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

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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, an effect found only among students attending schools without air conditioning. Results suggest that warming temperatures may lead to more student behavioral problems and that unequal access to air conditioning may exacerbate racial, ethnic, and socioeconomic disparities in school.

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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; Graff Zivin *et al.*, 2018). However, 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.[1] Understanding these relationships may offer valuable information about the effects of warming temperatures on students and the potential benefits of school infrastructure investments. In the United States, many schools are facing an unprecedented number of hot days, a trend that is expected to continue given the rapidly changing climate. At the same time, many school districts have deteriorating or outdated HVAC systems that are expensive to update.[2] Warming conditions are also experienced unequally; Black, Hispanic, and low-income students tend to live in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 leverage a highly-detailed panel of tens of millions of daily, student-level observations of approximately 70,000 K-12 students enrolled in a large urban school district from 2011 to 2019. In addition to allowing me to observe students over time, these data also allow me to link students with local weather data, school air conditioning information, and a measures of access to air conditioning at home, which I construct at the census block level from housing-unit level air conditioning information. The resulting data set provides a rich picture of student behavior, exposure to extreme temperatures, and access to adaptive

[1]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).

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

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 changes are easily observed. Second, the availability of student-level attendance data allows me to observe which students are absent and therefore unable to receive a behavioral referral on a given day. These two features of the school setting allow me to avoid a common challenge faced by studies of the effect of temperature on behavior, in which temperature may affect not only the type of behavior occurring but also the number of interactions people have and the observability of those interactions.[3]

I present three key findings about the effect of extreme temperatures on student behavior. First, extreme temperatures exacerbate absenteeism, especially for minority and lower-income students. Relative to school days with temperatures between 60–70°F, students are 34% more likely to be absent on days with temperatures below 30°F. Absences also increase in response to moderately and extremely hot temperatures; students are 8%, 10%, and 16% more likely to be absent on days where the temperature is in the 70s, 80s, and over 90°F, respectively. Consistent with Goodman (2014), I also that absences also increase in response to snow, particularly for Black, Hispanic, and lower-income students.[4]

Results suggest that hot, cold, and snowy conditions exacerbate existing racial/ethnic and socioeconomic disparities in absences, reducing instructional time for the most disadvantaged

[3] The detrimental effect of heat on cognitive and non-cognitive tasks as well as on aggressive behavior has been observed in laboratory (Anderson, 1989) and experimental (Almås *et al.*, 2019) settings. Mukherjee and Sanders (2021) discuss the challenges posed by the endogeneity of the observability and number of social interactions to temperature and highlight the advantage of greater observability and schedule consistency in their study of heat and misbehavior in prisons.

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

students. 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). I find the absences of Black and Hispanic students to be about twice as sensitive to hot conditions as the absences of white students, and over three times as sensitive to cold and snow. I also find existing socioeconomic disparities in attendance to be exacerbated by heat, cold, and snow.

Second, I find that disciplinary referrals increase in response to heat. On days with temperatures between 80–90°F and exceeding 90°F, students are 4% and 9% more likely to receive a disciplinary referral than on school days with temperatures between 60–70°F. To my knowledge, this paper presents the first evidence that reported behavioral issues in schools are sensitive to temperature.[5] Hot conditions would 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, 1989).

A few recent papers have documented the effect of heat on negative sentiment expressed online (Baylis, 2020) and workplace harassment complaints (Narayan, 2022). However, most observational work studying behavioral responses to heat has focused on adult crime, and evidence points to a heat-induced increase in violent crime in particular (Ranson, 2014; Burke *et al.*, 2015; Bondy *et al.*, 2018; Heilmann *et al.*, 2021; Behrer and Bolotnyy, 2022; Mukherjee and Sanders, 2021). 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

[5] 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.

to note that referrals may reflect student behavior, teacher discretion in responding to behavior, or a combination of the two. Evidence of harsher or less favorable decision-making by judges highlights the importance of considering observed behavior as a product of both actual behavior and the responses to and reporting of that behavior (Behrer and Bolotnyy, 2022; Heyes and Saberian, 2019). 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 that the increase in disciplinary referrals on hot days is driven entirely by changes in referrals among students attending schools without air conditioning. In these schools, referrals increase by 7% and 21% on days with temperatures between 80–90°F and above 90°F respectively, relative to days with temperatures between 60–70°F. Furthermore, results indicate that the increase increase in disciplinary referrals on hot days primarily affects students who not only lack access to air conditioning at school, but also live in neighborhoods with low levels of residential air conditioning. This finding underscores the importance of accounting for adaptive behavior when considering the effect of adverse environmental conditions on well-being and inequality (Deschênes and Greenstone, 2011; Kahn, 2016; Graff Zivin and Neidell, 2014; Park *et al.*, 2021).

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

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

2 District setting

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

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

Like many districts in the country, the LUSD is actively developing best practices to prioritize new air conditioning installations. For the first six years of the sample period, from 2011/12–2016/17, 55% of the student body attended schools without air conditioning. The school district made no changes to air conditioning in any existing buildings during this period, finding new installations to be prohibitively expensive. In the summer of 2017, the district began using funds from a recently-approved tax package to install air conditioning in the hottest school buildings; over the next two years, school air conditioning was provided to an additional 19% of the student body.

Initial planning prioritized schools for installation based on a 2015 temperature study, which measured the indoor temperatures of non-air-conditioned schools during a hot week of the year. In subsequent years, the district added to its priorities the goals of improving learning environments in "high-need" and high-utilization schools, while also considering “geographic equity.”[6] Understanding which students are most vulnerable to heat and who may most benefit from access to school air conditioning may help inform resource-constrained districts, including the LUSD, as they continue to make challenging decisions about which schools to prioritize for new air conditioning installations.

3 Data

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

3.1 Daily student-level attendance and discipline data

I use detailed, high-frequency student-level data provided by the LUSD. Longitudinal student-level administrative data include all students enrolled in the district at any time during the 2011/12–2018/19 school years. During these years, the district enrolled an average of about 70,000 K-12 students annually, who attended approximately 200 schools.[7] Unique student identifiers allow me to follow individual students across time.

Daily student-level data include enrolled and absent minutes and student discipline information. Student discipline 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), a large range of incidents and resulting disciplinary outcomes is documented. For each referral, the participant(s), the date and time, and all disciplinary responses to the incident, including whether a student was referred to law enforcement, are noted. I group incidents into eight broad categories based

[6] 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.

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

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 A1 and A2 for descriptions of these categories and the associated disciplinary responses).

3.2 Student demographic and geographic data

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

3.3 Student neighborhood characteristics

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

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

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

3.4 School and facility data

School and facility data, which I link to students using enrollment data, include information on school schedules and building characteristics. For each school, I use LUSD social media accounts, district calendars, and news articles to identify school vacations and unexpected school disruptions, including power outages, snow days, bomb threats, gas leaks, and other disturbances. I pull school facility information, including building age and air conditioning installation history, from district planning documents.[8]

3.5 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.[9] Maximum outdoor temperature is chosen as the key measure of temperature (instead of 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 are obtained from the National Oceanic and Atmospheric Administration's Daily Global Historical Climatology Network. Daily fine particulate matter ($PM_{2.5}$) and ground-level ozone (O_3) readings are obtained from monitor data provided by the U.S. EPA

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

[9]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.

Air Quality System.[10]

4 Descriptive statistics

Table 1 provides descriptive statistics of the K-12 student population between 2011/12 and 2016/17.[11] 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, and 63% of Hispanic students, are enrolled in English Language Learner programs.

4.1 Student and neighborhood characteristics and access to air conditioning

During the 2011/12–2016/17 school years, 45 percent of all students attended air-conditioned schools. Compared to non-white students, and especially Black students, white students attended air-conditioned schools at lower rates.[12] Air conditioning was also more common in elementary and middle schools than in high schools. Air-conditioned schools tended to be located in newer buildings and to serve students living in newer neighborhoods.[13]

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.

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

[11]Most descriptive statistics are provided for the period prior to the new air conditioning installations, which began in the 2017/18 school years, because the majority of the analysis in this paper focuses on this period.

[12]White and higher-income students do not appear to disproportionately select into air conditioned schools through the district's school choice program. Among high school students, for example, those switching into air conditioned schools from non-air conditioned schools are, on average, less likely to be white and more likely to live in lower-income neighborhoods (11% white, 64% LMI) than those switching into non-air conditioned schools from air conditioned schools (46% white, 50% LMI), those switching into different non-air conditioned schools (16% white, 63% LMI), or those attending the non-air conditioned schools to which they are automatically enrolled (25% white, 54% LMI).

[13]See Table A4 for greater detail on the characteristics of facilities and the student population by school air conditioning status. Students attending schools without AC lived in older neighborhoods (53% of homes built prior to 1950 vs. 26%) and slightly lower income neighborhoods (58% of households LMI vs. 57%). 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.

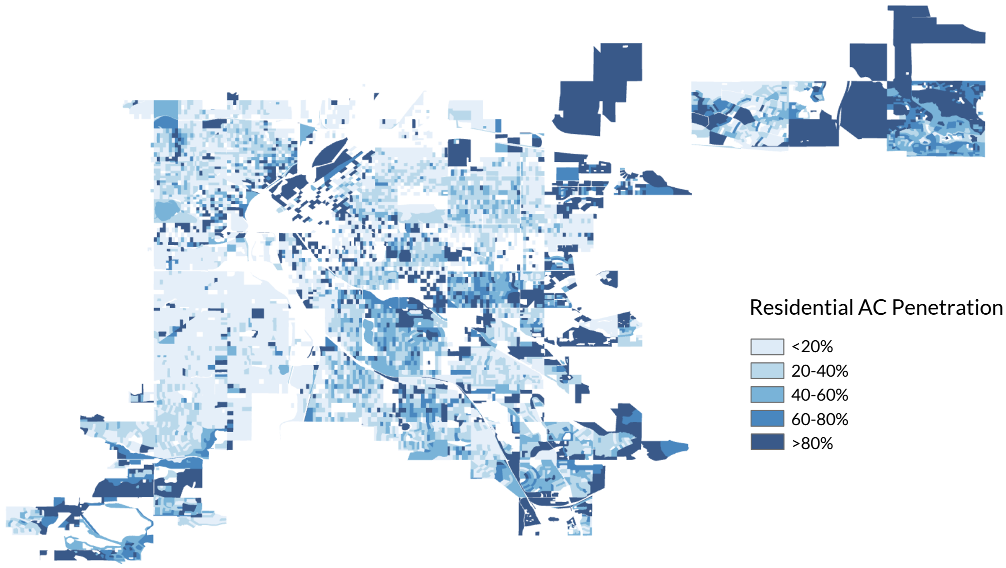
		Gender		Race/Ethnicity			Grade Level		
	All	Female	Male	White	Black	Hisp.	Elem.	Middle	High
Student and Neighborhood Characteristics									
Share of Enrollment (%)	100	49	51	20	16	57	48	24	28
% English Language Learners	42.5	42.7	42.3	6.3	15.1	63	42.3	44.8	40.8
Average % LMI	57.6	57.5	57.6	36.7	58.9	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
% 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 (%)									
Air-conditioned	45	45	45	36	52	46	48	47	38
Non-air-conditioned	55	55	55	64	48	54	52	53	62

Notes: The top panel shows, for each gender, race/ethnicity, and grade level, the share of enrollment, the percent of students enrolled in English Language Learners programs, the average percent of low- and moderate-income households in students' home census block groups, the average percent of houses built prior to 1950 in students' census block group, and the percent of homes with central air conditioning in each student's census block. The second panel shows the portion of each group that attending air-conditioned and non-air-conditioned schools. Descriptive statistics are shown for the 2011/12–2016/17 school years. All enrolled students are included, but statistics in columns 4–6 are only shown for the three largest racial/ethnic groups, which comprise 92% of the student body, on average.

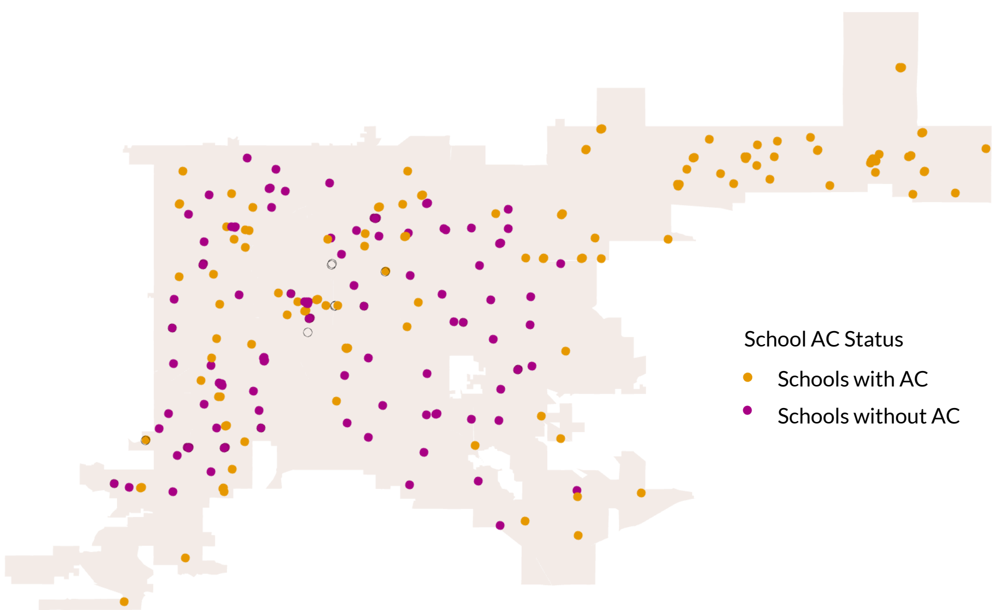
Racial/ethnic differences in home air conditioning penetration may stem from differences in housing stock age and income. Air conditioning penetration tends to be lower in both older neighborhoods and lower-income neighborhoods (see Figure A1).[14] Both white and Black students have greater access to residential air conditioning than Hispanic students, but examining the neighborhood characteristics of these groups points to 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. 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 A.

It is important to note that neighborhood income may also affect unobserved dimensions of heterogeneity in housing quality and access to air conditioning. For example, in addition to

[14] Davis and Gertler (2015) find adoption of air conditioning in Mexico to depend both on climate and household income, and the interaction of the two is the most predictive of adoption.



(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. Schools excluded from the sample because of moves or major renovations are shown as hollow circles.

affecting the likelihood of living in a home with central air conditioning, income may also affect air conditioning use and the purchase and use of alternative cooling technology (e.g., evaporative cooling, window air conditioning units). Income may also affect other dimensions of housing quality, like the quality of insulation, as well as the likelihood of renting versus owning a home. 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.[15]

Students living in neighborhoods with "high" residential air conditioning penetration are more likely to attend air-conditioned schools. However, substantial variation in school air conditioning status exists among students in both highly air conditioned and less-well air conditioned neighborhoods (see Table A3), making heterogeneity analyses of these two dimensions of air conditioning access more feasible. While census block estimates of residential air conditioning do not translate perfectly to access to home air conditioning for an individual student, the bimodal nature of the data allows for central air conditioning to 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 status of schools in the district as well as census-block average residential air conditioning penetration. The figure shows that, with the exception of a few areas, such as the far northeast region of the district, schools and neighborhoods with high air conditioning penetration appear to be relatively well-mixed.

4.2 Absences and disciplinary referrals

As shown in Table 2, the average number of absences and disciplinary referrals differ by race/ethnicity, age, and gender. Hispanic and Black students are more than 30% more likely than white students to be absent from school on any given day. They are also more likely to receive a behavioral referral and to face harsher, exclusionary discipline (suspensions, expulsions, or referrals to fire or law enforcement). This is especially true for Black students,

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

who are six times more likely than white students to receive a one of these more severe disciplinary outcomes 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 average year, approximately 10% of students receive at least one referral, and 4% of students receive multiple referrals.

TABLE 2. Student Behavioral Outcomes

		Gender		**Race/Ethnicity**			**Grade Level**		
	All	Female	Male	White	Black	Hisp.	Elem	Middle	High
Attendance									
% Absent on Avg. Day	6.1	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	.14	.08	.19	.05	.28	.14	.07	.26	.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. All enrolled students are included, but statistics in columns (4)-(6) are only shown for the three largest racial/ethnic groups, which comprise 92% of the student body, on average.

Referrals are made in response to a variety of different behaviors and result in disciplinary outcomes ranging from restorative approaches to expulsions (see Figures A4 and A5 for a visual representation of the average annual frequency and resulting disciplinary outcomes of each category of referral). The most common category of referral describes "disruptive" or "defiant" behavior, although this category became less prominent relative to other descriptions after 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 A5).

Both student attendance and behavioral referrals vary throughout a typical academic year (see Figures A2 and A3). Attendance follows a general downward trend throughout the year, with relatively small declines in attendance on the days on either end of school breaks. In a typical year, the rate of behavioral referrals (per present student) is characterized by a striking pattern around school breaks; referrals appear to "ramp up" at the beginning of the year and to "ramp down" at the end, and this pattern is also present near winter break.

At the beginning of the semester, this "ramping up" period may result from a combination of school policies that give students second chances and the gradual formation of social groups.[16] Pre-break testing as well as teacher or administrator fatigue in anticipation of a break may contribute to the decline in referrals at the end of the semester. While this trend is not surprising, it highlights the importance of carefully controlling for the time of the school year when estimating the effect of adverse environmental conditions on student outcomes so as not to mistakenly attribute typical trends in behavior throughout an academic year to seasonal patterns in environmental conditions.

During the sample period, an average of 14.6% of school days exceeded 80°F, 2.9% exceeded 90°F, and 3.7% fell below 30°F. Seasonal trends in temperature and interannual variation in temperature at a given time of the year are illustrated in Figure 2. It is important to note that temperature is correlated with ambient levels of ground-level ozone and fine particulate matter, which I control for in my empirical analysis.[17]

[16] 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).

[17] 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.

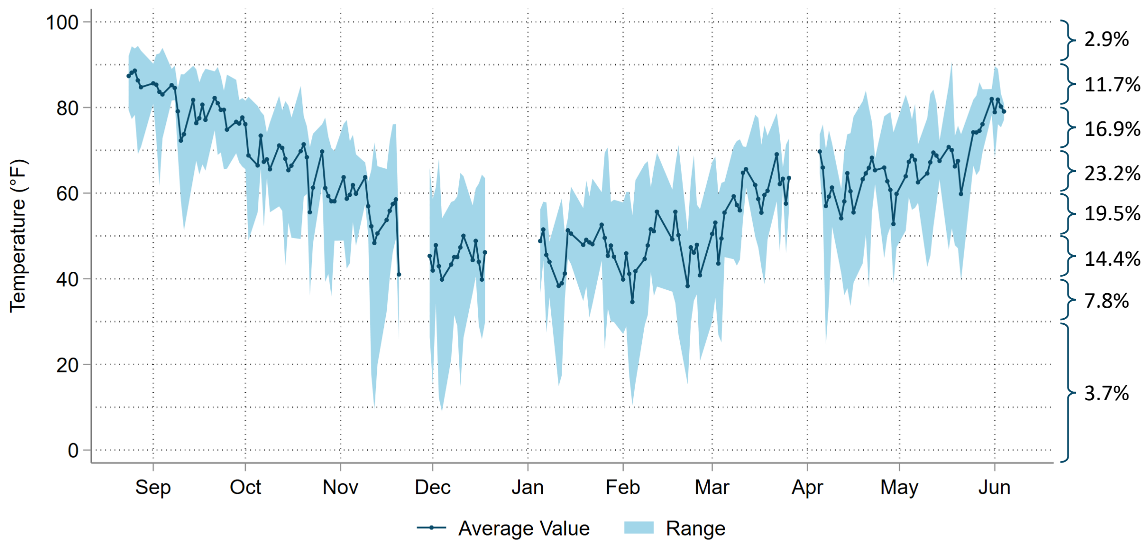


Figure 2. Interannual Variation in Maximum Temperature on School Days

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

5 Empirical Framework

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

5.1 Main estimating equation

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

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

where Y_{isty} is a binary indicator for whether student i enrolled in school s (1) is absent from school or (2) receives a behavioral referral on day t in academic year y. Only present students are included when estimating the latter relationship, but results are robust to the inclusion of absent students.[18]

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.[19] Controls

[18]Estimating equation (1) using a fixed effects Poisson model yields similar results (see Table A8).
[19]The threshold of 4 inches was selected following Goodman (2014).

for a set of student demographic characteristics (grade, race/ethnicity, gender, and English Language Learner status), C'_{iy}, and school fixed effects, η_s, are also included. Results are robust to the inclusion of student or student-by-year fixed effects in place of school fixed effects. In specifications that include student fixed effects, time-varying student demographic controls (grade) continue to be included.

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

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

5.2 Heterogeneity by school and residential air conditioning status

Heterogeneity in the temperature-behavior relationship may exist by the characteristics of schools, students, and neighborhoods. The effect of temperature on behavior, unmitigated by school air conditioning, is of particular interest. Therefore, 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

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

installations (2011/12–2016/17).

To explore heterogeneity in the relationship 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, year fixed effects, and day-of-school-year fixed effects. Including interactions with timing controls is necessary to avoid attributing differences in patterns in behavioral referrals by school characteristics within each school year to correlated environmental conditions.[21]

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

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 on the temperature-behavior relationship because air conditioning status is not randomly assigned.[22]

Given the non-random assignment of school AC, two key potential confounding effects should be noted when interpreting the results of this analysis. 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, relationship between school air conditioning and building age, and

[21] This is necessary in all heterogeneity analyses. For example, if more "chances" are given to certain groups of children before a referral is made, there may be fewer referrals early in the school year for this group, when temperatures are particularly hot. When comparing how sensitive referrals are to hot days between different groups of students, failing to account for how often referrals are typically made at a given time of the year for each group would cause one to confuse differences in sensitivity to differences in leniency/"second chances".

[22] 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.

exploration of school choice discussed earlier do not lend support to this hypothesis, at least in this district. Students attending air-conditioned schools are, on average, more likely to be English Language Learners and less likely to be white, although they live in neighborhoods with slightly higher levels of household income (57% of households are LMI vs. 58%).[23]

It is important to note, however, that because building age is predictive of school air conditioning status and 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, based on access to air conditioning at school and at home, and estimate the effect of temperature on behavioral referrals for each of these groups.[24]

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

In addition to studying heterogeneity by air conditioning penetration, I also examine differences in temperature sensitivity by race/ethnicity and by 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, following equation (2), create interaction terms by each relevant student/neighborhood characteristic.

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.

[23]Future work will examine heterogeneity by air conditioning status focusing on similar groups of students (e.g., Hispanic middle-school students living in similar neighborhoods).

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

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 then explore heterogeneity in the temperature-behavior relationship by access to residential air conditioning, race/ethnicity, and neighborhood income. Next, I discuss which types of disciplinary referrals appear to be particularly sensitive to heat.[25] Finally, I discuss potential interactions between absences and referrals and how changes in class size and composition may affect the behavior of present students.

6.1 Hot and cold conditions increase absenteeism

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

The estimated coefficients in Panel A of Table 3, which are also illustrated in Figure 3, demonstrate that absences are higher on both cold and hot days relative to days with a maximum temperature between 60–70°F. Absences are 34% higher on days below 30°F than on temperate days and are 10% and 16% higher on days between 80–90°F and exceeding 90°F, respectively.[26] Results indicate that extremely cold temperatures and even moderately hot

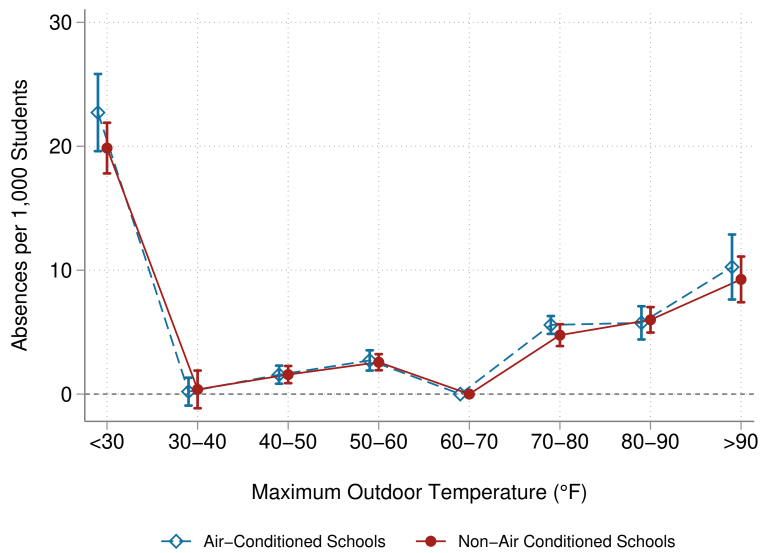
[25] In all tables and figures, I present estimates of temperature-induced changes as rates of absences or referrals per 1,000 students. For simplicity, when discussing results in the text, I refer to percent changes relative to the mean rate of absences or referrals, which is 61 and 1.4, respectively, in the 2011/12–2016/17 period. As discussed previously, the average rate of absences and referrals varies within a typical school year.

[26] 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

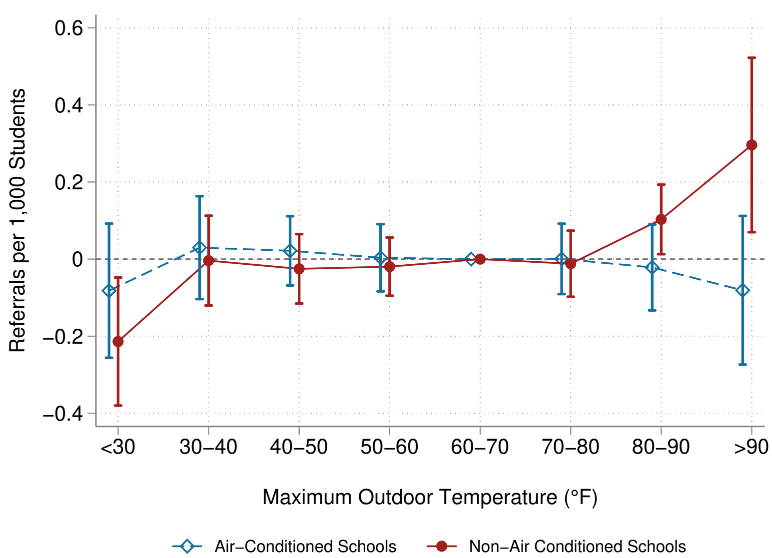
Table 3. Effect of Temperature on Absences and Behavioral Referrals

	All Schools				AC × Temp.
	(1)	(2)	(3)	No School AC	Interaction
Panel A: Absences per 1,000 Enrolled Students (N=60.2 mil.)					
<30F	21.088***	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 2011/12–2016/17 period. Regressions include year, day of school year (fit separately to pre-2013/14), and day before and after vacation fixed effects and controls for rain, snow, $PM_{2.5}$, and O_3. Columns 1, 2, and 4-5 include school or school-by-year fixed effects and demographic (grade, race/ethnicity, gender, "English learner") fixed effects. Column 3 includes student-by-year fixed effects. Interactions of indicators for school air conditioning status with all timing and environmental controls are included in the regression represented by columns 4-5. Heteroskedasticity robust standard errors are clustered at the school level. The sample comprises all students enrolled in schools during the 2011/12–2016/17 academic years. Panel B includes students present on a given day. Asterisks indicate coefficient significance level (2-tailed): *** $p<.01$; ** $p<.05$; * $p<.10$. The full set of coefficient estimates are provided in Tables A6 and A7.



(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 temperature range on (A) absences and (B) behavioral referrals relative to a 60–70°F day. Estimates are taken from regressions of daily, student-level outcomes on indicators for maximum daily temperature ranges. The mean rate of absences and referrals per 1,000 students is 61 and 1.4, respectively, in the 2011/12–2016/17 period. Regressions include school, demographic (grade, race/ethnicity, gender, "English learner"), school year, day of school year (fit separately to pre-2013/14), and day before and after vacation fixed effects and controls for rain, snow, $PM_{2.5}$, and O_3. Interactions of indicators for school air conditioning access with all timing and environmental controls are also included. Heteroskedasticity robust standard errors are clustered at the school level. The sample comprises all students enrolled in schools during the 2011/12–2016/17 academic years. In (B), students absent on a given day are excluded. Estimates are taken from column 4 and the sum of column 4 and 5 of Table 3.

temperatures reduce student attendance. It is possible that the increase in absences observed on 70–80°F days (relative to 60–70°F days) may reflect a different mechanism than the increase observed on days exceeding 80°F. For example, the former may reflect some more discretionary absences in response to pleasant days, while the latter may be more likely to reflect changes in student comfort or health. I do not find the observed relationship between temperature and absences to be sensitive to access to school air conditioning. However, the demographic characteristics of students in these sets of schools differ, and coefficient estimates may also reflect differences in how responsive attendance is to temperature by these characteristics. For example, non-air-conditioned schools have a disproportionately large share of white students, so if the absences of white students are less sensitive to temperature, this may disguise a potential mitigating effect of air conditioning on absences during hot days. Future work will re-estimate these relationships with a similar group of students attending air-conditioned and non-air conditioned schools.

6.2 Heat increases behavioral referrals in schools without air conditioning

Hot temperatures also affect disciplinary referrals. As shown in Panel B of Table 3, within all schools, referrals are 4% and 9% higher on 80–90°F and >90°F days respectively, compared with 60–70°F days, although these effects are not statistically significant. However, as illustrated in columns 4 and 5 of Table 3 and Figure 3, the estimated coefficients on hot temperatures in specifications that include all schools mask substantial heterogeneity in this relationship by school air conditioning status; indeed the increase in behavioral referrals on hot days appears to be 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 over 90°F days, this increase jumps to 19%.[27] The difference between temperature-induced referrals by school air conditioning status is also observed when

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.

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

estimating this relationship with a Poisson specification (see Table A8).[28]

Disciplinary referrals also appear to be sensitive to cold temperatures; on days below 30°F, behavioral referrals are 11% lower. However, school schedules changes on extremely cold days, when most elementary schools keep children indoors, so these days are less comparable to days in other temperature ranges than those days are to each other.[29] As I discuss later, it is also possible that this decrease, and the decrease seen on hot days in air-conditioned schools, may stem partly from changes in the size and composition of the present student body on these days.[30]

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

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

Results indicate that the difference in sensitivity of behavioral referrals to heat illustrated

[28]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.

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

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

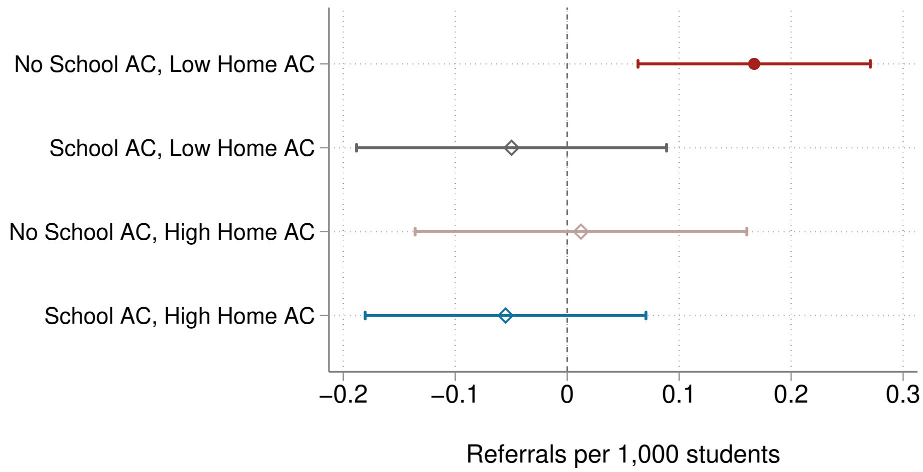


FIGURE 4. Heat, Behavioral Referrals, and Access to Air Conditioning

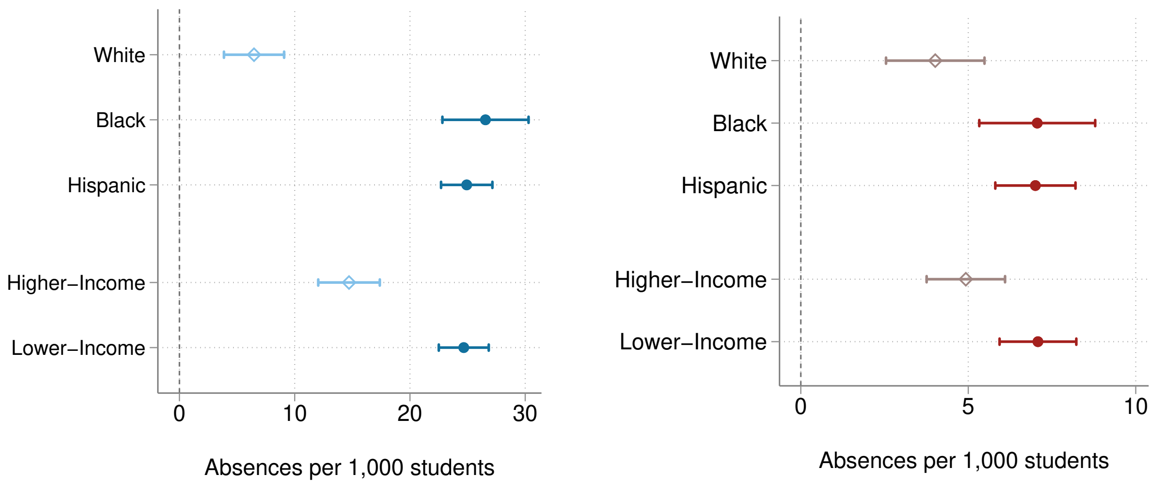
Notes: Shown above are coefficient estimates and 95% confidence intervals of the effect of a >80°F day on behavioral referrals relative to a 30-80°F day, taken from regressions of daily, student-level behavioral referrals on indicators for maximum daily temperature ranges. The mean rate of referrals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

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 those of students who lack access to air conditioning in both places.

A comparison of the temperature sensitivity of absences between these four groups of students does not indicate that lacking air conditioning at home and at school is especially predictive of an increased likelihood of being absent on hot days. Access to school AC is associated with slightly lower heat-sensitivity of absences for student with higher access to home AC, but this difference is not statistically significant (see Figure A6 for more detail).

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

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



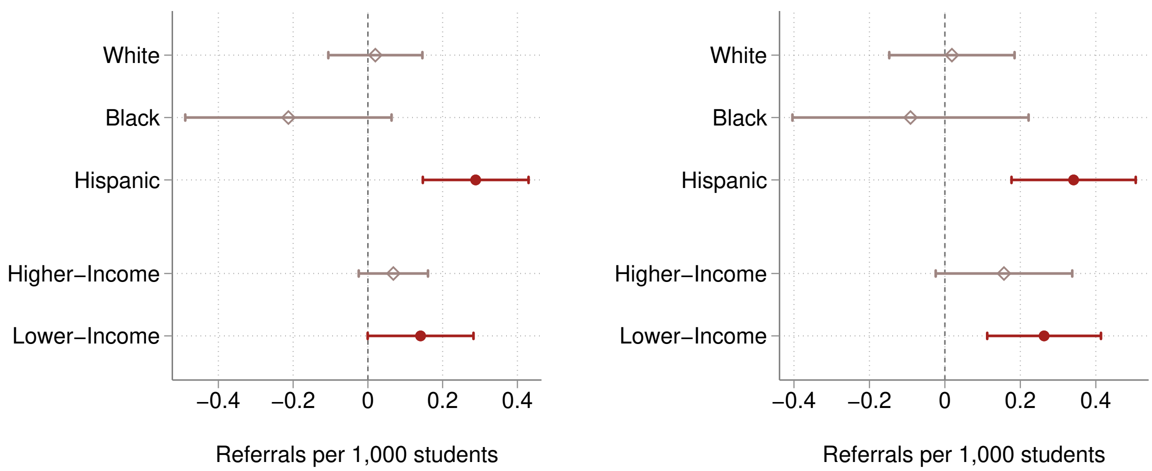
(A) Cold Days

(B) Hot Days

FIGURE 5. Heat, Cold, and Absences: Heterogeneity

Notes: 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 2011/12–2016/17 period. Regressions include school, demographic (grade, race/ethnicity, gender, "English learner"), school year, day of school year (fit separately to pre-2013/14), and day before and after vacation fixed effects and controls for rain, snow, $PM_{2.5}$, and O_3. Interactions of race or income group (split by median household income) with all timing and environmental controls are also included. Heteroskedasticity robust standard errors are clustered at the school level. The sample comprises all students enrolled in non-air conditioned schools during the 2011/12–2016/17 academic years. The full set of coefficient estimates from race-specific regressions is illustrated in Figure A9.

Coefficient estimates of the effect of <30°F and >80°F temperatures on absences are illustrated in Figure 5. 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, hot 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 lower-income students is also more sensitive to snow (see Figure A7).



(A) No Home AC Controls

(B) Controlling for Home AC

Figure 6. 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 2011/12–2016/17 period. Regressions include school, demographic (grade, race/ethnicity, gender, "English learner"), school year, day of school year (fit separately to pre-2013/14), and day before and after vacation fixed effects and controls for rain, snow, $PM_{2.5}$, and O_3. Interactions of race or income group (split by median household income) with all timing and environmental controls are also included. Race- or income-specific interactions between home air conditioning penetration and temperature bin are included in the regressions represented in (B), so coefficients reflect the estimated effect of heat on referrals for students 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.

Coefficient estimates of the effect of >80°F temperatures on behavioral referrals are illustrated in the Figure 6. Results indicate that referrals of Hispanic students are more responsive to temperature than referrals of either white or Black students.[31] 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 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

The most common category of behavior referrals, "disruptive behavior" is responsive to hot (>80°F) temperatures (see Figure A8). These referrals capture reports of irritability, anger, lack of respect, attention, or obedience. As discussed previously, more subjective referrals, like those for disruptive behavior, may be particularly likely to reflect teacher discretion in responding to behavior, so this result may lend support to the hypothesis that both student and teacher behavior is responsive to heat. Statistical power is limited when examining some categories of behavior, but referrals for bullying/harassment and recurring offenses also appear to increase in response to hot temperatures.

6.6 Potential interactions between absences and referrals

The two outcomes of interest, student absences and disciplinary referrals, may interact in several key ways. First, students are very unlikely to receive disciplinary referrals when they are absent from school.[32] 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 more (or less) 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. In this case, estimates would still capture the true effect of

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

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

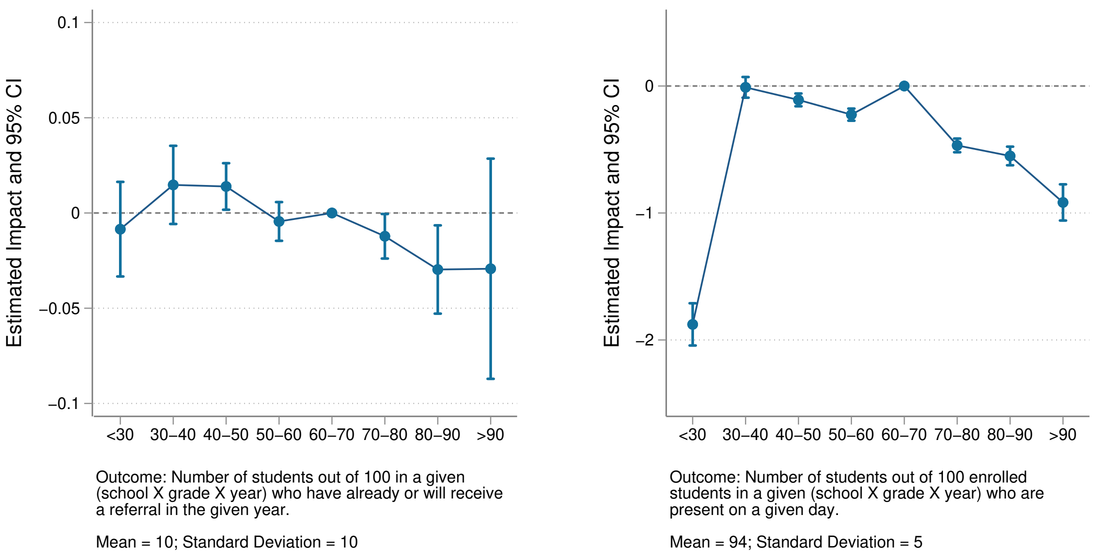
temperature on referrals, even if the effect of temperature on interpersonal interactions (in and outside of schools) may be underestimated. This is important to note, however, because if these estimates were applied to other settings (e.g. other districts) where the sensitivity of absences to temperature may be different, they may under- or overestimate the sensitivity of referrals to temperature.

Second, students may differ by their "baseline likelihood" of receiving a referral, either because of differences in student behavior or because teachers respond to the 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.

Third, the behavior of present students (and their teachers) 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 the effect of temperature on these measures of class size and composition by replacing the left-hand side of equation (1) with $\overline{Z}_{icty}$ and $\overline{R}_{icty}$ respectively. Figure 7 shows the effect of temperature on "class risk" and "class size".

As illustrated in Figure 7, 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 × 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 × grade of 100 students would be missing an additional 2 students.

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



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

FIGURE 7. 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 × grade × year), demographic (race/ethnicity, gender, "English learner"), day of school year (fit separately to pre-2013/14), and day before and after vacation fixed effects and controls for rain, snow, $PM_{2.5}$, and O_3. Heteroskedasticity robust standard errors are clustered at the school level.

student composition are relatively small, changes in class size, particularly on cold days, may be large enough to affect behavior if these changes are concentrated in certain classrooms. Future work will expand the analysis of the effects of class size and composition on student behavior.

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

How will climate change affect student behavioral outcomes and childhood and later life well-being? To explore this thought experiment, I rely on temperature projections, estimates from my modified empirical model, and studies of the effect of student behavioral outcomes on childhood and later-life outcomes.

7.1 Projected change in temperatures: 2000-2050

Climate change is expected to result in an increase in the number of school days with moderately and very hot temperatures. To estimate how temperature in a typical year will change in the future, I rely on a series of temperature projections from global circulation models (GCM) provided by Rasmussen *et al.* (2016), which include annual county-level projections of the number of days that fall within each 1°F bin from 1981 to 2100.[33] I draw from models of the Representative Concentration Pathway (RCP) 6.0 scenario, which corresponds to a warming of 3-4°C by 2100 relative to pre-industrial temperatures 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). In this thought experiment, I focus on the change in temperatures from 2000 to 2050, and to minimize noise in estimates, all estimates are made using 20-year ranges

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

centered around these years (1990–2010 and 2040–2060).[34] 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, which corresponds to a "mid-term" future reference period used by the IPCC, the average school year in the LUSD will be characterized by 64% more days with a maximum temperature exceeding 80°F than in 2000, and more than twice as many >90°F days. At the same time, cold conditions are expected to become less common, although the LUSD is expected to experience a smaller decrease in cold conditions than a pure mean shift in temperature would suggest; by 2050, the district is expected to experience an 18% decrease in the number of days with a maximum temperature below 30°F.[35] This lack of symmetry in changes in hot and cold conditions may reflect increased variability in temperature.[36] 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.

7.2 Projected change in behavioral outcomes: 2000-2050

To predict behavioral referrals and absences using modeled temperature, I estimate equation (1) for the 2011/12–2016/17 school years. I focus on non-air-conditioned schools to better capture the effect of warming conditions on student behavior, unmitigated by school air conditioning, and I also predict student outcomes specifically among those students who also have low access to residential air conditioning ($<$ 50% census block AC penetration). I also focus on a "no adaptation" scenario in which no new installations of air conditioning, either at school

[34]Estimates are made separately in each year in these ranges; temperatures are never averaged between years.

[35]These estimates come from comparing the projected number of days in each temperature bin between 1990-2010 to the number of days in each bin between 2040-2060.

[36]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."

or in student homes, are made from 2000 to 2050.[37] I make two changes to the specification outlined in equation (1). First, I exclude all non-temperature environmental controls when estimating this equation, effectively assuming that whatever environmental conditions typically accompany a day with a certain maximum temperature will continue to do so in the future. Second, due to the challenges and additional assumptions needed to predict the attendance of each *individual* student (predictions provide estimates of fractional absences), I rely on a model predicting the disciplinary referrals of all enrolled students, rather than all present students.

I use the resulting estimated coefficients and the projected temperatures to estimate the number of absences and behavioral referrals for each year from 1990-2010 and 2040-2060. I randomly select an academic year (2016/2017) from which I take all information about the enrolled student body, schools, and academic calendar. I then compare the projected average number of behavioral referrals and absences in the 2040-2060 period to the 1990-2010 period.[38]

My estimates suggest that, relative to 1990-2010, in 2040-2060 there will be approximately 0.8% more behavioral referrals and 0.8% fewer absences in a typical year among students attending schools without air conditioning. It is important to note, however, that absences are highly responsive to snow, so the response of attendance to future climate is dependent on how snowfall responds to warming conditions. The projected decrease in absences is made assuming that the current temperature-snowfall relationship will not change.[39]

The increase in behavioral referrals expected in 2040-2060 relative to 1990-2010 may translate into worse academic and later-life outcomes. While I do not observe these outcomes directly, previous studies linking school discipline to these outcomes may be used to illustrate the potential magnitude of the effect of warming conditions on academic and later-life outcomes.

[37] This is not meant to be the most likely case (especially given that the LUSD is planning to install more air conditioning). Instead, it serves as a thought experiment to study how climate-change-induced changes in temperature may affect the most vulnerable students and how the value of air conditioning may be affected by the warming climate.

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

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

For example, Bacher-Hicks *et al.* (2019) find that students quasi-randomly assigned to a stricter middle school due to a large school catchment area boundary change receive more suspensions and are also less likely to graduate from high school or attend a 4-year college and are more likely to be arrested and/or incarcerated in early adulthood.[40] While the effect of a suspension on the marginal student studied in each case (this study and Bacher-Hicks *et al.* (2019)) may differ for several reasons, their estimates may nevertheless provide a valuable way to interpret the results of this study.[41]

Estimating equation (1) for middle school students where the outcome variable is a binary indicator for a suspension, a referral to law enforcement, and/or an expulsion, and repeating the projection exercise outlined above, I find that in 2040-2060 there will be approximately 1.6% more suspensions of middle school students relative to 1990-2010. Scaling estimates from Bacher-Hicks *et al.* (2019) suggests that over this 50 year period, students will be 3% less likely to graduate, 2% less likely to attend 4-year college, 3% more likely to be arrested (leading to 4% more arrests), and 4% more likely to be incarcerated (leading to 5% more incarcerations) in late childhood and early adulthood (ages 16 to 21).[42] Warming-induced decreases in absences may reduce disruptions to learning, but the decrease in absences I

[40]Strictness is measured using pre-boundary change suspension rates after conditioning on student achievement and characteristics, which appear to have little effect on other measures of academic quality or workforce stability and are affected by principal discretion (Bacher-Hicks *et al.*, 2019).

[41]A few key differences are worth noting. First, while teacher and administrator behavior may have important roles in both contexts, school policy is central to the mechanism exploited by Bacher-Hicks *et al.* (2019). This suggests that in their setting, changes in *student* behavior may play a smaller role than discipline itself in driving the observed changes in student outcomes, especially if stricter disciplinary procedures act as a deterrent to students. In my setting, student disruptions to the classroom setting may accompany the increase in suspensions I observe. This may suggest that the increase in suspensions I observe could be more harmful to students and their peers; however, marginal suspensions received at particularly strict schools may be perceived as unfairly harsh. Heat-induced behavioral referrals are also concentrated at the beginning of the school year, which may interfere with the formation of student-teacher and student-peer relationships more so than suspensions received at other times of the year. Heat-induced referrals at the end of the school year may also be harmful if they interfere with testing and grade-completion, but I am not able to study the last two weeks of the school year in my analysis due to data quality issues.

[42]Bacher-Hicks *et al.* (2019) estimate how school assignment affects the number of days that a given student is suspended annually and the likelihood of receiving at least one suspension in a given year. I use the latter measure to scale my estimates because the number of days suspended may reflect more or longer suspension periods. If the increase in the number of suspensions conditional on receiving at least one suspension in a given year is greater (smaller) than the increase in the likelihood of having at least one suspension, these results may be overestimated (underestimated). I focus on out-of-school suspensions because I expect them to be more comparable across school districts, but including in-school suspensions or all types of referrals yields results of similar magnitude (a 1.1%versus 1.6% increase in incidents).

estimate is dependent on the snowfall-temperature relationship, and the positive effect of increased attendance on student outcomes is likely far outweighed by the negative effect of the increase in disciplinary referrals.[43]

It is important to note that these estimates only capture the effect of temperature changes during middle school on the measured behavioral outcomes. Students will experience hotter temperatures in-utero, as young children, and during elementary and high school. These estimates do not capture the effect of potential disciplinary referrals during those years or the direct effect of heat on learning and other student (e.g., test scores) and non-student outcomes (e.g., health, crime).[44]

These estimates suggest that global warming-induced increases in behavioral referrals may contribute to economically meaningful disruptions to human capital accumulation and increases in arrests and incarcerations. They also suggest that warming conditions will cause the benefit of school air conditioning to increase. Given the results presented earlier in the paper, this benefit is likely to be especially high for students who lack air conditioning at home. This benefit would also be in addition to any benefit school air conditioning installations currently have given today's temperatures. Future work will examine the costs and benefits of air conditioning installations given both future and current temperatures and will also explore the possible costs and benefits of other policies, such as shifting the school year or cancelling school more frequently in response to hot temperatures.

8 Discussion and conclusion

This paper explores the impact of extreme temperatures on student absences and disciplinary referrals, two components of student behavior which may be disruptive to learning and affect

[43]To my knowledge, no study directly compares the effect of absences with the effect of disciplinary referrals. Goodman (2014) finds that one moderate snow day-induced absence reduces student mathematics scores by 0.05 standard deviations, about 6% of the achievement gap between poor and non-poor students (measured by FRPL eligibility). I project approximately 0.1 fewer absent days per student per year in 2040-2060 relative to 1990-2010, a decrease concentrated among Black, Hispanic, and lower-income students.

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

later life well-being. To study this question, I link a data set of daily student-level behavioral outcomes from a large urban school district with environmental data and school and residential air conditioning information. I then leverage this data set to estimate the short-term response of student behavioral outcomes to temperature. My empirical strategy exploits between-year variation in temperature, while controlling for the exact day of the school year as well as time-invariant student and school characteristics. This research design as well as the rich data set of student, school, and neighborhood characteristics, allows for a nuanced exploration of heterogeneity in this relationship.

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

I further find that behavioral referrals increase in response to heat. This response is driven by students attending schools that lack air conditioning and is largest among lower-income and Hispanic students, 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 temperatures and the variability in the climate system, exposing students to hot temperatures more frequently, which may widen disparities in disciplinary referrals for those who can less easily adapt to these conditions. 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. Across the United States, existing racial/ethnic and socioeconomic differences in access to adaptive technology at home and at school suggest that warming conditions may exacerbate disparities in educational and later-life outcomes.

References

Abadie, A., Athey, S., Imbens, G. W. and Wooldridge, J. (2017). When should you adjust standard errors for clustering?, NBER Working Paper.

Almås, I., Auffhammer, M., Bold, T., Bolliger, I., Dembo, A., Hsiang, S. M., Kitamura, S., Miguel, E. and Pickmans, R. (2019). Destructive behavior, judgment, and economic decision-making under thermal stress, NBER Working Paper.

Alsan, M. and Yang, C. (2022). Fear and the safety net: Evidence from secure communities. Forthcoming. *Rev Econ Stat*.

Anderson, C. A. (1989). Temperature and aggression: Ubiquitous effects of heat on occurrence of human violence. *Psychological Bulletin*, **106** (1), 74.

— (2001). Heat and violence. *Current Directions in Psychological Science*, **10** (1), 33–38.

Aucejo, E. M. and Romano, T. F. (2016). Assessing the effect of school days and absences on test score performance. *Economics of Education Review*, **55**, 70–87.

Bacher-Hicks, A., Billings, S. B. and Deming, D. J. (2019). The school to prison pipeline: Long-run impacts of school suspensions on adult crime, NBER Working Paper.

Barnum, M. (2017). Exclusive: Too hot to learn: Records show nearly a dozen of the biggest school districts lack air conditioning.

Baylis, P. (2020). Temperature and temperament: Evidence from Twitter. *Journal of Public Economics*, **184**, 104161.

Behrer, A. P. and Bolotnyy, V. (2022). Heat, crime, and punishment. NBER Working Paper.

Bondy, M., Roth, S. and Sager, L. (2018). Crime is in the air: The contemporaneous relationship between air pollution and crime.

Burke, M., Hsiang, S. M. and Miguel, E. (2015). Climate and conflict. *Annu. Rev. Econ.*, **7** (1), 577–617.

Chen, S., Guo, C. and Huang, X. (2018). Air pollution, student health, and school absences: Evidence from China. *Journal of Environmental Economics and Management*, **92**, 465–497.

Craig, A. C. and Martin, D. C. (2019). Discipline reform, school culture, and student achievement.

Currie, J., Hanushek, E. A., Kahn, E. M., Neidell, M. and Rivkin, S. G. (2009). Does pollution increase school absences? *The Review of Economics and Statistics*, **91** (4), 682–694.

Dai, H., Milkman, K. L. and Riis, J. (2014). The fresh start effect: Temporal landmarks motivate aspirational behavior. *Management Science*, **60** (10), 2563–2582.

Davis, L. W. and Gertler, P. J. (2015). Contribution of air conditioning adoption to future energy use under global warming. *Proceedings of the National Academy of Sciences*, **112** (19), 5962–5967.

Deschênes, O. and Greenstone, M. (2011). Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US. *American Economic Journal: Applied Economics*, **3** (4), 152–85.

GAO (2020). *K-12 Education: School Districts Frequently Identified Multiple Building Systems Needing Updates or Replacement. Report to Congressional Addressees.* GAO-20-494.

Gershenson, S., Jacknowitz, A. and Brannegan, A. (2017). Are student absences worth the worry in US primary schools? *Education Finance and Policy*, **12** (2), 137–165.

Goodman, J. (2014). Flaking out: Student absences and snow days as disruptions of instructional time. NBER Working Paper.

Gottfried, M. A. (2010). Evaluating the relationship between student attendance and achievement in urban elementary and middle schools: An instrumental variables approach. *American Educational Research Journal*, **47** (2), 434–465.

Graff Zivin, J., Hsiang, S. M. and Neidell, M. (2018). Temperature and human capital in the short and long run. *Journal of the Association of Environmental and Resource Economists*, **5** (1), 77–105.

— and Neidell, M. (2014). Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics*, **32** (1), 1–26.

Heilmann, K., Kahn, M. E. and Tang, C. K. (2021). The urban crime and heat gradient in high and low poverty areas. *Journal of Public Economics*, **197**, 104408.

Heissel, J., Persico, C. and Simon, D. (2019). Does pollution drive achievement? The effect of traffic pollution on academic performance. NBER Working Paper.

Heyes, A. and Saberian, S. (2019). Temperature and decisions: Evidence from 207,000 court cases. *American Economic Journal: Applied Economics*, **11** (2), 238–265.

Hsu, A., Sheriff, G., Chakraborty, T. and Manya, D. (2021). Disproportionate exposure to urban heat island intensity across major US cities. *Nature Communications*, **12** (1), 1–11.

Kahn, M. E. (2016). The climate change adaptation literature. *Review of Environmental Economics and Policy*.

Lacoe, J. and Steinberg, M. P. (2019). Do suspensions affect student outcomes? *Educational Evaluation and Policy Analysis*, **41** (1), 34–62.

Mackworth, N. H. (1946). Effects of heat on wireless operators. *British Journal of Industrial Medicine*, **3** (3), 143.

Morris, E. W. (2007). “Ladies” or “loudies”? Perceptions and experiences of Black girls in classrooms. *Youth & Society*, **38** (4), 490–515.

— and Perry, B. L. (2016). The punishment gap: School suspension and racial disparities in achievement. *Social Problems*, **63** (1), 68–86.

Mukherjee, A. and Sanders, N. J. (2021). The causal effect of heat on violence: Social implications of unmitigated heat among the incarcerated. NBER Working Paper.

Narayan, A. (2022). The impact of extreme heat on workplace harassment and discrimination. *Proceedings of the National Academy of Sciences*, **119** (39), e2204076119.

National Center for Education Statistics (2020). Digest of education statistics: 2020.

Nolan, K. (2011). *Police in the hallways: Discipline in an urban high school*. U of Minnesota Press.

Noltemeyer, A. L., Ward, R. M. and Mcloughlin, C. (2015). Relationship between school suspension and student outcomes: A meta-analysis. *School Psychology Review*, **44** (2), 224–240.

Okonofua, J. A. and Eberhardt, J. L. (2015). Two strikes: Race and the disciplining of young students. *Psychological Science*, **26** (5), 617–624.

Park, R. J. (2022). Hot temperature and high-stakes performance. *Journal of Human Resources*, **57** (2), 400–434.

—, Behrer, A. P. and Goodman, J. (2021). Learning is inhibited by heat exposure, both internationally and within the United States. *Nature Human Behaviour*, **5** (1), 19–27.

—, Goodman, J., Hurwitz, M. and Smith, J. (2020). Heat and learning. *American Economic Journal: Economic Policy*, **12** (2), 306–339.

Persico, C. L. and Venator, J. (2021). The effects of local industrial pollution on students and schools. *Journal of Human Resources*, **56** (2), 406–445.

Ranson, M. (2014). Crime, weather, and climate change. *Journal of Environmental Economics and Management*, **67** (3), 274–302.

Rasmussen, D., Meinshausen, M. and Kopp, R. E. (2016). Probability-weighted ensembles of us county-level climate projections for climate risk analysis. *Journal of Applied Meteorology and Climatology*, **55** (10), 2301–2322.

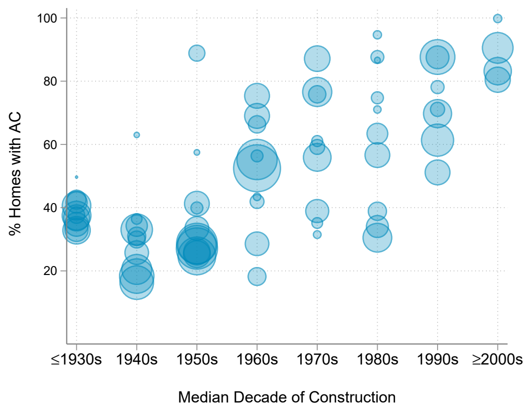
Rodgers, K. B., Lee, S.-S., Rosenbloom, N., Timmermann, A., Danabasoglu, G., Deser, C., Edwards, J., Kim, J.-E., Simpson, I. R., Stein, K. *et al.* (2021). Ubiquity of human-induced changes in climate variability. *Earth System Dynamics*, **12** (4), 1393–1411.

Schlenker, W. and Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to US crop yields under climate change. *Proceedings of the National Academy of Sciences*, **106** (37), 15594–15598.

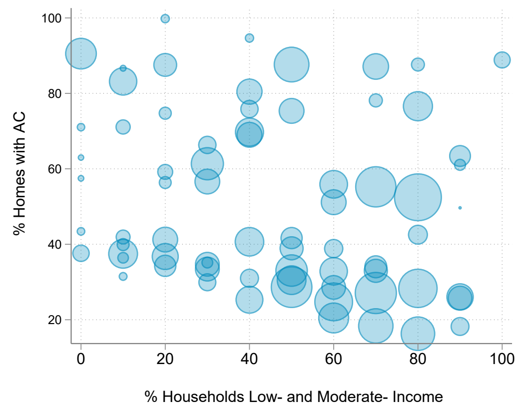
Seppanen, O., Fisk, W. J. and Lei, Q. (2005). Ventilation and work performance in office work. Available at: https://indoor.lbl.gov/sites/all/files/lbnl-60946.pdf.

A Appendix

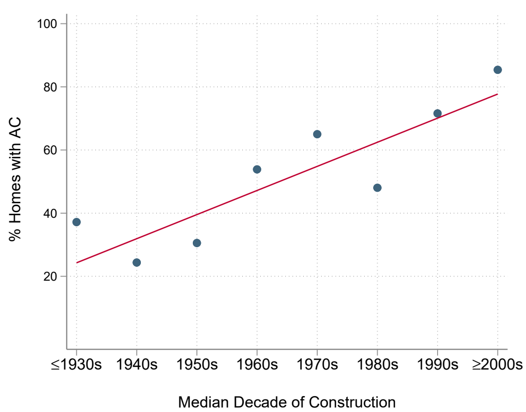
A.1 Additional figures



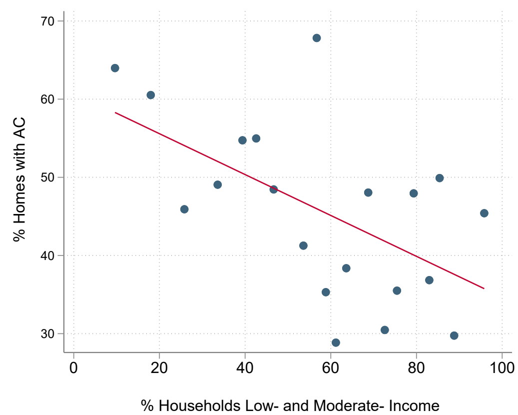
(A) Home AC by Neighborhood Age



(B) Home AC by Neighborhood Income



(C) Home AC by Neighborhood Age



(D) Home AC by Neighborhood Income

FIGURE A1. Air Conditioning, Housing Stock Age and Household 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.

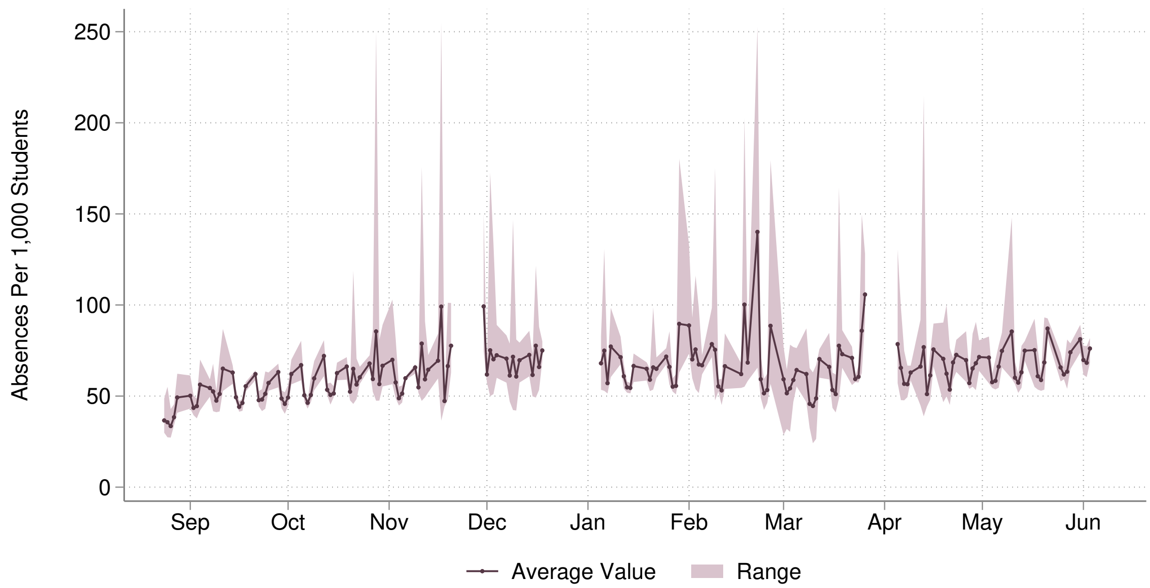


FIGURE A2. Interannual Variation in Absences per 1,000 Students

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

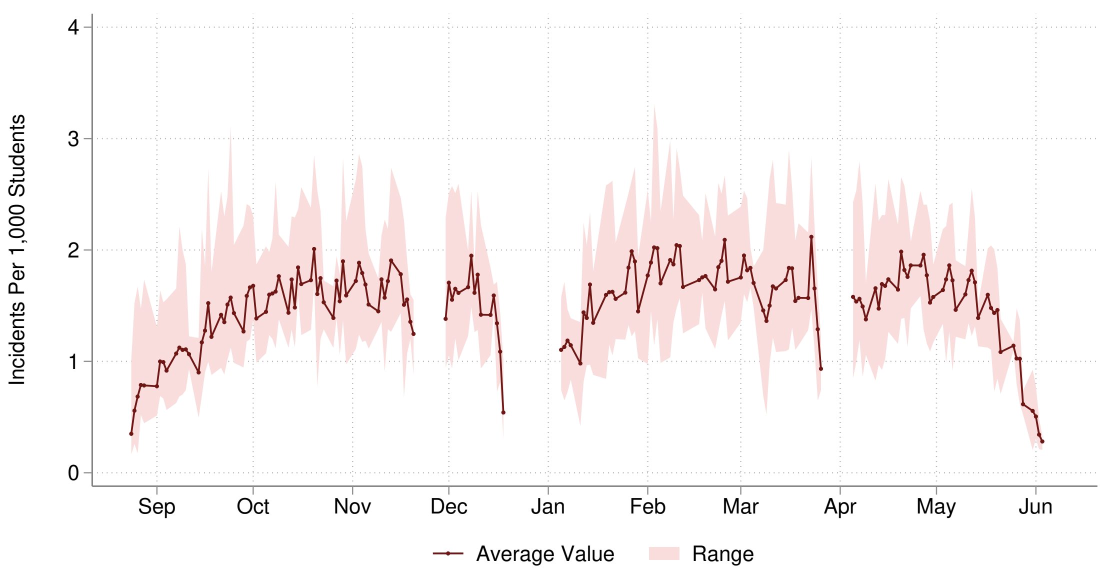


FIGURE A3. Interannual Variation in Referrals per 1,000 Present Students

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

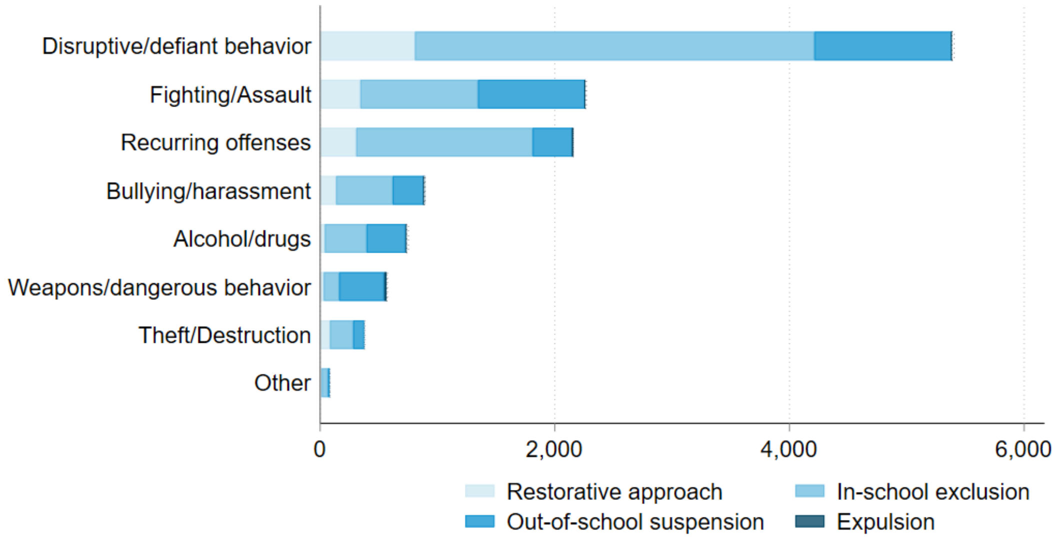


FIGURE A4. Behavioral Referrals by Category and Disciplinary Outcome (2014/15-2018/19).

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

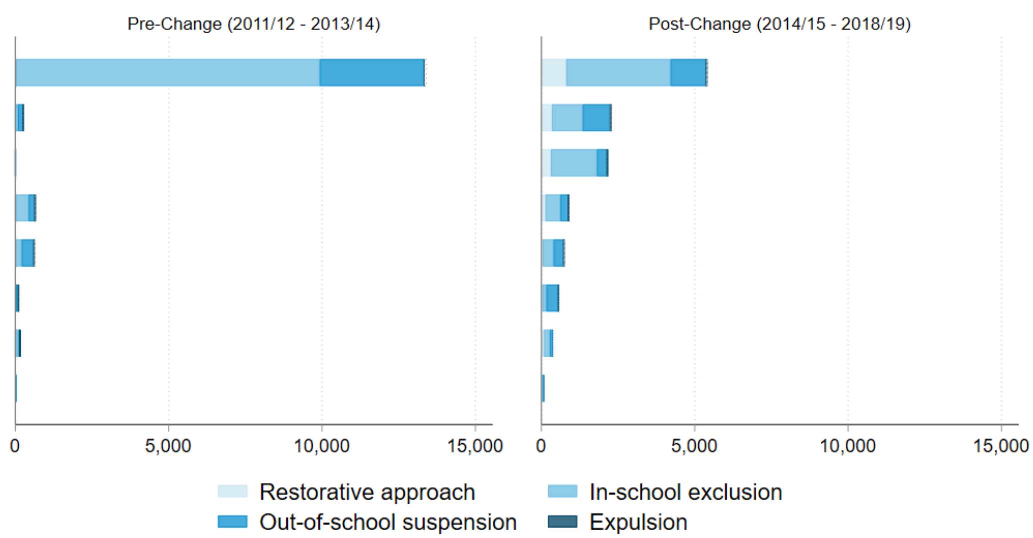


FIGURE A5. Behavioral Referrals by Category, Disciplinary Outcome, and Period

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

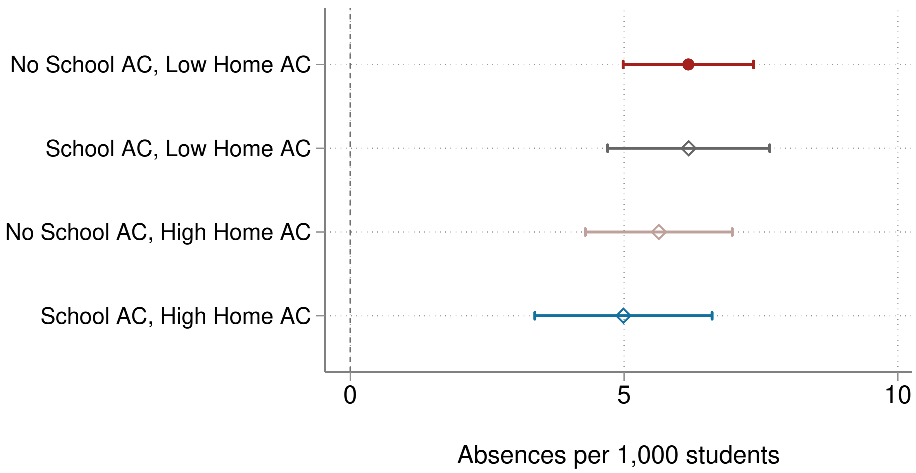
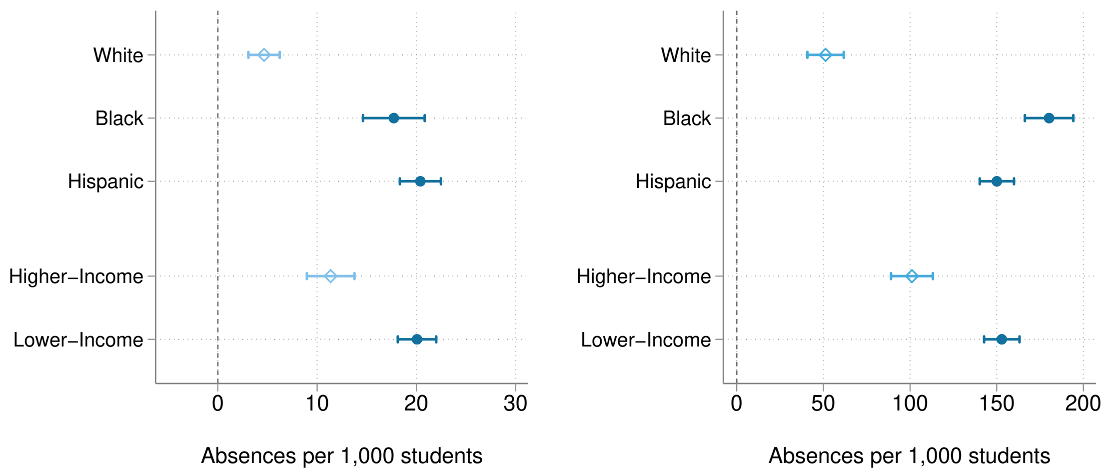


Figure A6. Heat, Absences, and Access to Air Conditioning

Notes: Shown above are coefficient estimates and 95% confidence intervals of the effect of a >80°F day on absences relative to a 60–70°F day, taken from regressions of daily, student-level absences on indicators for maximum daily temperature ranges. The mean rate of absences per 1,000 students is 61 in the 2011/12–2016/17 period. Regressions include school, demographic (grade, race/ethnicity, gender, "English learner"), school year, day of school year (fit separately to pre-2013/14), and day before and after vacation fixed effects and controls for rain, snow, $PM_{2.5}$, and O_3. Interactions of four indicators of air conditioning access with all timing and environmental controls are also included. Each student's home census block is defined as "High" or "Low" Home AC based on a 50% residential air conditioning penetration threshold. Heteroskedasticity robust standard errors are clustered at the school level. The sample comprises all present students attending schools during the 2011/12–2016/17 academic years.



(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 2011/12–2016/17 period. Regressions include school, demographic (grade, race/ethnicity, gender, "English learner"), school year, day of school year (fit separately to pre-2013/14), and day before and after vacation fixed effects and controls for rain, $PM_{2.5}$, and O_3. Interactions of race or income group (split by median household income) with all timing and environmental controls are also included. Heteroskedasticity robust standard errors are clustered at the school level. The sample comprises all students enrolled in non-air conditioned schools during the 2011/12–2016/17 academic years.

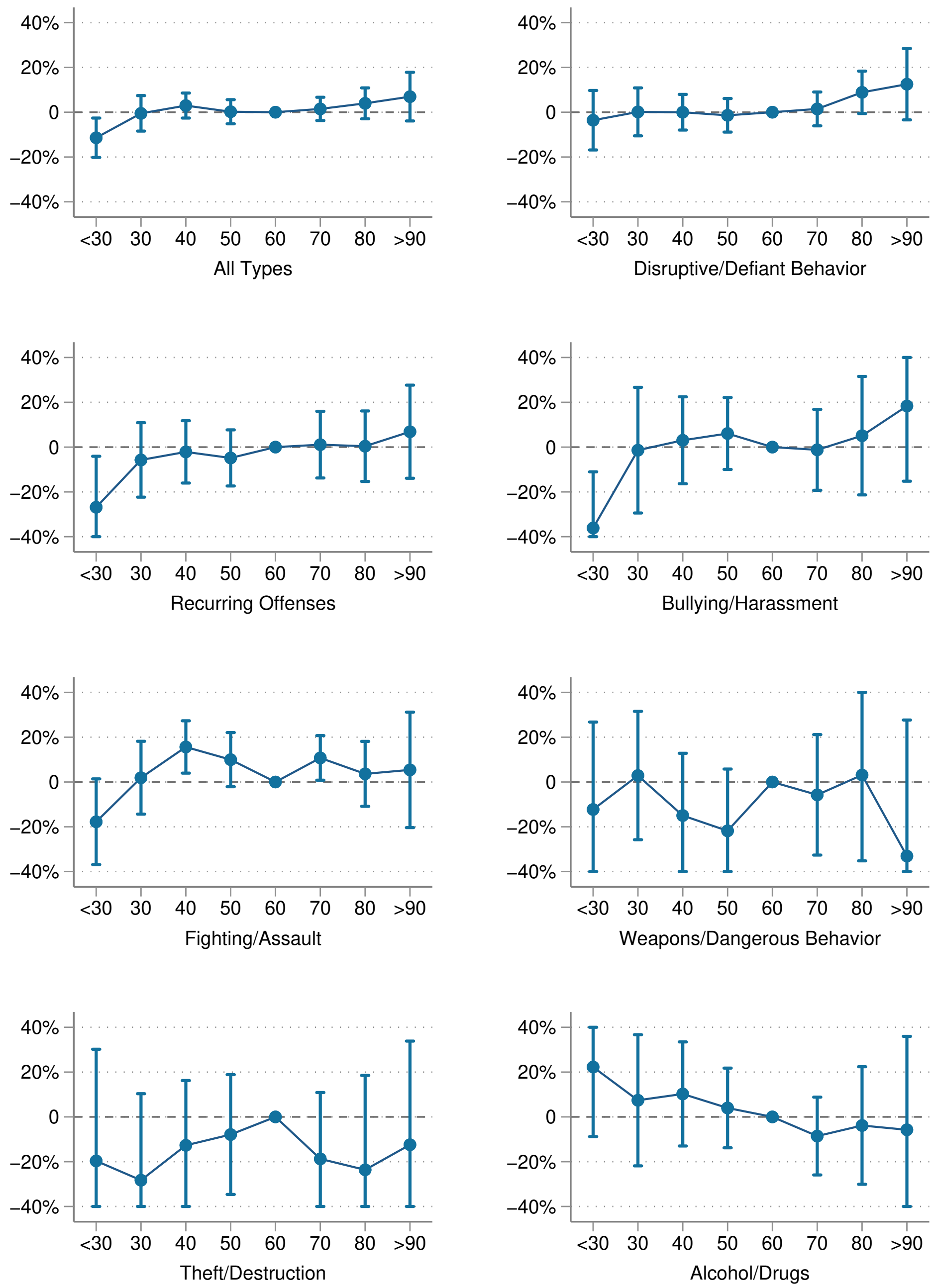
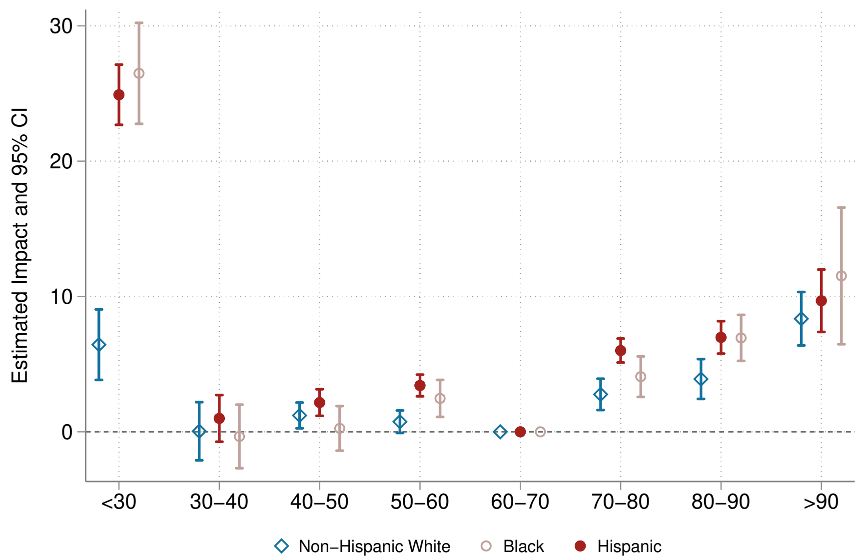
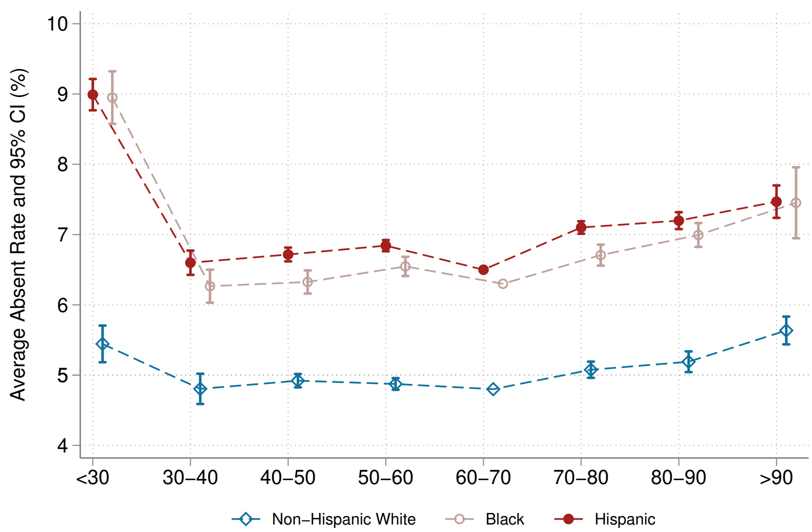


Figure A8. Temperature and Referrals (by Type)

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



(A) Estimated Coefficients



(B) Estimated Coefficients + Race-Specific Means

Figure A9. 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 for students attending schools without AC. The mean rate of absences per 1,000 students is 61 in the 2011/12–2016/17 period. 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 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.

A.2 Additional tables

Table A1. 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 A2. 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 A3. 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 % 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						
White(%)	23	21	26	17	11	21
Black(%)	20	21	18	13	16	11
Hispanic(%)	47	47	46	63	67	60
Grade Level						
Elementary(%)	52	59	43	48	49	48
Middle(%)	24	23	24	24	27	22
High (%)	24	18	32	28	24	30

[1]"High" and "Low" AC neighborhoods are defined as census blocks where the majority and minority of housing units have central air conditioning, respectfully.

Notes: The top panel shows student characteristics by air conditioning status. Characteristics are shown just for 2011/12-2016/2017 school years.

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

	Air-Conditioned	Non-Air-Conditioned
Student Characteristics		
Share of Enrollment (%)	45	55
% English Language Learners	45.9	39.7
Average % LMI	57.1	58
Average % Built <1950	26.3	53.3
Facility Characteristics		
Number of Schools	116	103
Number of Buildings	82	78
Average Building Age (As of 2017)	34	74

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

Table A5. 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	0.7	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	0.5	0.4	0.5	0.4	0.5	0.5	0.5	0.2	0.5	0.6
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	0.8	4.9	15
Recurring Offenses	17	15.6	17.6	15.3	18	15.9	17.9	14.2	16.8	19.7
Other	0.7	0.7	0.6	0.6	0.7	0.8	0.7	0.4	0.8	0.7

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 A6. Effect of Temperature on Absences

	All Schools (1)	(2)	(3)	No School AC	AC × Temp. 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 2011/12–2016/17 period. Regressions include year, day of school year (fit separately to pre-2013/14), and day before and after vacation fixed effects and controls for rain, snow, $PM_{2.5}$, and O_3. Columns 1, 2, and 4-5 include school or school-by-year fixed effects and demographic (grade, race/ethnicity, gender, "English learner") fixed effects. Column 3 includes student-by-year fixed effects. Interactions of indicators for school air conditioning status with all timing and environmental controls are included in the regression represented by columns 4-5. Heteroskedasticity robust standard errors are clustered at the school level. The sample comprises all students enrolled in schools during the 2011/12–2016/17 academic years. Asterisks indicate coefficient significance level (2-tailed): *** p<.01; ** p<.05; * p<.10.

Table A7. 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 2011/12–2016/17 period. Regressions include year, day of school year (fit separately to pre-2013/14), and day before and after vacation fixed effects and controls for rain, snow, $PM_{2.5}$, and O_3. Columns 1, 2, and 4-5 include school or school-by-year fixed effects and demographic (grade, race/ethnicity, gender, "English learner") fixed effects. Column 3 includes student-by-year fixed effects. Interactions of indicators for school air conditioning status with all timing and environmental controls are included in the regression represented by columns 4-5. Heteroskedasticity robust standard errors are clustered at the school level. The sample comprises all present students attending schools during the 2011/12–2016/17 academic years. Asterisks indicate coefficient significance level (2-tailed): *** p<.01; ** p<.05; * p<.10.

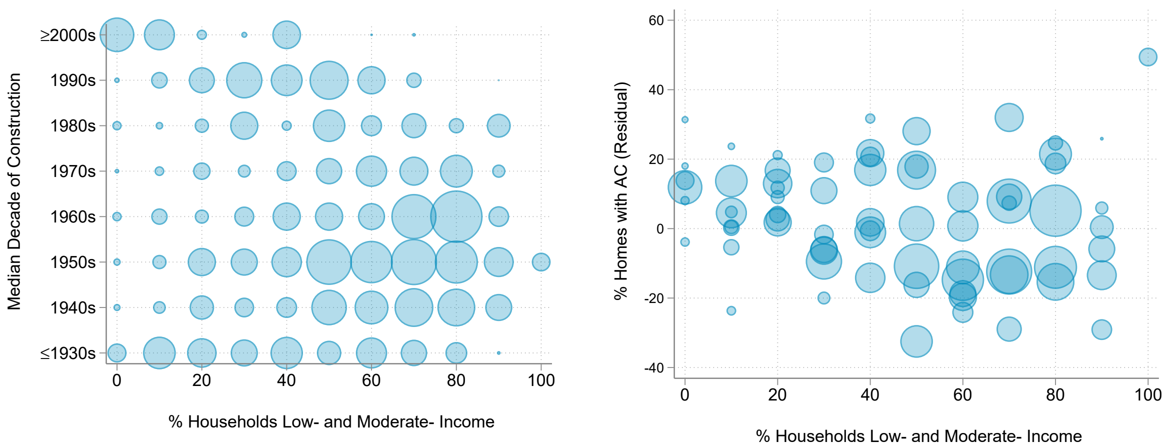
Table A8. Alternative Specifications: Absences and Referrals

	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 2011/12–2016/17 period. Estimates in column 1 are expressed per 1,000 enrolled students. Estimates from Poisson regressions are unchanged. Regressions include year, day of school year (fit separately to pre-2013/14), and day before and after vacation fixed effects and controls for rain, snow, $PM_{2.5}$, and O_3. 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.

A.3 Predictors of residential air conditioning

As illustrated in Figure A10, 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 A10. 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 A9, 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 A9. 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.