000	0.000	0.000
				(.)	(.)	(.)
Hispanic				-14.584***	-13.051***	-11.561***
				(3.880)	(1.676)	(1.725)
Constant	77.021***	60.337***	84.301***	54.022***	85.128***	86.566***
	(3.783)	(6.292)	(4.090)	(3.823)	(2.958)	(3.528)
Observations	541,324	541,324	541,324	541,447	541,324	541,324

Notes: Each column represents a linear regressions modeling the average home air conditioning penetration of an individual student's census block group as a function of the median housing stock age, the percent of households that are low or moderate income, and/or the student's race/ethnicity. Percents range from 0-100. Each observation represents a student who was enrolled in school sometime during the 2011/12-2018/19 school year (one observation per student per year). Housing age is measured in decades from the year 2000. The lowest and highest housing ages are 0 and 70 due to top- and bottom-coding. Heteroskedasticity robust standard errors are clustered at the census block group level. Asterisks indicate coefficient significance level (2-tailed): *** p<.01; ** p<.05; * p<.10.