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

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Abstract

This paper investigates how extreme temperatures affect school absences and disciplinary referrals, two dimensions of student behavior that are predictive of worse academic and later life outcomes. Using daily student-level data from a large urban school district, I leverage between-year variation to estimate the causal effect of temperature on student behavior. Absenteeism increases in response to both hot and cold conditions, particularly for Black and Hispanic students. Hot conditions also increase the likelihood that a student will receive a disciplinary referral, a result driven by students attending schools without air conditioning. I find that extreme temperatures widen existing racial and socioeconomic disparities in student behavioral outcomes. Results offer a pathway through which academic outcomes are affected by heat and suggest that warming conditions will exacerbate inequality in the student experience, particularly for children who lack access to air conditioning.

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1 Introduction

Climate change is expected to result in more frequent extreme temperatures. In the United States, schools are already facing a record number of hot days, and many struggle with deteriorating or outdated infrastructure that is insufficient to protect their students from these conditions.[1] Black and Hispanic students and lower-income students have less access to air conditioning at school and at home and tend to live in hotter areas, contributing to concerns that climate change will exacerbate social inequality (Goodman et al., 2018). Previous literature has highlighted the detrimental and unequal effect of heat on learning, finding that children exposed to hotter conditions at school tend to perform worse on tests and to graduate at lower rates (Goodman et al., 2018; Park, 2022; Park et al., 2021). Much less is known about how temperature extremes affect two important dimensions of student behavior, both of which are linked to worse academic and later life outcomes: being absent from school and receiving a disciplinary referral.

In this paper, I examine the causal impact of extreme temperatures on student absenteeism and disciplinary referrals using daily, school- and student-level administrative data from a large urban school district. By linking a panel of student-level data with facility-level data and high spatial- and temporal-resolution environmental data, I construct a data set that offers a uniquely detailed picture of student behavior, exposure to extreme temperatures, and access to adaptive technology. The richness of the data set – which comprises over 90 million student-day observations from roughly 200 schools – allows me to capture the nuanced ways in which temperature affects student behavior, including which students are most affected, what types of behavior are most responsive to heat and cold, and the mitigating effect of access to air conditioning. Using these data, I am able to estimate the temperature-behavior relationship by leveraging purely between-year variation in environmental conditions, while accounting for the exact day of the school year as well as student and school characteristics.

I find that student absenteeism increases by approximately 10% on days when the maximum temperature exceeds 80°F and students are 4% more likely to receive a disciplinary referral on these days.[2] The increase in disciplinary referrals on hot days is driven entirely by non-air conditioned schools, where the likelihood of receiving a referral increases by 9% on days exceeding 80°F. Heterogeneity analyses indicate that both extreme heat and ex-

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

[2] Throughout the paper, I refer to "extreme temperature" as those that are particularly hot or cold relative to the typical range of temperatures experienced by students in the district.

treme cold exacerbate existing racial disparities in behavioral outcomes. On the coldest days (<30°F), the increase in absences for Black and Hispanic students is more than triple the increase in absences of their white peers, and their attendance is also much more affected by snow. On hot days (>80°F), the increase in disciplinary referrals is driven largely by Hispanic students, who disproportionately live in older, lower-income neighborhoods, two housing stock characteristics correlated with lower home air conditioning penetration.

This paper is related to a growing body of research exploring the effect of climate on behavior and economic outcomes, both in children and adult populations. This work includes research on the effect of temperature shocks on human health (Barreca et al., 2016; Bernstein et al., 2022; Sun et al., 2021; Deschenes, 2014; Obradovich et al., 2018),[3] labor supply and productivity (Somanathan et al., 2021; Graff Zivin and Neidell, 2014), and climate adaptation (Deschênes and Greenstone, 2011; Burke et al., 2015b). More specifically, this paper builds on research exploring the effect of environmental shocks on student absenteeism and achievement (Goodman et al., 2018; Heissel et al., 2019; Park, 2022; Park et al., 2021; Persico and Venator, 2021; Gilraine and Zheng, 2022; Duque and Gilraine, 2022), and examining the impact of temperature on adult crime (Ranson, 2014; Burke et al., 2015a; Bondy et al., 2018; Heilmann and Kahn, 2019; Behrer and Bolotnyy, 2022).

This paper makes several contributions to existing literature. While studies have drawn important connections between exposure to environmental conditions and absenteeism, this research has largely focused on ambient air pollution (Currie et al., 2009; Chen et al., 2018). In this study, I control for the day of the school year and identify the temperature-absenteeism relationship purely using differences in conditions between years. This strategy, which avoids drawing problematic conclusions from correlated seasonal trends and trends in student behavior within an average school year, is particularly important when studying heat. The beginning and end of the school year look different from the rest of the school year for reasons not related to temperature, and even monthly controls fail to capture the within-year average trends in student behavior that are observed at these times.

To my knowledge, this is the first paper to examine the effect of temperature on disciplinary referrals, even though the importance of these incidents on student outcomes is well established (Craig and Martin, 2019; Bacher-Hicks et al., 2019; Morris and Perry, 2016; Noltemeyer et al., 2015)[4], and existing research provides evidence for a physiological mechanism between hot temperatures and changes in behavior. The increase in disciplinary referrals that I observe in response to hot temperatures may partly explain previous findings that

[3]Bernstein et al. (2022) finds that exposure to even moderately hot weather is associated with more all-cause emergency department visits among children, especially for heat-related illness.

[4]Several papers study the effect of absenteeism on student outcomes (Aucejo and Romano, 2016; Goodman, 2014; Gottfried, 2010; Gershenson et al., 2017).

academic outcomes are affected by heat. Results also offer the first evidence that warming conditions will likely exacerbate existing racial disparities in the school discipline system and in absenteeism.

In addition to being motivated by the observed relationship between heat and crime in adults, this paper also makes several contributions to the literature exploring how environmental conditions affect socially disruptive behavior. First, my setting allows me to study the relationship between adverse environmental conditions and behavioral issues in a much broader population than has been examined in most previous papers. My results indicate hot conditions exacerbate behavioral issues, not only among the portion of the adult population that will at some point be convicted of a crime, but also among the broad set of children who at some point receive a disciplinary referral. The types of behavior and severity of incidents studied in this paper are also wide-ranging, capturing even minor instances of irritability, argumentativeness, and distraction. Unlike most papers examining heat and crime in adult populations, I do not find evidence that "violent behavior" is particularly sensitive to heat. Instead, I find that the increase in behavioral referrals on hot days is composed largely of referrals for "disruptive" behavior, a broad, catch-all category which includes irritability, anger, lack of respect, and disobedience. It is important to note that behavioral referrals are an imperfect measure of student behavior as they may also reflect teacher behavior, or a combination of the two. Broader categories of behavior, particularly those reflecting teacher-student interpersonal encounters, like those for defiance or disruptive behavior, are understood to be particularly likely to reflect teacher bias or frustration (Okonofua and Eberhardt, 2015).

The school setting also allows for easier identification of the effect of stressful environmental conditions on behavior than most settings.[5] Observing the temperature-crime relationship outside of the laboratory is often made challenging by the endogeneity of many behaviors to temperature; social interactions and even police behavior change in response to temperature shocks (Heilmann et al., 2021). Schools are one of the few places where the opportunities for interactions in which socially disruptive behavior may occur are relatively easily observed, especially when accounting for absences. The ability to easily observe behavior and absenteeism is particularly important on days characterized by extreme temperatures.

The remainder of the paper is organized as follows. In Section 2, I introduce the institutional setting of the study and provide additional details on the data, and I present key summary statistics in Section 3. Section 4 outlines my empirical strategies. In Section 5,

[5]Mukherjee and Sanders (2021) highlight the advantage of greater observability and schedule consistency in their study of heat and misbehavior in prisons.

I provide my main results, heterogeneity analysis, and robustness checks. In Section 6, I discuss the implications of my results and conclude.

2 District Setting and Data

The setting of my study is a large urban school district (LUSD), one of the 50 largest K-12 public school districts in the country and the largest in its state. Compared to these other large districts, students enrolled in the LUSD are relatively more likely to qualify for free and reduced price lunch, to live in poverty, and to not graduate high school. The metropolitan area where the district is located is characterized by very hot and very cold school days. Many of the district's schools are not fully air conditioned, and hot temperatures in non-air conditioned schools have been a contentious issue among students, parents, educators, and the local community. For the first six years of the sample period, only 47% of the student body attended schools with 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 and fall of 2017, the district used funds from a recently-approved tax package to begin installing air conditioning in the hottest school buildings, providing an additional 19% of the student body with access to school air conditioning over the next two years.[6]

Like many districts in the country, the LUSD is actively developing and updating best practices to prioritize new air conditioning installations. Initial planning prioritized schools for installation based on a 2015 temperature study, which measured the indoor temperatures of non-air conditioned schools during a hot week of the year. However, the district now prioritizes improving learning environments in "high-need" schools,[7] while also considering building utilization and "geographic equity" (ensuring schools in all regions of the city see some improvements). The need to prioritize future air conditioning installations, both in this district and in districts across the country, provides additional motivation to examine which

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

[7] To identify high-need schools, the district relies on a newly-developed "equity index":

$$EquityIndex : \frac{\%FRPL + \%ELL + \%SPED + \%Volatility}{\sum_{s=1}^{S}(\%FRPL_s + \%ELL_s + \%SPED_s + \%Volatility_s)}$$

This index, which is calculated for each school, compares the sum of several measures of the percentage of "harder to serve" students in each school to other schools in the district. These measures include the percent of students who are eligible for free or reduced price lunch (FRPL), who are English Language Learners (ELL), or who have special education needs (SPED). It also includes a measure of teacher turnover (Volatility).

characteristics of students and schools are predictive of the sensitivity of student outcomes to high temperatures and/or a strong effect of air conditioning in mitigating this response.

2.1 Student-Level and Facility-Level Data

I use detailed student-level and facility-level data provided by the LUSD. Longitudinal student-level administrative data include all students enrolled in the district at any time during the sample period (2011/12 - 2018/19). During the sample period, the district enrolled an average of about 70,000 K-12 students, who attended approximately 200 schools.[8] Unique student identifiers allow me to follow individual students across time. Daily student-level data include enrolled and absent minutes and student disciplinary referral information. Demographic information, which is provided at the annual level, includes student ethnicity, gender, and grade, and the census block of each student's home residence, which is reported at an annual level.

Student disciplinary referral data include every incident in the study period that merited administrative involvement. While some minor forms of misbehavior do not require administrator involvement (e.g. profanity, use of cell phones in class, etc.), the range of documented incidents and their disciplinary outcomes is large. For each referral, participant(s), the date and time, and all disciplinary responses to the incident, including whether a student was referred to law enforcement, are noted. I group incidents into eight broad categories based on about 50 incident descriptions: fighting/assault, bullying and harassment, weapons and dangerous behavior, theft and destruction, disruptive behavior, alcohol and drugs, recurring offenses, and other incidents. A list of event descriptions that fall into each category is provided in Table A1. I also categorize the disciplinary responses to these incidents in Table A2.

I link students to schools using enrollment data. For each school, I compile information using the LUSD social media accounts, district calendars, and news articles to identify school vacations and unexpected school disruptions, including power outages, snow days, bomb threats, gas leaks, and other disturbances to students' school day. I also construct school facility information, including building age and air conditioning installation history, from district planning documents.[9]

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

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

2.2 Daily Environmental Data

Daily meteorological data come from three main sources. Information on maximum temperature and precipitation come from Schlenker and Roberts (2009), who create a 2.5 x 2.5 mile grid from PRISM data while maintaining a consistent set of weather stations. 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.[10] Maximum outdoor temperature is chosen as the key measure of temperature (vs. minimum or average temperature), both because students attend schools during the day, and also because this region is characterized by substantial diurnal variation in air temperature. For example, the average minimum temperature on days with a maximum temperature between 80-90°F days is 55°F. Snow data come from the National Oceanic and Atmospheric Administration's Daily Global Historical Climatology Network. Daily fine particulate matter ($PM_{2.5}$) and ozone (O_3) readings come from monitor data provided by the U.S. EPA Air Quality System.

2.3 Neighborhood-Level Data

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

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

3 Descriptive Statistics

Table 1 provides descriptive statistics of the K-12 student population between 2011/12 and 2018/19. As a share of total enrollment, 20% of students are white, 16% are Black, 57% are Hispanic and 8% are another race. 42% of students are enrolled in English Language Learner programs, the majority of whom are Hispanic and speak Spanish as their first language.

[10] 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.

TABLE 1: Student and neighborhood characteristics and access to school air conditioning.

		Gender		Race/Ethnicity			Grade Level		
	All	Female	Male	Black	Hisp.	White	Elem	Middle	High
Student and Neighborhood Characteristics									
Share of Enrollment (%)	100	49	51	16	57	20	47	24	30
% English Language Learners	41.6	41.8	41.4	15.5	61.9	6.1	40.5	44.4	41
Average % VLI or LMI	57.3	57.3	57.3	58.9	64.9	36.7	56.9	57.7	57.5
Average % Built <1950	40.8	40.9	40.6	27.8	44.1	43.1	41	40.2	40.9
% Living in Hottest 25th Pct of Neighborhoods	25	25.1	24.9	29.8	25.5	19.9	25.8	25.6	23.2
Share of Enrollment by Access to School AC (%)									
Always AC (108 schs.)	47	47	47	55	48	39	49	50	41
Never AC (67 schs.)	33	100	100	25	33	43	43	34	18
AC starts 2017/18 (18 schs.)	12	13	12	10	15	8	5	15	22
AC starts 2018/19 (7 schs.)	7	8	7	10	5	10	3	2	18

Notes: The top panel shows, for each gender, race, and grade level, the share of enrollment, percent of English Language Learners, the average percent of very low income or low middle income households in students' home census block groups, the average percent of houses built prior to 1950 in students' census block group, and the percent of students living in the hottest 25th percentile of census blocks. The second panel shows the portion each group that attended schools that always had AC, never had AC, or received AC installations that were completed in 2017/18 or 2018/19 respectively. Descriptive statistics are shown for the three largest racial/ethnic groups, which comprise 93.9% of the student body, on average.

Prior to the fall of 2017, approximately half of all students attended schools with complete air conditioning, and both white students and high school students were slightly less likely to attend these schools. Table A3 provides greater detail about the characteristics of facilities and the student population by school air conditioning status. Schools that had air conditioning for the full sample period tended to be in newer buildings and to serve students living in newer neighborhoods.[11]

While race does not appear to be highly predictive of access to school air conditioning in this particular district, differences in neighborhood characteristics suggest that access to air conditioning at home likely *does* differ by race. Black and Hispanic students are substantially more likely than white students to live in neighborhoods with a high proportion of very low income (VLI) or low- and middle-income (LMI) households and with a higher average land surface temperature. The distribution of land surface temperature by race is illustrated in Figure A1. Compared to Black students, both white and Hispanic students are more likely to live in neighborhoods with older housing stocks. However, as illustrated in Figure A2 the older neighborhoods where white students live are disproportionately higher-income, even for

[11]A simple regression estimating the importance of building age, region, grade level, and building size shows that building age as of 2017 was 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 ago, respectively.

TABLE 2: Student behavioral outcomes.

		Gender		Race/Ethnicity			Grade Level		
	All	Female	Male	Black	Hisp.	White	Elem	Middle	High
Attendance									
% Absent on Avg. Day	6.6	6.6	6.6	6.9	7.1	4.9	6.2	6	7.9
Behavioral Referrals									
% Referred in Avg. Year	9.7	6.6	12.7	17.2	9.9	4.3	5.2	16.2	11.7
% Susp./Law in Avg. Year	4.4	2.9	5.9	8.9	4.4	1.5	1.9	7.9	5.5
% Referred $\geq$1 in Avg. Year	3.8	2.2	5.4	7.9	3.7	1.3	1.9	7.1	4.3
Avg Ann. Ref. $\mid \geq$1 Ref.	2.1	1.8	2.2	2.3	2	1.8	1.9	2.3	1.9
% Referred on Avg. Day	0.13	0.08	0.18	0.26	0.13	0.05	0.06	0.24	0.15

Notes: This table shows, for each gender, race, and grade level, the percent of students absent on an average day, the percent of students referred or absent 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 three largest racial/ethnic groups, which comprise 93.9% of the student body, on average.

that population. By contrast, Hispanic students tend to be concentrated in neighborhoods that are characterized by both an aging housing stock and relatively low-income households. These neighborhood characteristics suggest that Hispanic students, and, to a lesser extent, Black students, may be both exposed to hotter outdoor temperatures and have lower access to air conditioning at 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.[12]

The average number of absences and disciplinary referrals also differ by race, as well as by age and gender, as shown in Table 2. Hispanic and Black students are nearly 50% more likely than white students to be absent from school. They are also more likely to receive a behavioral referral and are more likely to face harsher exclusionary discipline (suspensions, expulsions, or referrals to fire or law enforcement). This is especially true among Black students, who are six times more likely than white students to receive a severe penalty during a given year. Male students are more often involved in reported incidents than female students, and middle school students are the most likely age group to be involved in incidents. In an average year, approximately 10% of students receive at least one referral, and 4% of students receive multiple referrals.

Both student attendance and behavioral referrals vary substantially throughout the academic year. Patterns in school attendance throughout a typical school year are included in Panel A of Figure A3, demonstrating a general downward trend throughout the year and

[12]See, for example, Alsan and Yang (2018) for a discussion of factors that may discourage Hispanic households from enrolling in benefit programs.

dips in attendance around school breaks. Panel B of Figure A3 illustrates this trend after excluding snowy days and known city-wide events expected to affect attendance.

The daily count of incidents across the district is illustrated in Figure A4. Even a cursory look at trends in incident frequency reveals a striking pattern around school breaks, with incident frequency falling in the days leading up to a break and rising in the days coming out of one. At the beginning of the semester, this is likely due to a combination of school policies that give students second chances and the gradual formation of social groups.[13] Pre-break testing as well as teacher or administrator fatigue in anticipation of a break may contribute to the decline in referrals at the end of the semester. While this trend is not surprising, it highlights the importance of carefully controlling for the time of the school year when estimating the effect of adverse environmental conditions on student outcomes so as not to mistakenly conflate academic year trends with seasonal patterns in environmental conditions.

Seasonal patterns in temperature over the academic year are illustrated in Figure A5, with the percent of schools days that fall in each temperature bin indicated on the right vertical axis. Seasonal trends in temperature are correlated with both ambient levels of ground-level ozone and fine particulate matter, which are illustrated in Figure A6. 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.

Referrals are made in response to a variety of different behaviors. The average annual frequency and resulting disciplinary outcomes of each category of referral, from 2014/15-2018/19, is illustrated in Figure A7. A similar figure illustrating these categories in previous years (2011/12-2013/14), when incident descriptions were often not recorded at the same level of detail, is provided in Figure A8. 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. As explained in Appendix B, trends in behavioral referrals suggest that this policy may have had an effect on the number of behavioral incidents reported, particularly for Black students.

A comparison of the composition of referrals for each demographic group, as shown in Table A4, suggests that Black students receive more referrals for fighting and disruptive

[13]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).

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.

4 Empirical Framework

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

4.1 How does temperature affect student behavior?

In my main specification, I estimate the following 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 is (1) absent from school or (2) receives a behavioral referral on day t in academic year y. Only present students are included when estimating the latter relationship, but results are robust to the inclusion of absent students.

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 and more than 4 inches of snow are included.[14] School fixed effects, η_s, and controls for a set of student demographic characteristics (grade, race, gender, and English Language Learner status), C'_{iy}, are also included.

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

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, which each correspond to a day of the school year (first day of school, second day of school, etc.). These fixed effects are estimated separately for a pre- and post-2014/15 reporting policy change, so a total of 310 "day of school year" fixed effects are included.[15] The last two weeks of the spring semester are excluded because many schools have testing, and enrollment declines substantially over these two weeks. 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.

A linear probability model is used in the main specification to allow for a clear interpretation of the analysis of heterogeneity in the temperature-behavior relationship. Results appear similar when estimating the temperature-behavior relationship with alternative specifications, including a fixed effects Poisson model estimated using maximum likelihood (Hausman et al., 1984; Wooldridge, 1999; Correia et al., 2020). Poisson estimators have been used by some to more easily account for data with many zeros, such as crime data, and may be preferred to other models because they avoid the incidental parameters problem (Charbonneau, 2012).

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.

The two outcomes of interest, student absences and behavioral referrals, interact in several notable ways. First, students are very unlikely to receive behavioral referrals when they are absent from school.[16] The effect of temperature on behavioral referrals can therefore only be observed off of present students. If students whose referrals are more temperature sensitive than average are absent on particularly hot and/or cold days, the estimated effect of temperature on behavioral referrals will be lower than if absences did not also vary in response to temperature. Students may also differ by their "baseline likelihood" of receiving a behavioral referral, either because students behave differently or because teachers respond

[15]The district discouraged teachers and administrators from describing incidents using broad, "catch-all" descriptions, like "disruptive behavior".

[16]Possible exceptions would occur if students were referred prior to the start of the school day or for online behavior (harassment).

to their behavior differently. The baseline likelihood that the average present student will receive a referral may also vary by temperature. Student fixed effects, or student-by-year fixed effects, which are included in some specifications, may capture daily differences in the baseline likelihood of the present student to receive a behavioral referral.

Present students may also 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, $\overline{Z_{ict}}$, of present student i in class c on day t as the percent of their enrolled peers who are present. I define class risk, $\overline{R_{ict}}$, as the percent of their present peers who receive at least one referral in the given year. Both are constructed as leave-out-means. I then estimate equation (1) where the outcome variable is $\overline{Z_{ict}}$ or $\overline{R_{ict}}$. The inclusion of $\overline{Z_{ict}}$ and $\overline{R_{ict}}$ in equation (1) when estimating the effect of temperature on behavioral referrals did not substantially change the coefficient estimates on binned temperature.[17]

4.2 Heterogeneity by school air conditioning status

The relationship between temperature and both referrals and absences estimated by equation (1) masks substantial heterogeneity in the temperature-behavior relationship by the characteristics of schools and students The effect of temperature on behavior, unmitigated by school air conditioning, is of particular interest, so in addition to estimating equation (1) with the full set of schools and years, I also estimate how this relationship varies by school air conditioning status, again focusing on the years prior to the start of new air conditioning installations (2011/12-2016/17).

To identify the heterogeneous 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, and year and day of school year fixed effects.[18]

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

[18] These latter interactions are necessary to avoid attributing different patterns in behavior within each school year with the correlated environmental conditions.

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

The results from this analysis provide cross-sectional evidence of the causal effect of temperature extremes on student behavioral outcomes, unmitigated by school air conditioning. However, they should not be interpreted as estimating the mitigating effect of school air conditioning alone.[19] While the school district did not target specific schools for air conditioning prior to the fall of 2017, air conditioning is not randomly distributed among students. In particular, new neighborhoods are more likely to have air-conditioned schools. Homes in these neighborhoods may be more likely to have central air conditioning, so results may reflect the effect of both home and school air conditioning.

To explore whether results are driven entirely by differences in home air conditioning, I create a proxy for home air conditioning status using the air conditioning status of nearby elementary schools.[20] To the extent that school and home air conditioning status are related, elementary schools may provide the best proxy because they have smaller catchment zones than middle and high schools. I then estimate equation (2) for neighborhoods where less than 1/3 of elementary school students attend schools with air conditioning and for neighborhoods where more than 2/3 of elementary school students attend schools with air conditioning. An advantage of this approach is that many elementary schools are located in a relatively small area, providing variation in school air conditioning status even within census block groups. Comparisons of the composition of students by race and income do not support the hypothesis that remaining variation in school air conditioning status results from the selection of more advantaged students into air-conditioned schools. Within the set of census block groups where less than 1/3 of elementary school students attend schools with air conditioning, students attending air-conditioned schools are, on average, more likely to live in an area with slightly more elementary AC penetration (mean of 18% vs. 16%), to live in a low income area (40% vs. 38% LMI), and to be non-white (81% vs. 74%).

[19]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.

[20]Specifically, I calculate the mean school air conditioning status of elementary school students living in each census block group.

4.3 Heterogeneity by student and neighborhood characteristics

To study heterogeneity in the relationship between temperature and behavior, I restrict the sample to non-air conditioned schools (2011/12-2016/17), and split the sample of students by a variety of characteristics.[21] In addition to examining heterogeneity by key student demographic characteristics (race, grade), I also include several neighborhood characteristics that may be important predictors of home air conditioning status: the percent of households characterized as low middle income and the median age of the housing stock, both of which are measured at the census block group level.

District-wide coefficient estimates on binned temperature are presented as a percent change from the district-wide mean absence (0.065) and referral rates (0.013). The mean absence and referral rates differ by student and neighborhood characteristics. To allow for an easier interpretation of heterogeneity in these relationships and resulting changes in disparities in educational outcomes, I present results of the heterogeneity analysis in terms of level changes. Coefficient estimates in behavioral referral regressions are expressed as a change in the number of students who receive a referral per 1,000 students. Coefficient estimates in attendance regressions are expressed as a change in the number of absent students per 15 students. These adjustments are approximately equivalent to expressing coefficient estimates as a percent of the district-wide mean in the respective outcome variables.

5 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 schools with and without air-conditioning. I discuss how changes in class size and composition may affect the behavior of present students. I then examine how the impact of temperature varies by student and neighborhood characteristics.

5.1 Hot and cold conditions increase absenteeism

Panel A of Table 3 demonstrates that absences are higher on both cold and hot days relative to a day with a maximum temperature between 60-70°F. Absences are 32% higher on days below 30°F than on temperate days. Absences are also 9% higher and 15% higher on days between 80-90°F and exceeding 90°F, respectively compared to 60-70°F days.[22] Coefficient

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

[22] I highlight the hottest and coldest temperature bins here. Even moderately hot temperatures appear to increase absences, but more temperate days appear to be generally more similar to each other than

TABLE 3: Effect of temperature on absences and behavioral referrals relative to a day with a maximum temperature between 60-70°F.

	Basic	All Enrolled	Poisson	No School AC	+ With AC
Panel A: Absences					
<30F	0.323***	–	0.253***	0.304***	0.044
	(0.014)	–	(0.010)	(0.010)	(0.029)
80-90F	0.090***	–	0.089***	0.092***	-0.004
	(0.006)	–	(0.004)	(0.007)	(0.013)
>90F	0.148***	–	0.135***	0.142***	0.015
	(0.012)	–	(0.015)	(0.014)	(0.025)
Obs. (millions)	60.2	–	56.0	60.2	–
Panel B: Referrals					
<30F	-0.118**	-0.179***	-0.165***	-0.161**	0.100
	(0.046)	(0.048)	(0.043)	(0.064)	(0.092)
80-90F	0.037	0.044	0.040	0.078**	-0.094*
	(0.027)	(0.028)	(0.028)	(0.035)	(0.055)
>90F	0.101	0.094	0.176*	0.223**	-0.284**
	(0.061)	(0.065)	(0.096)	(0.087)	(0.114)
Obs. (millions)	56.5	60.2	5.8	56.5	–
Pre-2017/18	X	X	X	X	–
Day of Year FE	X	X	X	X	–
School FE	X	X		X	–
Student X Year FE			X		–

Notes: Coefficient estimates are from linear regressions modeling daily, student-level absences or behavioral referrals on indicators for binned temperature and school, demographic (grade, race, 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. An indicator for school AC and interactions with environmental and timing controls are included in the specification represented by columns 4-5, which show coefficient estimates on temperature and interaction between temperature and school AC. Heteroskedasticity robust standard errors are clustered at the school level and estimates are normalized by the mean daily district-wide absent rate (6.5%) or referral rate (0.13%). Asterisks indicate coefficient significance level (2-tailed): *** p<.01; ** p<.05; * p<.10.

estimates on all temperature bins for both air conditioned and non-air conditioned schools are illustrated in Panel A of Figure 1. Results indicate that extreme cold temperatures and even moderately hot temperatures reduce student attendance and that these results are not sensitive to school air conditioning status.

5.2 Heat increases behavioral referrals in schools without air conditioning

Referrals are also sensitive to both hot and cold temperatures. As shown in Panel B of Table 3, referrals are 4% and 10% higher on 80-90°F and >90°F days, respectively, compared with 60-70°F days. However, this effect is not statistically significant when estimated for all schools.

The inclusion of school air conditioning status interaction terms in columns 4 and 5 of Table 3 suggests that the estimated coefficients on hot temperatures in specifications that include all schools mask substantial heterogeneity in this relationship by school air conditioning status. The comparison between air conditioned and non air conditioned schools, which is illustrated Figure 1, suggests that the increase in behavioral referrals on hot days is entirely driven by students attending schools without air conditioning. In schools without air conditioning, referrals are 8% higher on days with a maximum temperature between 80-90°F. On days with a temperature exceeding 90°F, this increase jumps to 22%.[23]

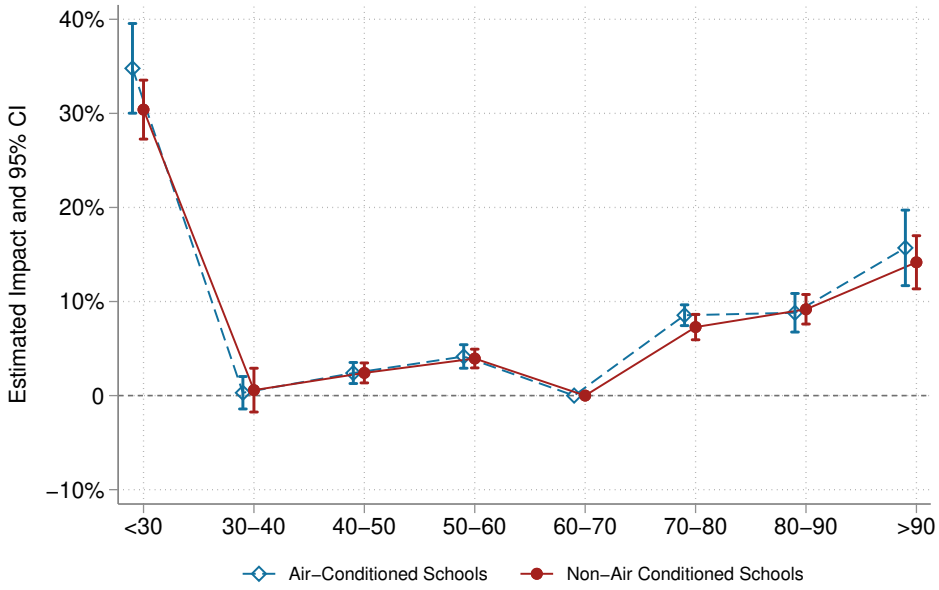
As noted previously, school air conditioning status is not randomly assigned, so the results illustrated in Figure 1 should not be interpreted as capturing the causal effect of air conditioning on behavior. It should be noted, however, that students who attend air conditioned schools are not generally more advantaged in other ways; these students, on average, live in hotter neighborhoods, are less white, and are approximately as likely to live in a low middle income or very low income neighborhoods as students attending schools without air conditioning.

A comparison of the temperature-behavior relationship between students who live in neighborhoods with similar likelihoods of having home air conditioning status, shown in Figure A9, suggests that the results illustrated in Figure 1 do not stem solely from differences in home air conditioning status. They also suggest that access to school air conditioning may be particularly beneficial for students living in homes without air conditioning.

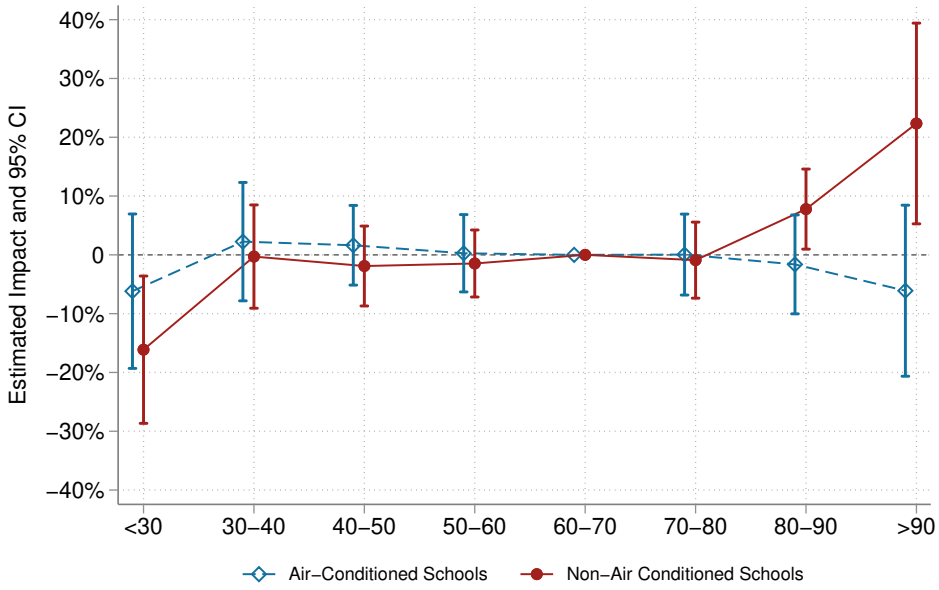
Referrals also appear to be sensitive to cold temperatures; on days below 30°F, behavioral referrals are 12% lower. It is possible that this decrease, and the decrease seen on hot days in

days characterized by more extreme temperatures. When controls for snowfall are not included, days with a maximum temperature below 30°F have absences that are 44% higher than 60-70°F days. Coefficient estimates of bins below 60°F are also sensitive to the inclusion of snowfall controls.

[23]Temperatures is highly serially correlated, so results may capture previous-day and cumulative effects of temperature.



(A) Absences

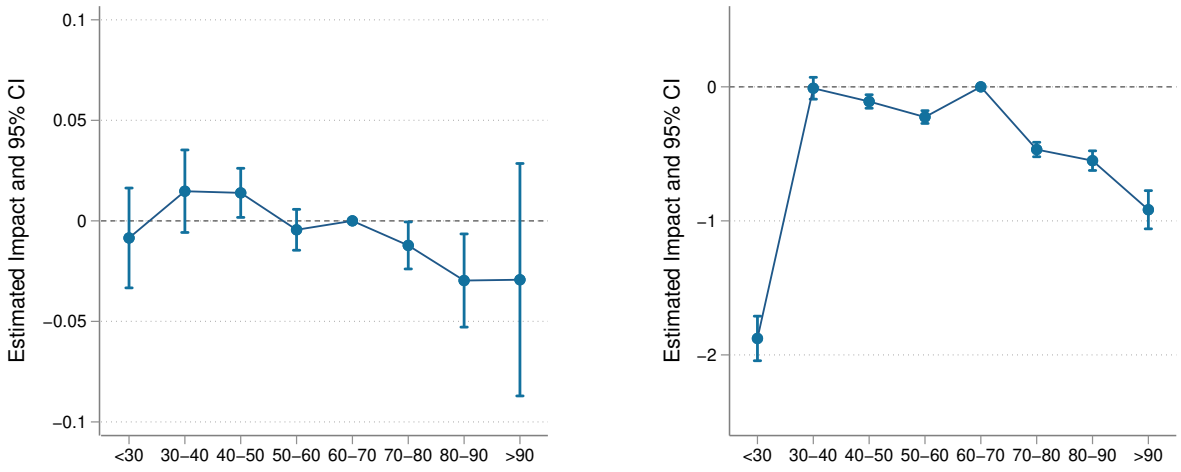


(B) Behavioral Referrals

Notes: Coefficient estimates are taken from a linear regression modeling daily, student-level (A) absences and (B) behavioral referrals, conditional on being present, on indicators for binned temperature for the 2011/12-2016/17 academic years for students in schools with and without AC. All estimates are expressed as a percent of the mean, district-wide daily absent rate (6.5%) or referral rate (0.13%). Regressions include school, demographic (grade, race, 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. An indicator for school AC and interactions with environmental and timing controls are also included.

FIGURE 1: Effect of temperature on (A) absences and (B) behavioral referrals relative to a day with a 60-70°F max temperature, by school air conditioning status (2011/12-2016/17).

air conditioned schools, may stem partly from the size and composition of the present student body. As noted previously, the probability of a student receiving a behavioral referral on a given day may be affected both by whether that individual student is present and also by the number and composition of other students present in their class. The high rate of absences on cold days, and to a lesser extent, hot days, raises the possibility that aspects of the school experience, like class size and composition, may differ on these days. Figure 2 shows the effect of temperature on "class risk" and "class size". The effect of hot and cold conditions on class risk is very small; results suggest that on a 90° day, 0.03 fewer students with a high-propensity to receive a referral would be present in a school x grade of 100 students. Class size is more affected, although the magnitude of the change does not appear to be large. On the coldest days, the average school x grade of 100 students would be missing an additional 2 students.



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

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

FIGURE 2: Effect of temperature on measures of "class risk" and "class size".

The inclusion of these measures of class size and composition in the main temperature-behavioral referral regression do not substantially affect results. However, the simple inclusion of these measures is insufficient to account for the effect of class size and composition on behavior. While observed changes in student composition are relatively small, changes

in class size, particularly on cold days, may be large enough to affect behavior, especially if these changes are concentrated in certain classrooms. For elementary school students, school schedules also change on particularly cold days, when students are kept indoors during recess. According to district representatives, similar protocols for schedule changes on hot days do not exist, with the exception of designated "heat days".[24]

The types of behavior affected by heat and cold are illustrated in Figures A10 and A11. While patterns are only suggestive, disruptive behavior appears to be the most responsive to hot (>80°F) temperatures.[25] These referrals capture reports of irritability, anger, lack of respect, attention, or obedience. More subjective referrals, like those for disruptive behavior, may be particularly likely to reflect teacher bias or frustration, so this result may lend support to the hypothesis that both student and teacher behavior is responsive to heat.

5.3 The detrimental effects of extreme temperature on behavior exacerbate racial disparities in behavioral outcomes

I next explore heterogeneity in the effect of temperature by student characteristics. In this analysis, I focus on schools without air conditioning. For simplicity, I construct >80°F bins when estimating both absences and referrals. I also construct a 30-80°F bin when estimating referrals. Coefficient estimates of the effect of <30°F and >80°F temperatures on absences are illustrated in Figure 3. Results indicate that although the attendance of students of all races is affected by temperature, both Black and Hispanic students are more likely to be absent on particularly cold days (and, to a lesser extent, hotter days) than are white students.[26] Absences of lower income students(over 50% LMI) also appear to be more sensitive to temperature. The combined effect of living in an low-income neighborhood with older houses (median home built in the 1950s or earlier) does not appear to be more important than neighborhood income itself when explaining heterogeneity.

While statistical power to identify heterogeneity in the temperature-behavioral referral relationship is more limited, results, illustrated in Figure 4 indicate that referrals of Hispanic students are more responsive to temperature than referrals of either white or Black students. Referrals of Black students are imprecisely estimated for all temperature bins. 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. While differences are not statistically significant, a comparison of students living in neighborhoods with an older housing stock (median home built in the 1950s or earlier) and

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

[25]Referrals for bullying/harassment and recurring offenses also appear to increase with temperature.

[26]The full set of coefficient estimates from race-specific regressions is illustrated in Figure A12

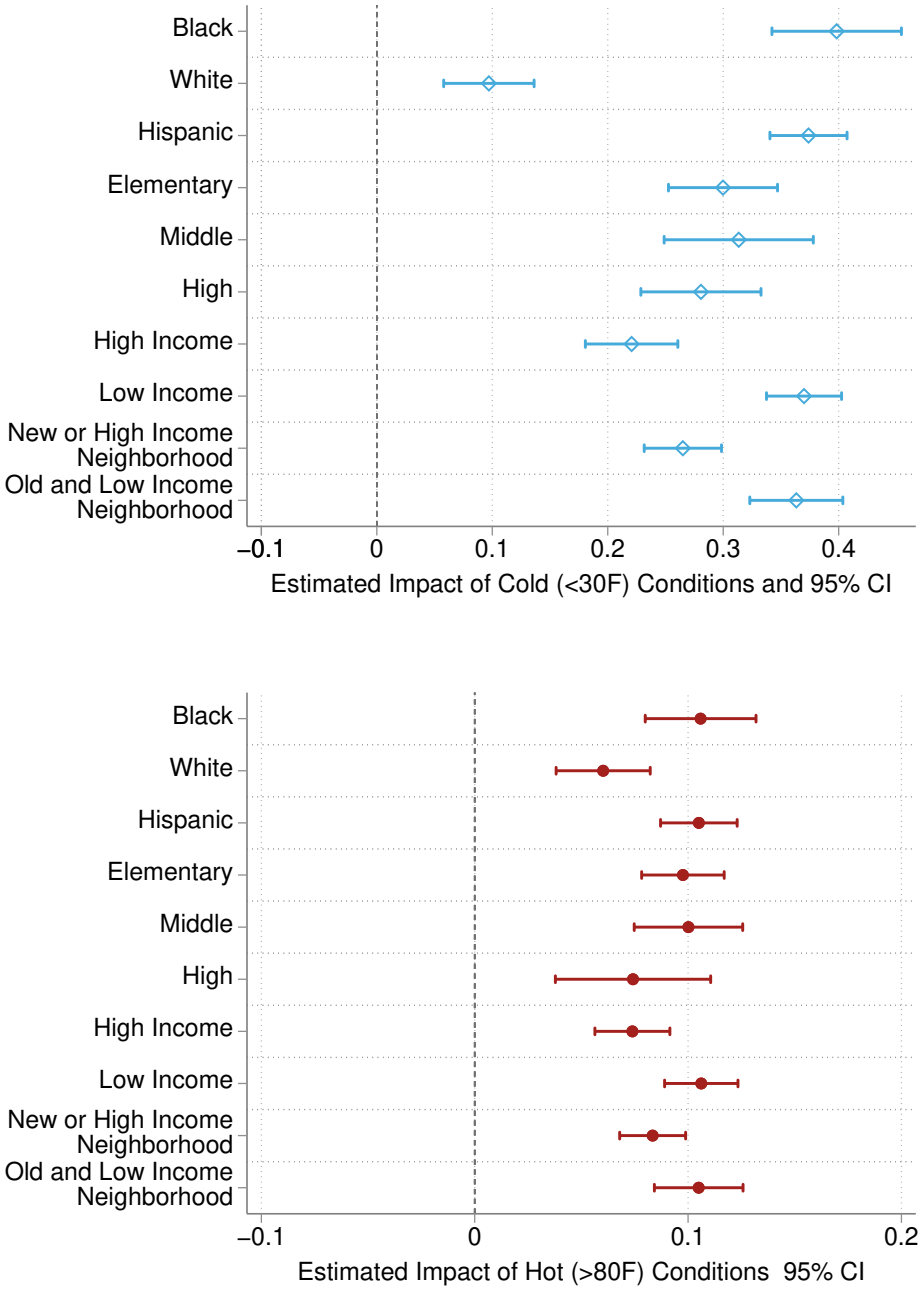
relatively low-income households (over 50% LMI) with other students suggests that students from older, lower-income neighborhoods may be more sensitive to heat.

6 Discussion and Conclusion

This paper explores the impact of extreme temperatures on student attendance and disciplinary referrals, two components of student behavior which may be disruptive to learning and affect later life well-being. Using data from a large US urban school district, which links daily student-level information about attendance and behavioral referrals with facility and environmental data, I estimate the short-term behavioral response of student outcomes to temperature. I find that both hot and cold temperatures have a causal, statistically significant impact on student attendance. The attendance of both minority and low-income students is more affected by cold, and, to a lesser extent, by heat. 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 Hispanic students. My empirical strategy exploits between-year variation in temperature and includes a flexible set of controls to identify the causal effect of temperature on behavioral outcomes. This research design as well as a rich data set of student, school, and neighborhood characteristics, allows for a nuanced exploration of heterogeneity in this relationship.

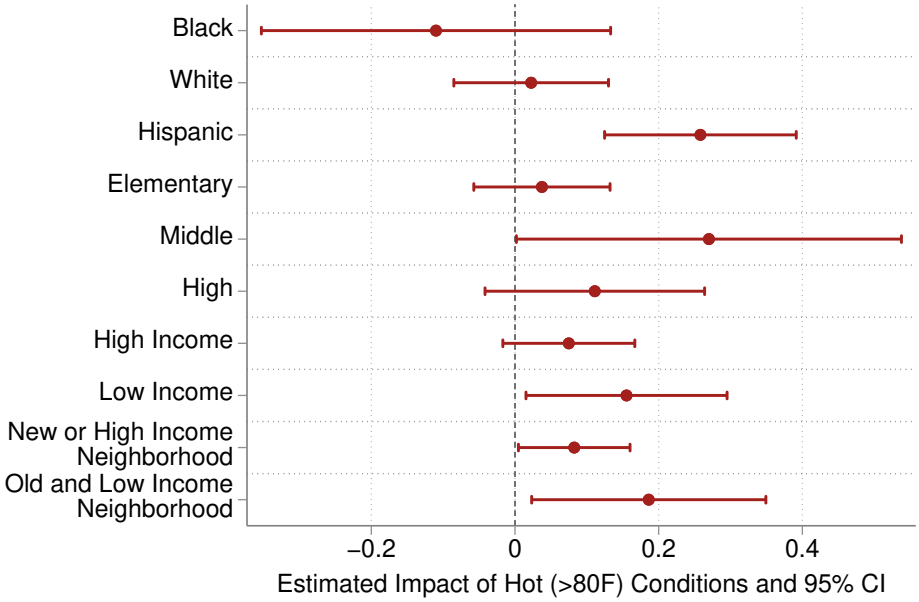
Results indicate that, relative to temperate days with an outdoor maximum temperature between 60-70°F, days with a temperature between 80-90°F and exceeding 90°F result in an estimated 9% and 15% increase in absences. While relatively rare, very cold conditions, those with temperatures below 30°F result in a 34% increase in absences. In schools without air conditioning, behavioral referrals are 8% and 22% higher on days with a temperature between 80-90°F and exceeding 90°F, respectively.

Results have important implications in the context of a rapidly changing climate. Many schools lack air conditioning, and school closures on "heat days" are becoming more common. Climate change is expected to increase the variability in the climate system, exposing students to atypical temperatures more frequently, which may widen disparities in attendance and disciplinary referrals for those who can less easily adapt to temperature extremes. Heat-induced increases in behavioral referrals offer a channel for the observed relationship between heat and academic outcomes and highlight a possible benefit of improving school infrastructure. Existing access to adaptive technology at home and at school is characterized by racial and socioeconomic differences, suggesting that warming conditions may exacerbate disparities in educational and later-life outcomes.



Notes: Coefficient estimates are taken from linear regressions modeling daily, student-level absences on indicators for binned temperature for the 2011/12-2016/17 academic years for students in schools with and without AC. All estimates are expressed as a percent of the mean, district-wide daily absent rate (6.5%) or referral rate (0.13%). Regressions include school, demographic (grade, race, 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.

FIGURE 3: Coefficient estimates of the effect of (A) <30°F conditions and (B) >80°F conditions on absences relative to a day with a 60-70°F max temperature, by student and neighborhood characteristics in schools without air conditioning (2011/12-2016/17).



Notes: Coefficient estimates are taken from a linear regression modeling daily, student-level absences on indicators for binned temperature for the 2011/12-2016/17 academic years for students attending schools without AC. All estimates are expressed as a percent of the mean, district-wide daily absent rate (6.5%) or referral rate (0.13%). Regressions include school, demographic (grade, race, 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.

FIGURE 4: Coefficient estimates of the effect of >80°F conditions on absences relative to a day with a 30-70°F max temperature, by student and neighborhood characteristics in schools without air conditioning (2011/12-2016/17).

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Appendix A: Additional Figures

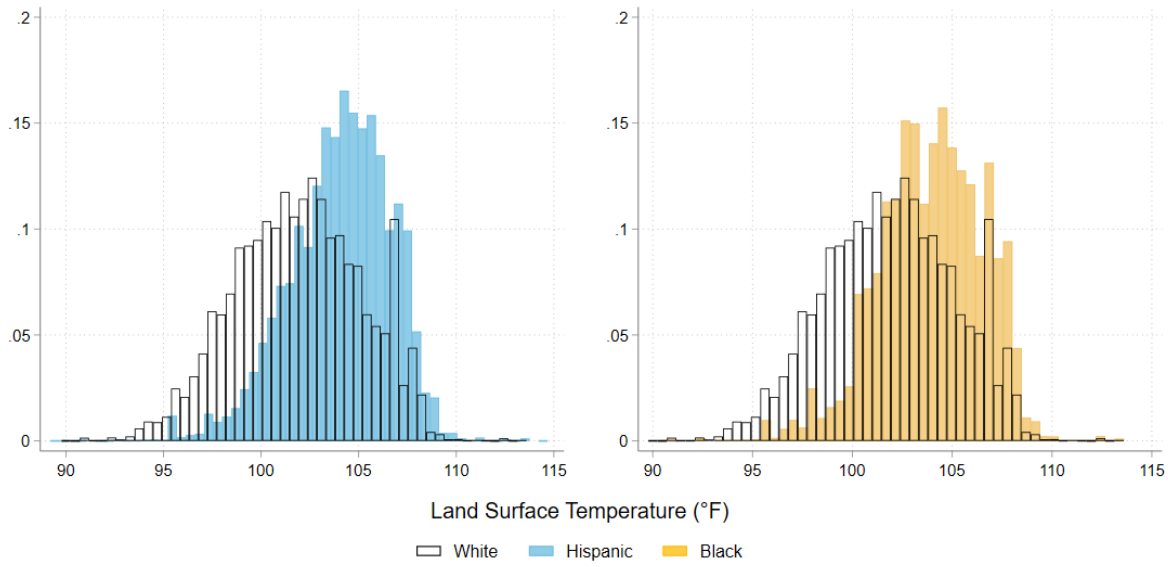
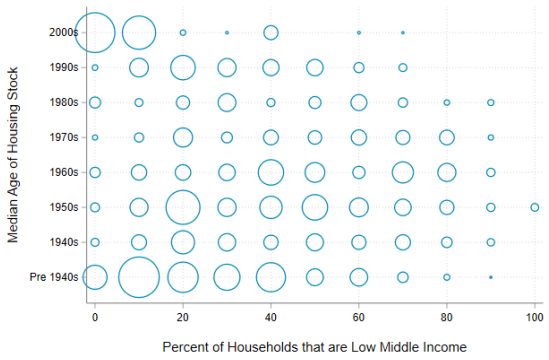
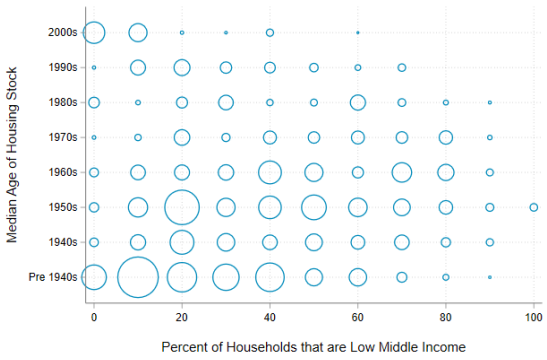


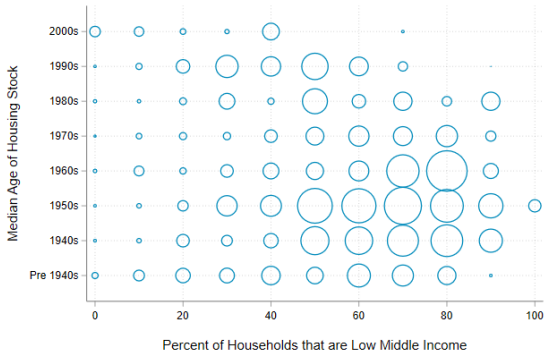
FIGURE A1: Distribution of summer land surface temperature by race for the three most common races.



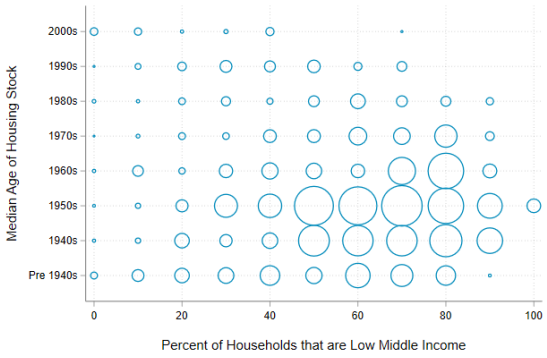
(A) White



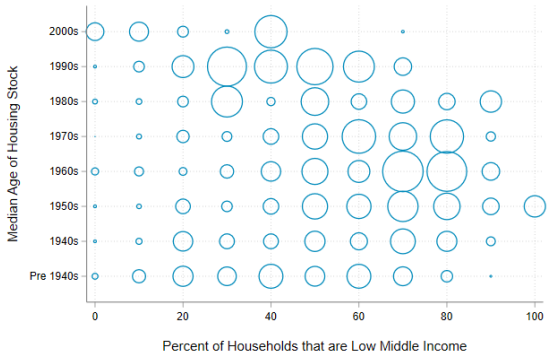
(B) White (No AC)



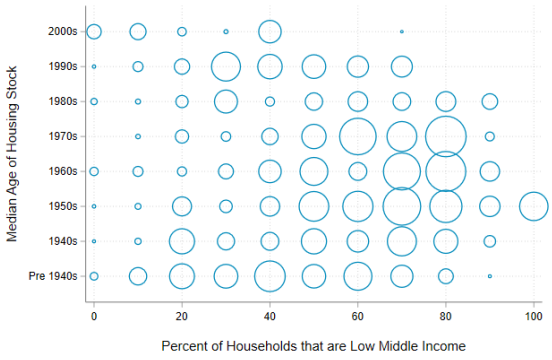
(C) Hispanic



(D) Hispanic (No AC)



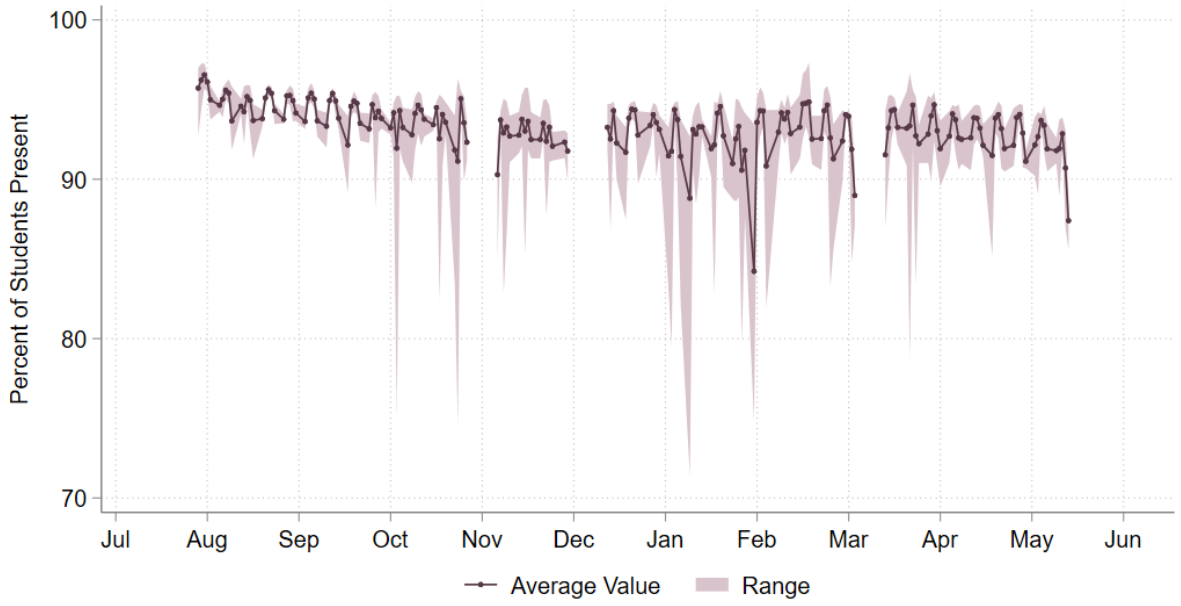
(E) Black



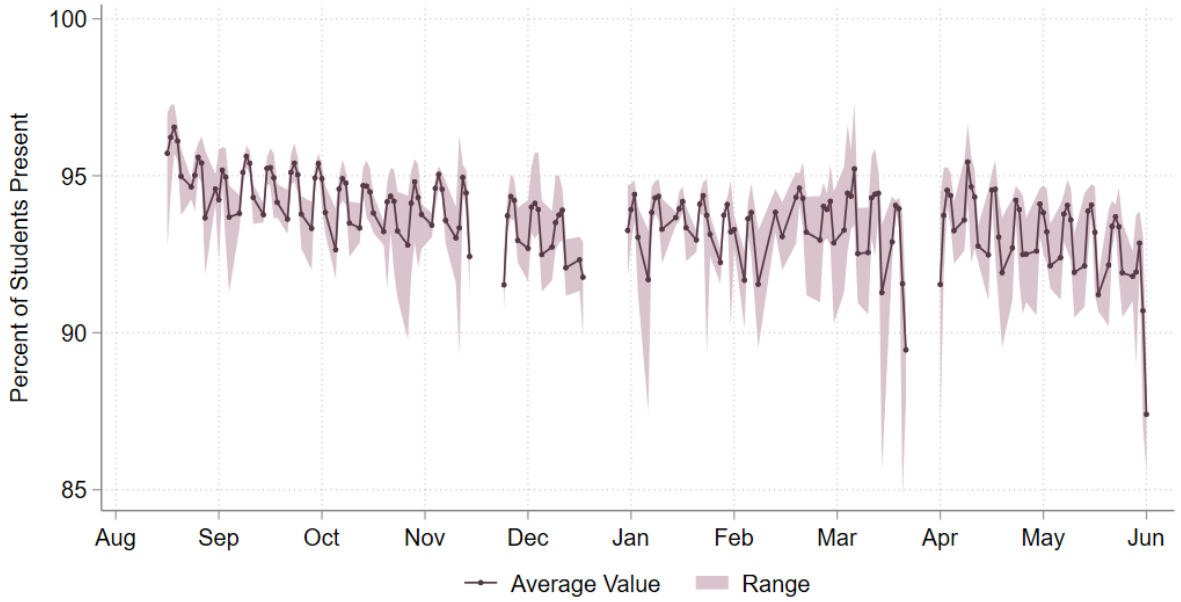
(F) Black (No AC)

Notes: Scatter plots represent the combination of neighborhood characteristics (median housing stock age and percent low middle income) that is most common for each race of students. Students attending all schools and schools without air conditioning are displayed separately. Only the 2011/12-2018/19 school years are included here.

FIGURE A2: Neighborhood housing stock age and percent low middle income by race and school air conditioning status



(A) All School Days



(B) All School Days, Excluding Known Anomalies

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

FIGURE A3: Percent of student body present, grades K-12, 2011/12-2018/19.

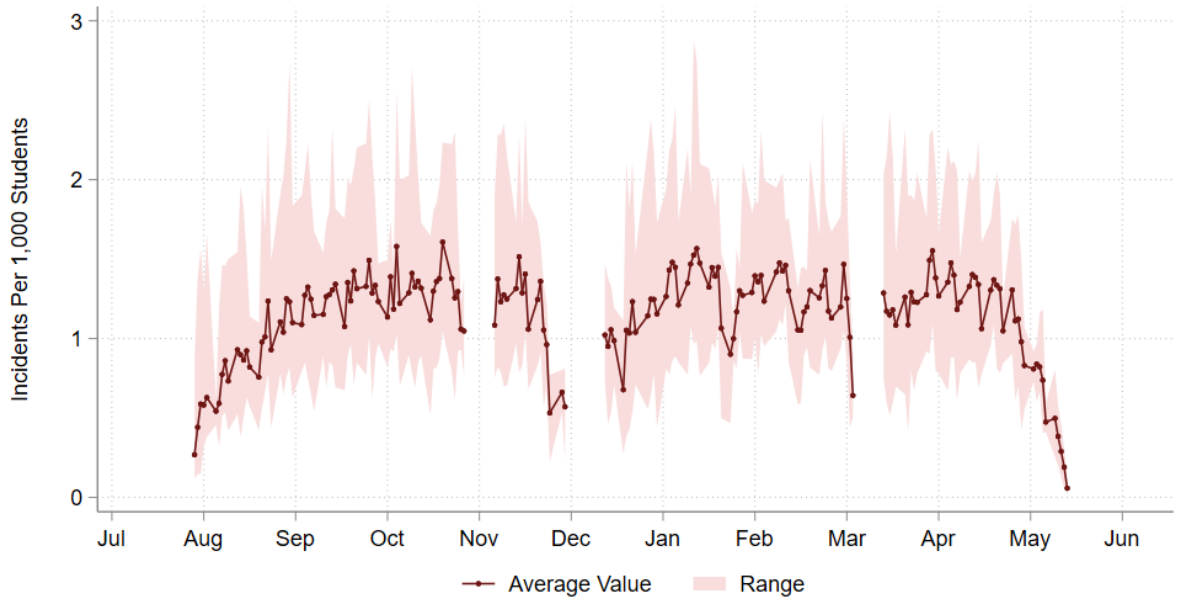
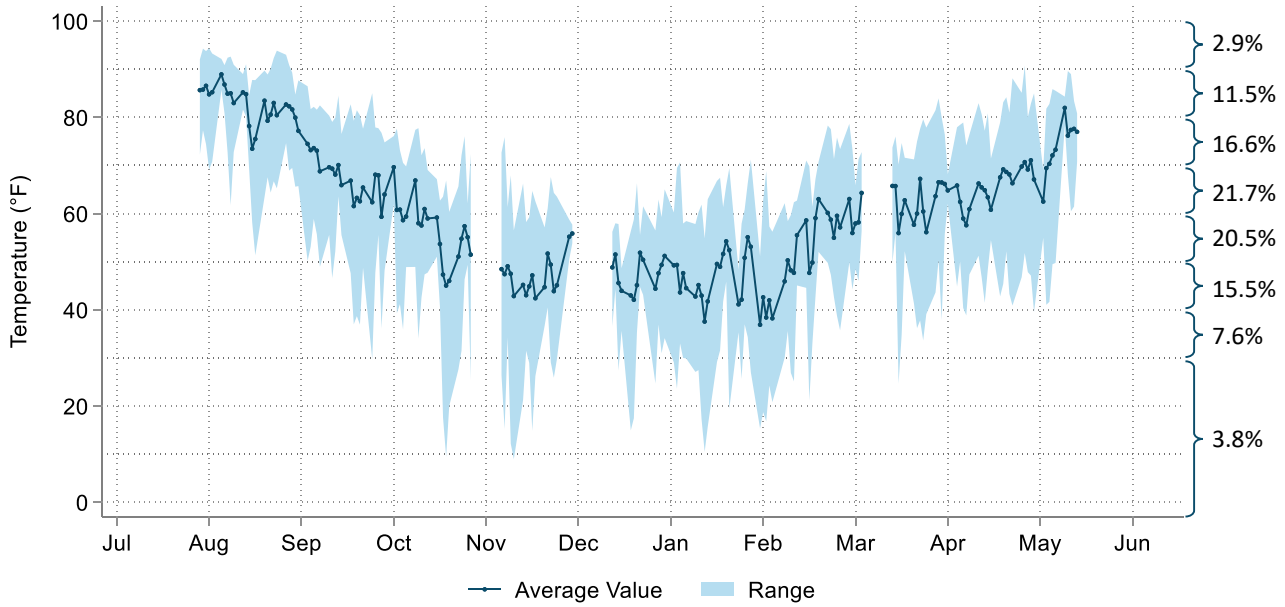
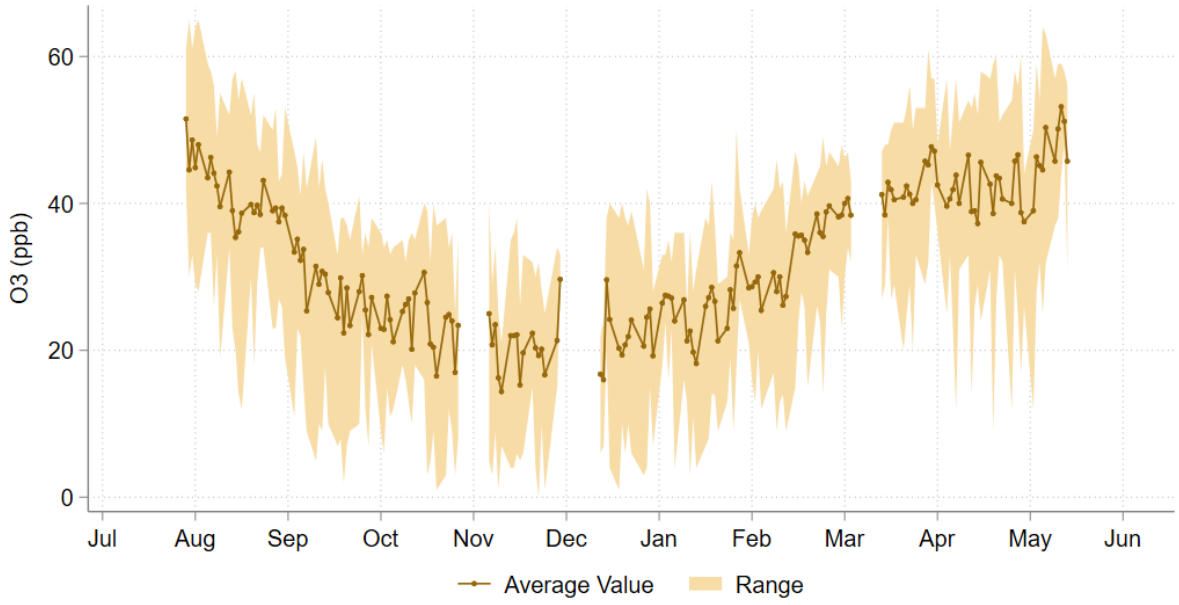


FIGURE A4: Incident count per 1,000 present students, grades K-12, 2011/12-2018/19. For the purpose of this image, the annual school year is shifted so that weekends are aligned. Blank spaces represent school breaks.

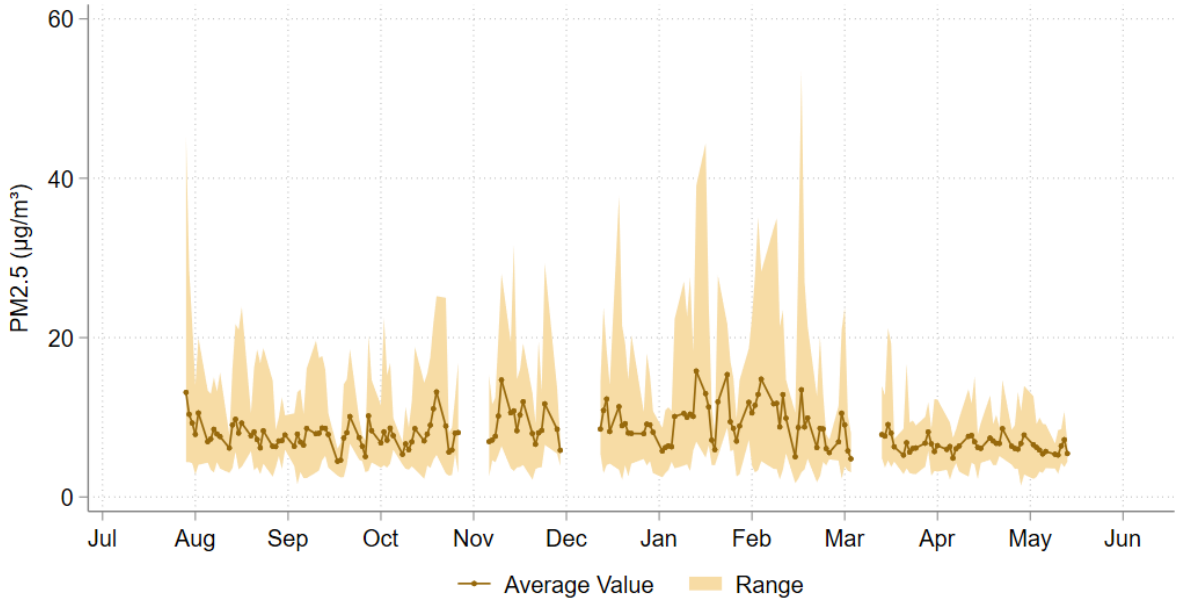


Notes: District-wide maximum temperature is calculated for all school days by averaging the outdoor temperature at all school locations. In this image, the academic school year is shifted to align weekends. Temperature values from the realigned data are displayed for a given day if it corresponds to a school day in at least two academic years.

FIGURE A5: Trends in daily maximum temperature during the academic year (2011/12-2018/19.)

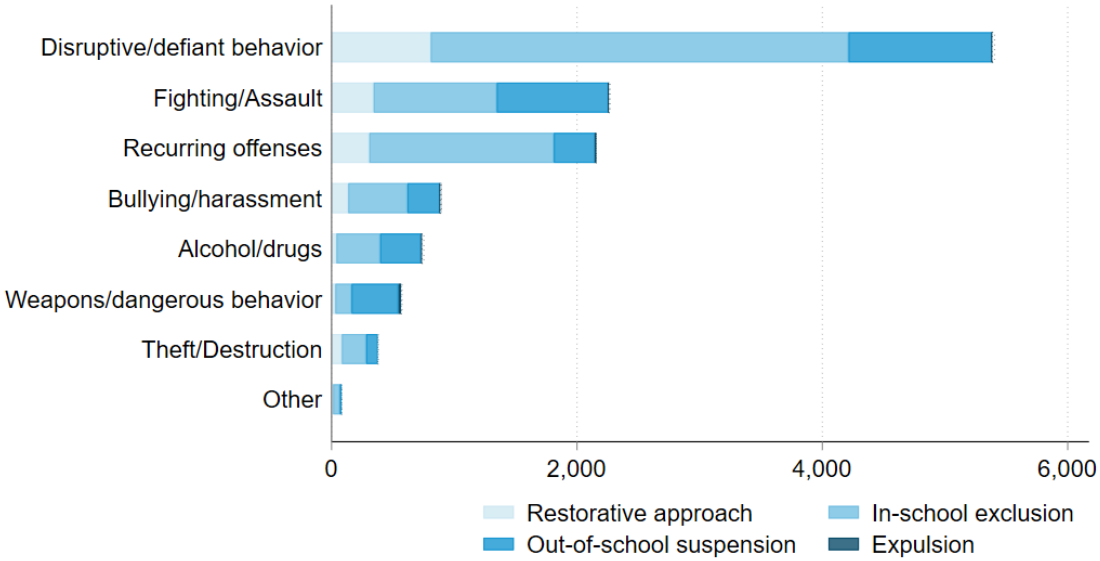


(A) Ambient Levels of Ground Level Ozone (O_3)



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

FIGURE A6: District-wide seasonal trends in (a) O_3 and (b) $PM_{2.5}$ over the academic year. For the purpose of this image, the annual school year is shifted so that weekends are aligned. Blank spaces represent school breaks. Yellow and orange lines indicate "Moderate" and "Unhealthy for Sensitive Groups" levels of Air Quality Index health concern.



Notes: Referrals made on school days for all students during the 2014/15-2018/19 schools years are included. Details about categorization of referrals by behavior and discipline can be found in Tables A1 and A2 respectively. This figure shows only school-level discipline; referrals to law enforcement (police or fire) are not displayed here.

FIGURE A7: Behavioral referrals in an average year, by category and disciplinary outcome (2014/15-2018/19).

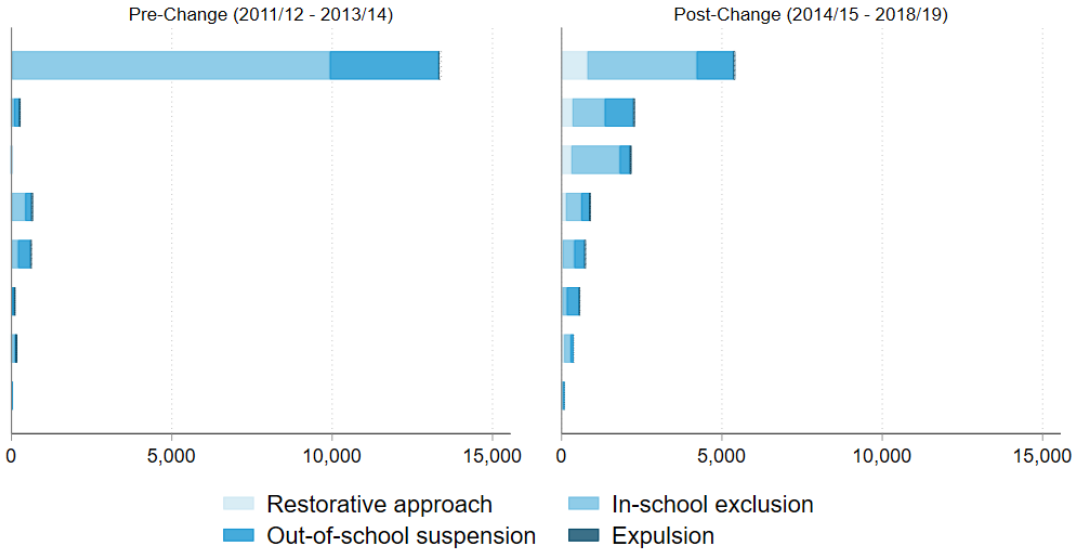
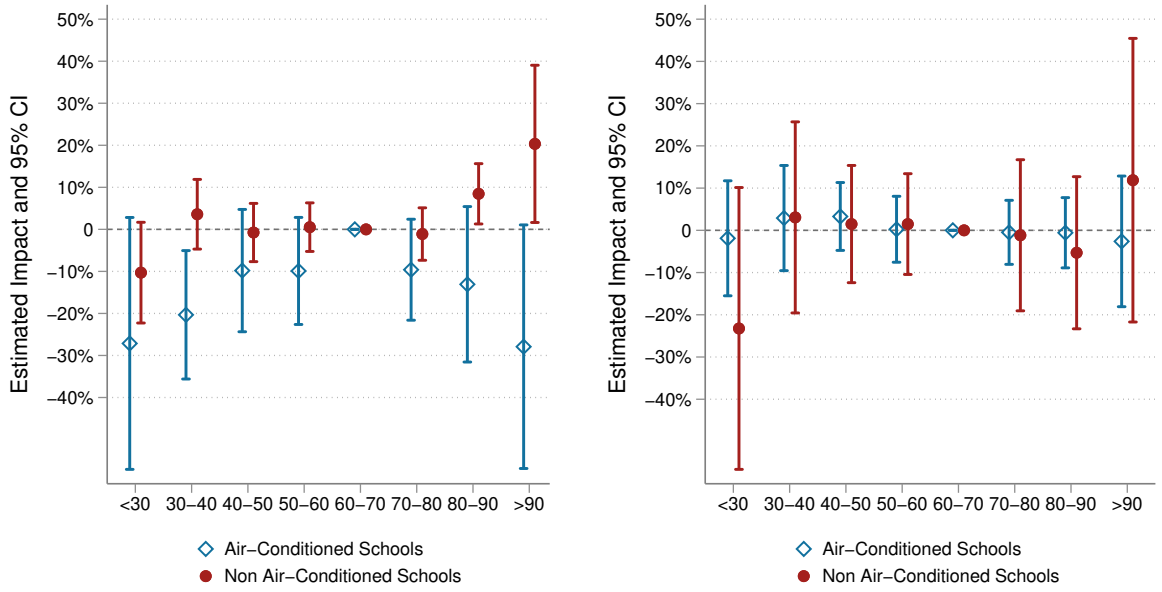


FIGURE A8: Behavioral incidents in an average year before and after reporting policy change, by category and disciplinary outcome.

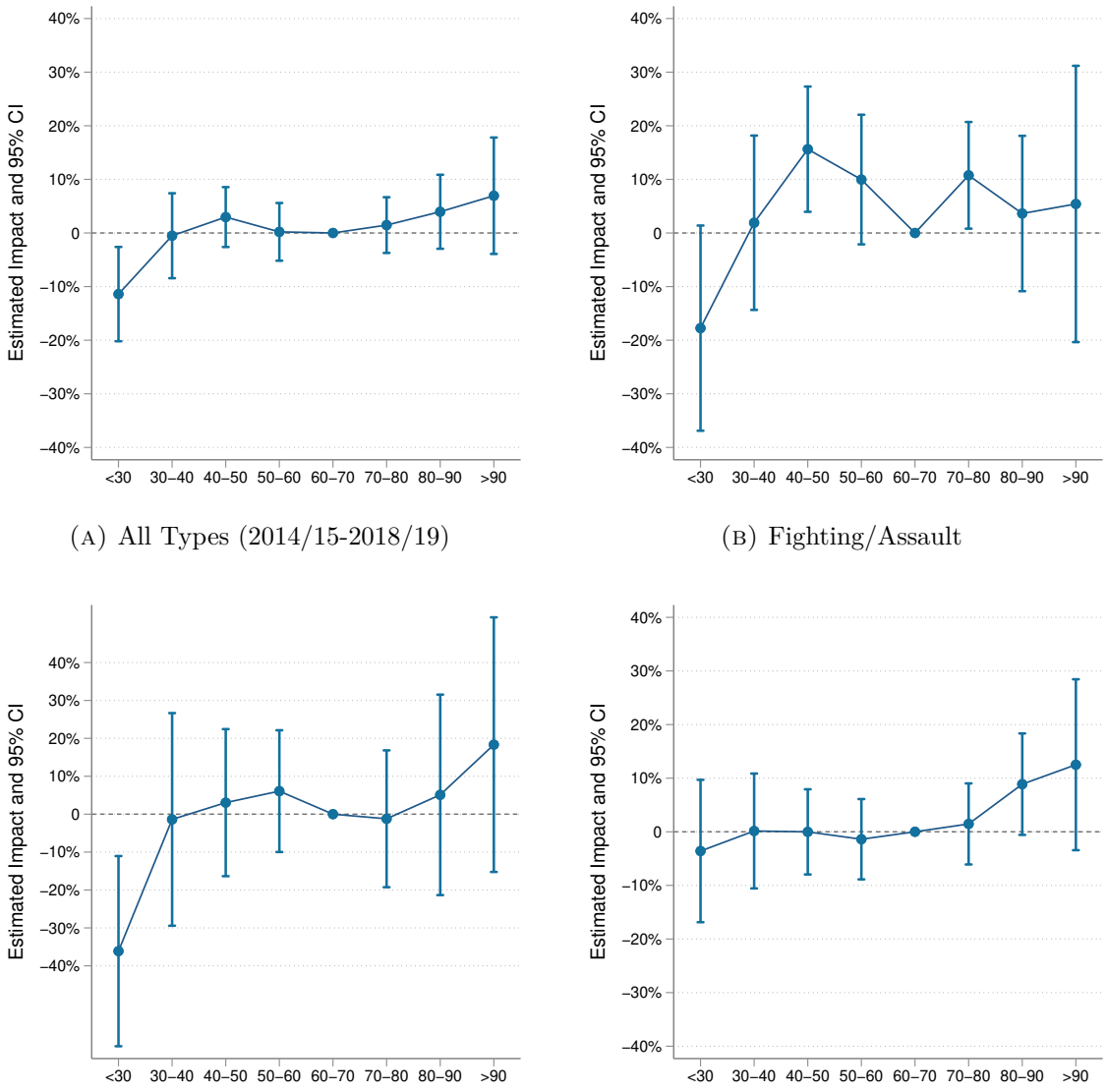


(A) Estimated $< \frac{1}{3}$ Home AC

(B) Estimated $> \frac{2}{3}$ Home AC

Notes: Coefficient estimates are taken from linear regressions modeling daily, student-level behavioral referrals on indicators for binned temperature for the 2011/12-2016/17 academic years for students attending schools with and without AC. Panel A shows this relationship for students in neighborhoods where less than a third of nearby elementary schools have air conditioning. Panel B shows this relationship for students in neighborhoods where more than a third of nearby elementary schools have air conditioning. All estimates are expressed as a percent of the mean, district-wide daily referral rate (0.13%). Regressions include school, demographic (grade, race, 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.

FIGURE A9: Effect of temperature on behavioral referrals relative to a day with a maximum temperature between 60-70°F, by school air conditioning status and a proxy of home air conditioning penetration.



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

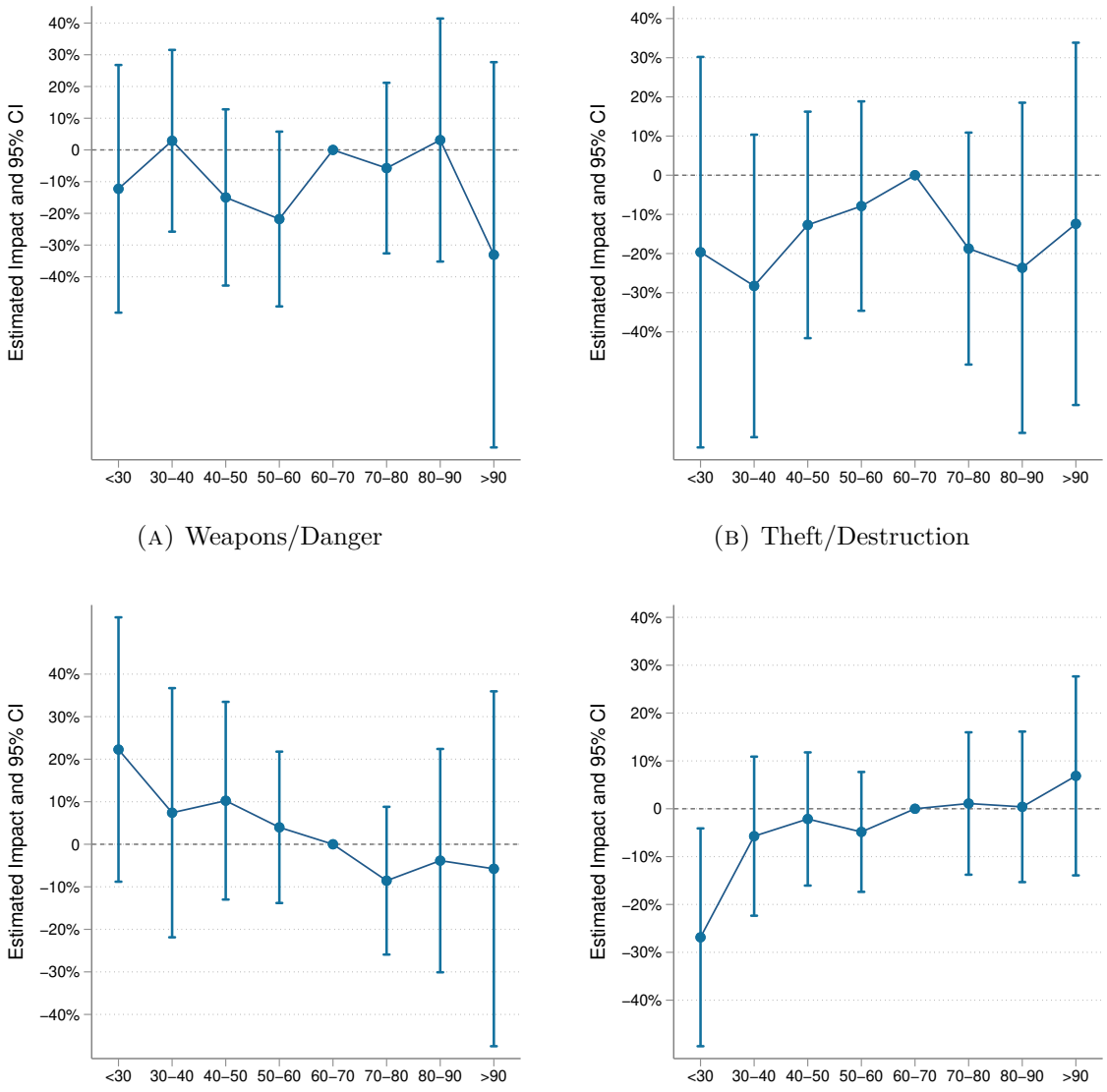
(B) Fighting/Assault

(C) Bullying/Harassment

(D) Disruptive/Defiant Behavior

Notes: Coefficient estimates are taken from linear regressions modeling daily, student-level behavioral referrals on indicators for binned temperature for the 2015/16-2018/19 academic years. All estimates are expressed as a percent of the mean daily rate of behavioral referrals of that type. Regressions include school, demographic (grade, race, 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.

FIGURE A10: Effect of temperature on referrals (separated by type of incident) relative to a day with a maximum temperature between 60-70°F.



(A) Weapons/Danger

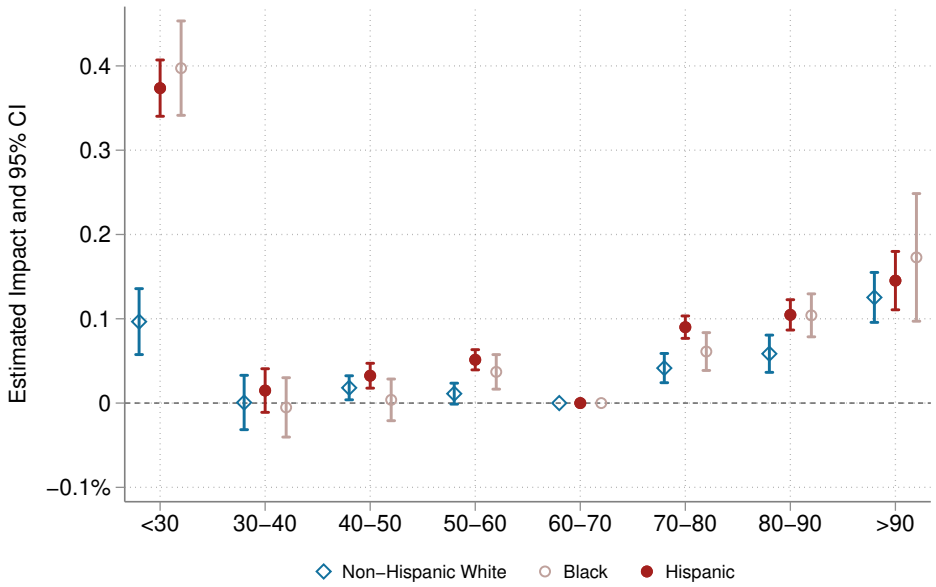
(B) Theft/Destruction

(C) Alcohol/Drugs

(D) Recurring Offenses

Notes: Coefficient estimates are taken from linear regressions modeling daily, student-level behavioral referrals on indicators for binned temperature for the 2015/16-2018/19 academic years. All estimates are expressed as a percent of the mean daily rate of behavioral referrals of that type. Regressions include school, demographic (grade, race, 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.

FIGURE A11: Effect of temperature on referrals (separated by type of incident) relative to a day with a maximum temperature between 60-70°F.



Notes: Coefficient estimates are taken from a linear regression modeling daily, student-level absences on indicators for binned temperature for the 2011/12-2016/17 academic years for students attending schools without AC. All estimates are expressed as a percent of the mean, district-wide daily absent rate (6.5%) or referral rate (0.13%). Regressions include school, demographic (grade, race, 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.

FIGURE A12: Effect of temperature on absences relative to a day with a 60-70°F max temperature, by race, for students attending schools without AC (2011/12-2016/17).

Appendix B: 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)

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 and facility characteristics by air conditioning status.

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

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

TABLE A4: Incident Categories by Student Demographic Characteristics.

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

Notes: This table reflects the population of students who were enrolled in school on at least one "school day" during the sample period. The composition of behavioral referrals by category is provided for gender, race, 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.