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

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This Draft: October 21, 2022

Link to Current Draft[1]

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 leverage between-year variation to estimate the causal effect of temperature on two dimensions of student behavior that are predictive of worse academic and later life outcomes: school absences and disciplinary referrals. Absenteeism increases in response to both hot and cold conditions, particularly for Black and Hispanic students. Hot conditions also increase the likelihood that a student will receive a disciplinary referral, a result driven by students attending schools without air conditioning. Results offer a potential mechanism through which academic outcomes are affected by hot temperatures and suggest that unequal access to adaptive technology, like air conditioning, both at home and at school, may exacerbate racial, ethnic, and socioeconomic disparities in school.

*I thank David Cutler, Joseph Aldy, Marcella Alsan, and Edward Glaeser for their continued guidance and support. I am grateful to the partnering school district for providing data access and assistance throughout this research process. I am also grateful to Joshua Goodman, Jisung Park, and Mark Shepard for their valuable feedback, as well as the participants of the Harvard Environmental Economics Workshop and Seminar, the Public Finance/Labor Workshop and Seminar, the Economics and Social Policy Workshop and Seminar, and the Northeast Workshop on Energy Policy and Environmental Economics. I gratefully acknowledge financial support from the Joseph Crump Fellowship at Harvard University.

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

1 Introduction

How does student behavior respond to extreme temperatures, and who is most affected? Students exposed to hotter conditions tend to perform worse on tests and to graduate at lower rates (Goodman et al., 2018; Park, 2022; Park et al., 2021).[1] Although both school absences and disciplinary referrals are disruptive to learning and predictive of worse academic and later life outcomes, little is known about how they are affected by extreme temperatures.[2] Understanding these relationships may have important implications for school district priorities. In the United States, many schools are facing a record number of hot days, a trend that is expected to continue in a rapidly changing climate. At the same time, many school districts have deteriorating or outdated HVAC systems that are expensive to update.[3] Black, Hispanic, and low-income students tend to live in hotter areas and to have less access to air conditioning at school and at home (Goodman et al., 2018; Hsu et al., 2021). This contributes to concerns that climate change will exacerbate existing inequality in student outcomes as well as childhood and later life-well-being.

To estimate the causal impact of extreme temperatures on student absenteeism and disciplinary referrals, I link local weather data to a panel of daily, student-level data for approximately 70,000 K-12 students enrolled in a large urban school district from 2011 to 2019. I also construct measures of school and residential air conditioning penetration, which I match to each student. The resulting data set provides a detailed picture of student behavior, exposure to extreme temperatures, and access to adaptive technology. School- and student-fixed effects regressions identify the temperature-behavior relationship by leveraging purely between-year variation in environmental conditions, while accounting for the exact day of the school year as well as time-invariant student and school characteristics.

My identification strategy relies on the assumption that, across different school years, environmental conditions on a specific day of the school year are uncorrelated with unobserved determinants of student behavior. Several features of the school setting lend support to this assumption. First, changes in school schedules which might affect behavior are rarely made in response to environmental conditions, and when changes are made (e.g., snow days), those responses are easily observed. Attendance data allow me to observe which students

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

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

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

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

I present three primary findings about the effect of extreme temperatures on student behavior.[5] First, extreme temperatures exacerbate absenteeism, especially for minority and low-income students. Relative to school days with temperatures in the 60s (°F), students are 32% more likely to be absent on days with temperatures below 30°F. Moderately to extremely hot temperatures also result in an increase in absenteeism. Students are 8%, 9%, and 15% more likely to be absent on days where the temperature is in the 70s, 80s, and over 90°F, respectively. The absences of Black and Hispanic students are about twice as sensitive to hot conditions as the absences of white students, and over three times as sensitive to cold.[6] Consistent with Goodman (2014), I find that absences also increase in response to snow, particularly for Black, Hispanic, and low-income students.[7] 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.[8] Results suggest that both hot and cold conditions exacerbate existing racial and socioeconomic disparities in absences, reducing instructional time for the most disadvantaged students.

My second key finding is that disciplinary referrals increase in response to heat. On days with temperatures in the 80s (°F) and exceeding 90°F, students are 4% and 10% more likely to receive a disciplinary referral than on school days with temperatures in the 60s (°F). To my knowledge, this paper presents the first evidence that reported behavioral issues in schools are sensitive to temperature.[9] Hot conditions might be expected to exacerbate disciplinary problems if either students or their teachers experience a physiological response to heat that leads to irritability and anger, a mechanism hypothesized by a broad set of papers to explain evidence of heat-induced behavioral changes in adult populations (Anderson, 2001). Compared to adults, children are less able to regulate their body temperature, so their

[4]Observing the temperature-behavior 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). Mukherjee and Sanders (2021) highlight the advantage of greater observability and schedule consistency in their study of heat and misbehavior in prisons.

[5]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.

[6]Low income students are also more sensitive to both heat and cold, although the differences, as measured by neighborhood family income, are smaller than differences by race.

[7]Work by Currie et al. (2009); Chen et al. (2018) shows that absences also increase in response to higher levels of ambient air pollution.

[8]This difference in the likelihood of being absent translates into an average difference in instructional time of more than 2.5 days per typical school year (with 170 school days.

[9]A few papers explore the effect of annual shocks in pollution exposure 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 annual behavioral incidents (>95% of which result in suspensions). Persico and Venator (2021) find that close proximity of a student's school to an operating Toxic Release Inventory site is associated with a 1.6 percentage point increase in the annual likelihood of being suspended.

behavior may be particularly responsive to heat.[10]

With the exception of a few papers examining negative sentiment expressed online (Baylis, 2020) and workplace harassment complaints (Narayan, 2022), most of the work studying behavioral responses to heat has focused on adult crime, and evidence points to a heat-induced increase in violent crime in particular (Ranson, 2014; Burke et al., 2015; Bondy et al., 2018; Heilmann et al., 2021; Behrer and Bolotnyy, 2022). By contrast, in this study, I examine the broad range of behaviors that result in a disciplinary referral, including minor behavioral issues. These referrals capture real disruptions to learning, productivity, and interpersonal relationships but are rarely recorded in non-school settings. I find that the increase in behavioral referrals on hot days is composed largely of "disruptive" behavior, a category of referrals which includes irritability, anger, lack of respect, and disobedience. It is important to note that referrals may reflect student behavior, teacher behavior, or a combination of the two. Broad categories of referrals, particularly those involving teacher-student interpersonal encounters, like those for defiance or disruptive behavior, are understood to be particularly likely to stem from teacher bias or frustration (Okonofua and Eberhardt, 2015).

Finally, I find the increase in disciplinary referrals on hot days to be driven entirely by students attending schools without air conditioning. In these schools, referrals increase by 8% on days with temperatures in the 80s (°F) relative to days with temperatures in the 60s (°F), and above 90°F days see a 22% increase in referrals. I further find that the increase in disciplinary referrals on hot days is observed mainly among students who not only lack access to air conditioning at school, but also live in neighborhoods with low levels of residential air conditioning. The highest sensitivity is observed among Hispanic students, who, in this district, live in older, lower-income neighborhoods with the lowest levels of residential air conditioning penetration. These findings highlights the potential importance of the environment and access to adaptive technology in explaining racial and socioeconomic disparities in student behavioral outcomes and suggest that heat-induced behavioral changes may contribute to the observed negative effect of heat on learning.

The remainder of the paper is organized as follows. In Section 2, I introduce the institutional setting of the study and provide additional details on the data. I present key summary statistics in Section 3. Section 4 outlines my empirical strategies. In Section 5, I provide my main results and heterogeneity analysis. I discuss predictions from climate models in Section 6. In Section 7, I discuss the implications of my results and conclude.

[10] Exposure to even moderately hot weather is also associated with more all-cause emergency department visits among children, including for heat-related illness (Bernstein et al., 2022).

2 District Setting and Data

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

Many of the district's schools are not fully air conditioned, and hot temperatures in non-air conditioned schools have been a contentious issue among students, parents, educators, and the local community. For the first six years of the sample period, 53% 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 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.[11]

Like many districts in the country, the LUSD is actively developing best practices to prioritize new air conditioning installations. Initial planning prioritized schools for installation based on a 2015 temperature study, which measured the indoor temperatures of non-air conditioned schools during a hot week of the year. However, the district now prioritizes improving learning environments in "high-need" schools, while also considering building utilization and "geographic equity" (ensuring schools in all regions of the city see some improvements).[12] The need to prioritize future air conditioning installations, both in the LUSD and in districts across the country, provides additional motivation to examine which characteristics of students and schools are predictive of high sensitivity of student outcomes to heat and/or the effectiveness of air conditioning in mitigating this response.

[11]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.

[12]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).

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.[13] Unique student identifiers allow me to follow individual students across time. Daily student-level data include enrolled and absent minutes and student disciplinary referral information. Demographic information, which is provided at the annual level, includes student race/ethnicity, English Language Learner status, gender, and grade, and the census block of each student's home residence, which is reported at an annual level.

Student disciplinary referral data include every incident in the study period that merited administrative involvement. While some minor forms of misbehavior do not require administrator involvement (e.g., profanity, use of cell phones in class, etc.), the range of documented incidents and their disciplinary outcomes is large. For each referral, participant(s), the date and time, and all disciplinary responses to the incident, including whether a student was referred to law enforcement, are noted. I group incidents into eight broad categories based on about 50 incident descriptions: fighting/assault, bullying and harassment, weapons and dangerous behavior, theft and destruction, disruptive behavior, alcohol and drugs, recurring offenses, and other incidents. A list of event descriptions that fall into each category is provided in Table B4. I also categorize the disciplinary responses to these incidents in Table B5.

I link students to schools using enrollment data. For each school, I compile information using the LUSD social media accounts, district calendars, and news articles to identify school vacations and unexpected school disruptions, including power outages, snow days, bomb threats, gas leaks, and other disturbances to students' school days. I also construct school facility information, including building age and air conditioning installation history, from district planning documents.[14]

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

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

[14]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.

2.5 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.[15] Maximum outdoor temperature is chosen as the key measure of temperature (vs. minimum or average temperature), both because students attend schools during the middle of the day, and also because this region is characterized by substantial diurnal variation in air temperature. For example, the average minimum temperature on days with a maximum temperature between 80-90°F days is 55°F. Snow data come from the National Oceanic and Atmospheric Administration's Daily Global Historical Climatology Network. Daily fine particulate matter ($PM_{2.5}$) and ground-level ozone (O_3) readings come from monitor data provided by the U.S. EPA Air Quality System.

2.3 Neighborhood-Level Data

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

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

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.

[15] 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.

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. 43% of students are enrolled in English Language Learner programs, the majority of whom are Hispanic and speak Spanish as their first language.

3.1 Student and Neighborhood Characteristics and Access to Air Conditioning

Prior to the fall of 2017, approximately half of all students attended schools with complete air conditioning. Compared to non-white students, and especially black students, white students were less likely to attend air conditioned schools. Air conditioning was also more common in elementary and middle schools than high schools. Table B3 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.[16]

Access to residential air conditioning also differs by race/ethnicity. Relative to their white and Black peers, who tend to live in neighborhoods (census block groups) where 48-49% of homes are air conditioned, Hispanic students live in neighborhoods where, on average, only 34% of homes are air conditioned. Racial/ethnic differences in home air conditioning penetration may reflect differences in housing stock age and income, both of which are predictive of access to residential air conditioning.[17]

As illustrated in Figure A1, housing stock age is highly correlated with home air conditioning penetration, with newer housing units being substantially more likely to be air conditioned. Air conditioning penetration is also higher in high-income neighborhoods, although substantial variation within income groups remains. Hispanic and white students tend to live in older neighborhoods than Black students. However, white students are substantially less likely to live in lower-income neighborhoods than both Black and Hispanic students. On average, white, Black, and Hispanic students live in neighborhoods where 37%, 59%, and 65% of households are low or moderate income (LMI), respectively.[18] Therefore, compared to their Black and white peers, Hispanic students tend to be concentrated in neighborhoods

[16]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.

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

[18]Black and Hispanic students are also substantially more likely than white students to live in neighborhoods with a higher average land surface temperature. The distribution of land surface temperature by race is illustrated in Figure A3.

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

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

that are characterized by *both* an aging housing stock and relatively low-income households.

As illustrated in Figure A2, 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 set of regressions predicting neighborhood residential air conditioning penetration from housing age, income, and race, the results of which are shown in Table B1, suggest that both income and housing age may be independently important predictors of home AC. A ten year increase in the median age of the housing stock is associated with a 7% decrease in average AC 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 AC penetration, Black students tend to live in neighborhoods with 5 percentage points lower AC penetration than white students after controlling for building age. After controlling for building age, Hispanic children live in neighborhoods with 13 percentage points lower AC penetration than white students.[19]

[19] The coefficient estimate on income is sensitive to the inclusion of housing age and, to a greater extent, race/ethnicity.

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

Both school and home air conditioning are correlated with building age, but substantial variation in residential air conditioning exists among both air conditioned and non-air conditioned schools. The correlation between school air conditioning and home air conditioning is 0.17. Within the "high" and "low" neighborhood AC categorization I create (above or below 50% AC penetration), school and home AC are even less correlated (correlation of 0.02 and 0.06 respectively). While census block estimates of residential air conditioning do not translate perfectly to access to home air conditioning for an individual student, the strongly bimodal nature of the data allows for central AC to be predicted precisely for many students: 22% of students live in census block groups with 0 or 100% residential air conditioning penetration.

3.2 Absences and Disciplinary Referrals

The average number of absences and disciplinary referrals differs by race/ethnicity, as well as by age and gender, as shown in Table 2. Hispanic and Black students are more than 30% more likely than white students to be absent from school. They are also more likely to receive a behavioral referral and are more likely to face harsher exclusionary discipline (suspensions, expulsions, or referrals to fire or law enforcement). This is especially true for Black students, who are six times more likely than white students to receive a severe penalty during a given year. Male students are more often involved in reported incidents than female students, and middle school students are the most likely age group to be referred for an incident. In an average year, approximately 10% of students receive at least one referral, and 4% of students receive multiple referrals.

Referrals are made in response to a variety of different behaviors. The average annual

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

Table 2: Student behavioral outcomes.

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

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 2011/12-2018/19 school years. All enrolled students are included, but statistics are only broken down by the three largest racial/ethnic groups, which comprise 92% of the student body, on average.

frequency and resulting disciplinary outcomes of each category of referral, from 2014/15-2018/19, is illustrated in Figure A8. 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 A9. 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, as shown in Table B6, 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.

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 A4, demonstrating a general downward trend throughout the year and dips in attendance around school breaks. Panel B of Figure A4 illustrates this trend after excluding snowy days and known city-wide events expected to affect attendance.

The daily rate of behavioral referrals across the district is illustrated in Figure A5. Even a cursory look at trends in referral rates reveals a striking pattern around school breaks, with the rate of referrals 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.[21] 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 A6, 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 A7. 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.

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 Main Estimating Equation

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

[21] 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).

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.[22] 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. Results are robust to including student- or student-by-year fixed effects in place of school and student demographic controls.

Year fixed effects, γ_y, and a set of daily timing controls, δ'_{ty}, are included to ensure that the model is identified off of variation between academic years, holding the time of the year constant. These daily timing controls include fixed effects for the day of the week and the day before and after a holiday as well as 155 "day of school year" fixed effects, each of which corresponds to a day of the school year (first day of school, second day of school, etc.). 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.[23] The last two weeks of the spring semester are excluded because many schools have testing during this time, and enrollment declines substantially over these weeks. Heteroskedasticity-robust standard errors are clustered at the school level because temperature is experienced differently for students living in different neighborhoods and mitigating technology differs at the school level.

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,

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

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

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 in these specifications.

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.[24] The effect of temperature on behavioral referrals can therefore only be identified off of present students. If students whose referrals are particularly temperature-sensitive are also particularly likely to be absent on hot and/or cold days, then the estimated effect of temperature on 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 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 be affected by the number and composition of their peers. To understand how the number and composition of students present in class varies by temperature, I construct measures of the "size" and "risk" of each school-by-grade-by-year group, which, in the absence of classroom assignment data, I define as a "class". I define the class size, $\overline{Z_{icty}}$, of present student i in class c on day t in academic year y as the percent of their enrolled peers who are present. I define class risk, $\overline{R_{icty}}$, as the percent of their present peers who receive at least one referral in the given year. Both are constructed as leave-out-means. I then estimate equation (1) where the outcome variable is $\overline{Z_{icty}}$ or $\overline{R_{icty}}$. The inclusion of $\overline{Z_{icty}}$ and $\overline{R_{icty}}$ in equation (1) when estimating the effect of temperature on behavioral referrals does not substantially change the coefficient estimates on binned temperature.[25]

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

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

4.2 Heterogeneity by school and residential air conditioning status

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

To 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. Including interactions with timing controls in all heterogeneity analyses is necessary to avoid attributing different patterns in behavioral referrals within each school year to correlated environmental conditions.[26]

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

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 this relationship because air conditioning status is not randomly assigned.[27] Two key concerns may arise when interpreting this relationship. First, if students are able to select into air conditioned schools or if families with more resources are more successful in lobbying for air conditioning to be installed in their local schools, it may be the case that students who are less exposed or vulnerable to heat (e.g., have fewer chronic condi-

[26] For example, if more "chances" are given to certain groups of children (e.g., younger children) before a referral is made, there may be fewer referrals early in the school year for this group, when temperatures are particularly hot. When comparing how sensitive referrals are to hot days between older and younger children, failing to account for how often referrals are typically made at a given time of the year for each group would cause one to confuse differences in sensitivity to differences in leniency/"second chances".

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

tions, live in neighborhoods with more trees, etc.) may be more likely to attend schools with air conditioning. The descriptive statistics discussed earlier and provided in Tables 1 and B3 do not lend support to this hypothesis, however. Students attending air conditioned schools are, on average, more likely to live in low-income neighborhoods and hot neighborhoods, more likely to be English Language Learners, and less likely to be white.

However, because building age is predictive of school air conditioning status and the housing age is predictive of residential air conditioning penetration, students attending schools with air conditioning are also more likely to live in homes with air conditioning. Observed heterogeneity by school air conditioning status may therefore capture differences in sensitivity by both school and home air conditioning. To examine these two dimensions of heterogeneity separately, I divide the sample into four groups of students, which are described in Table B2: students with access to air conditioning at home and at school, students without air conditioning in both places, and students who have access to air conditioning just at home, or just at school.[28]

4.3 Heterogeneity by race/ethnicity and income

In addition to studying heterogeneity by air conditioning penetration, I also examine differences in temperature sensitivity by race/ethnicity and neighborhood measures of household income. When studying these dimensions of heterogeneity, I restrict the sample to non-air conditioned schools (2011/12-2016/17), and create interaction terms by each student/neighborhood characteristic, following equation (2).[29] I show that the heat-behavioral referral relationship is sensitive to access to air conditioning so when examining heterogeneity in this relationship, I include race/ethnicity-specific or income group-specific controls for residential air conditioning penetration. This offers evidence as to whether differences in access to residential air conditioning explain any observed heterogeneity by race/ethnicity and income.

In most specifications, including those described in subsections 5.1-5.3 coefficient estimates on binned temperature are presented as a percent change from the district-wide mean absence (0.065) and referral rates (0.013). Average absence and referral rates differ substantially by race/ethnicity and income. To allow for an easier interpretation of heterogeneity in these relationships and resulting changes in disparities in educational outcomes, I present results of the specifications described in this section in terms of level changes. Coefficient es-

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

[29]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).

timates 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 explore heterogeneity in the temperature-behavior relationship by access to residential air conditioning, race/ethnicity, and neighborhood income. Finally, I discuss which types of disciplinary referrals appear to be particularly sensitive to heat.

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.[30] Coefficient 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 access to school air conditioning status.

5.2 Heat increases behavioral referrals in schools without air conditioning

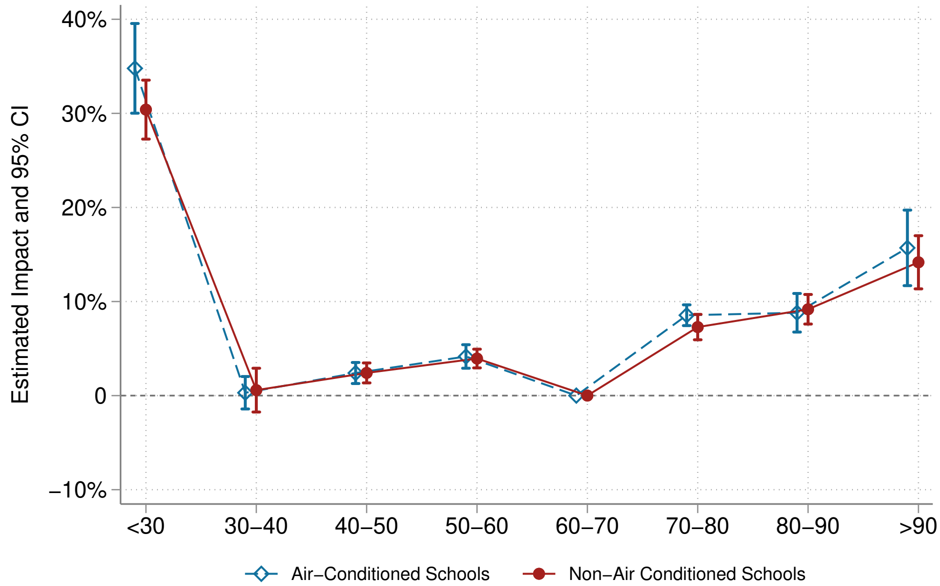
Referrals are also affected by both hot and cold temperatures. As shown in Panel B of Table 3, referrals are 4% and 10% higher on 80-90°F and >90°F days, respectively, compared with 60-70°F days. However, this effect is not statistically significant when estimated for all schools.

[30] I highlight the hottest and coldest temperature bins here; the full set of coefficient estimates are provided in Tables B7 and B8. Even moderately hot temperatures appear to increase absences, but more temperate days appear to be generally more similar to each other than days characterized by more extreme temperatures. When controls for snowfall are not included, days with a maximum temperature below 30°F have absences that are 44% higher than 60-70°F days. Coefficient estimates of bins below 60°F are also sensitive to the inclusion of snowfall controls.

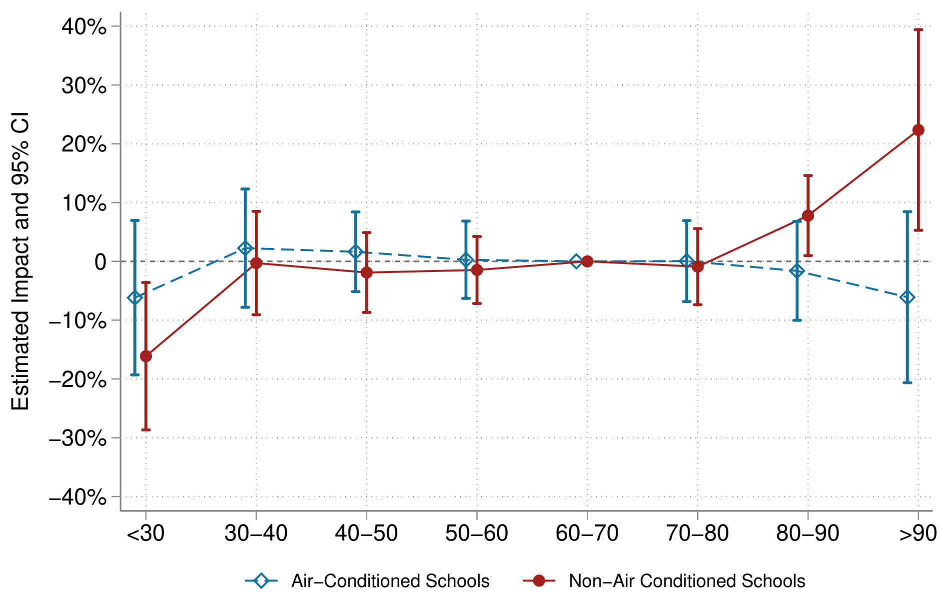
Table 3: Effect of temperature on absences and behavioral referrals relative to a day with a maximum temperature between 60-70°F.

	Linear	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 and poisson regressions modeling daily, student-level behavioral referrals on indicators for binned temperature and 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. Specifications 1, 2, and 4 include school and demographic (grade, race, gender, "English learner") fixed effects. Specification 3 includes student-by-year fixed effects. 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 the 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. The full set of coefficient estimates are provided in Tables B7 and B8



(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).

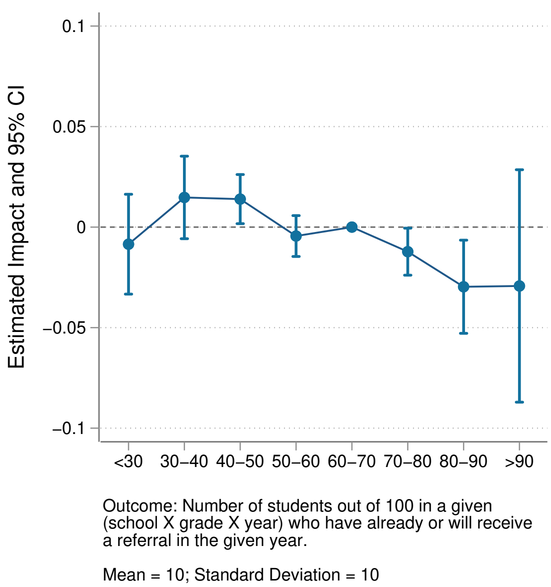
The inclusion of school air conditioning status interaction terms in columns 4 and 5 of Table 3 suggests that the estimated coefficients on hot temperatures in specifications that include all schools mask substantial heterogeneity in this relationship by school air conditioning status. The comparison between air conditioned and non air conditioned schools, illustrated Figure 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%.[31]

Disciplinary 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 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°F day, 0.03 fewer students with a high-propensity to receive a referral would be present in a school x grade of 100 students. Class size is more affected, although the magnitude of the change does not appear to be large. On the coldest days, the average school x grade of 100 students would be missing an additional 2 students.

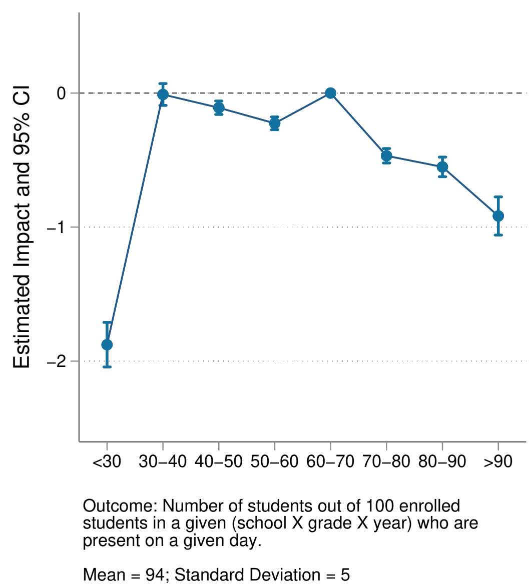
The inclusion of these measures of class size and composition in the main temperature-behavioral referral regression does not substantially affect results. However, the simple inclusion of these measures is insufficient to account for the effect of class size and composition on behavior. While observed 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".[32]

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

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



(A) "Class Risk"



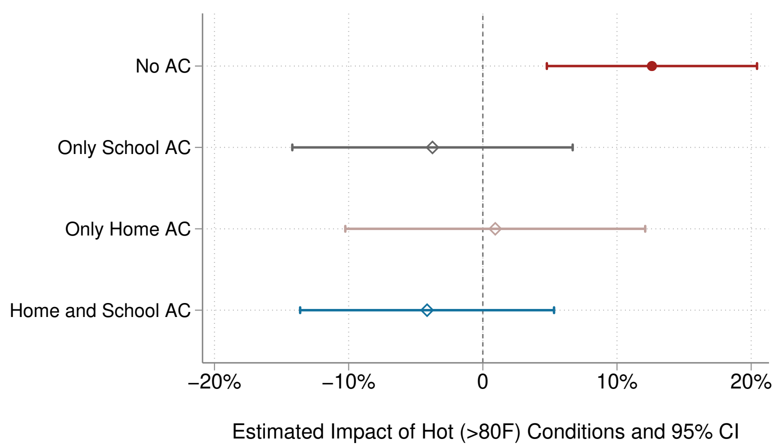
(B) "Class Size"

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".

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

School air conditioning status is not randomly assigned, so results illustrated in Figure 1 should not be interpreted as capturing the causal effect of school air conditioning on behavior. Schools in newer neighborhoods are more likely to be air conditioned, and new neighborhoods also have higher rates of residential air conditioning penetration (correlation of 0.17). Using census block-level estimates of residential air conditioning penetration, I identify "high residential AC" neighborhoods as those where the majority of housing units have central air conditioning. I then use this measure to compare how behavioral referrals respond to hot conditions among four groups of students: those who don't have access to AC, those who only have AC at school, those who only have AC at home, and those who have access to AC in both places. For simplicity and to avoid a lack of power, I combine the highest two temperature bins in this analysis, constructing a >80°F bin. I also combine bins representing a maximum temperature between 30 and 80°F. The coefficient estimates on the >80°F bin are shown in Figure 3.



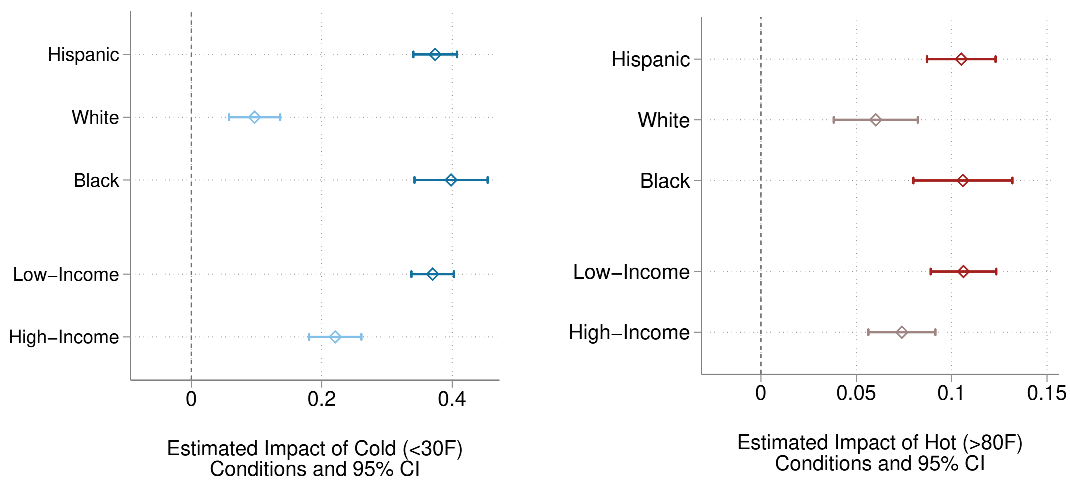
Notes: Coefficient estimates are taken from a linear regression modeling daily, student-level referrals on indicators for binned temperature for the 2011/12-2016/17 academic years for students living within the county limits. "Home AC" indicates that a student is living in a neighborhood where the majority of housing units have central AC. 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 3: Coefficient estimates of the effect of >80°F conditions on behavioral referrals relative to a day with a 30-70°F max temperature, by home and school air conditioning status (2011/12-2016/17).

Results indicate that the difference in sensitivity of behavioral referrals to heat illustrated in Figure 1 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 AC in both places, but the disciplinary referrals of students who have access to air conditioning *either* at home or at school are also less sensitive to heat than students who lack access to air conditioning in both places.

5.4 The effect of extreme temperature on behavior varies by race and socioeconomic status

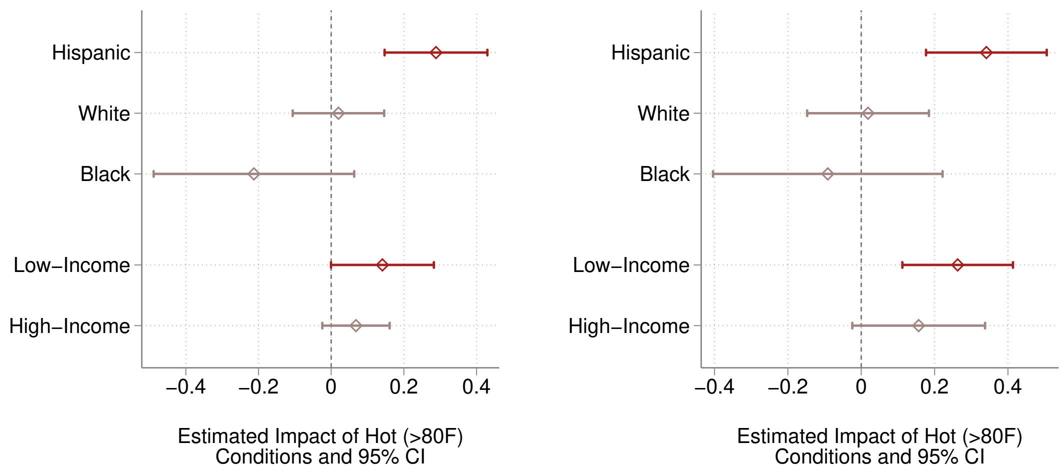
I next explore heterogeneity in the effect of temperature by student and neighborhood characteristics, focusing particularly on the students who attend schools without air conditioning. For simplicity and to avoid a lack of power, I combine the highest two temperature bins in this analysis, constructing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



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 without AC. Estimates are expressed as absences per 15 students, which is approximately equivalent to normalizing by the mean, district-wide daily absent rate (6.5%). 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 cold (<30°F) and hot (>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).

Coefficient estimates of the effect of <30°F and >80°F temperatures on absences are illustrated in Figure 4. 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.[33] Absences of students in lower income neighborhoods, defined as having greater than the median percent of low- or moderate-income households (over 60%) also appear to be more sensitive to temperature. The attendance of Black, Hispanic, and low-income students is also more sensitive to snow, as illustrated in Figure A10.



(A) Without Home AC Controls (B) With Home AC Controls

Notes: Coefficient estimates are taken from a linear regression modeling daily, student-level behavioral referrals on indicators for binned temperature for the 2011/12-2016/17 academic years for students attending schools without AC. Estimates are expressed as absences per 1,000 students, which is approximately equivalent to normalizing by 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 5: Coefficient estimates of the effect of >80°F conditions on behavioral referrals relative to a day with a 30-80°F max temperature, by student and neighborhood characteristics in schools without air conditioning (2011/12-2016/17).

Coefficient estimates of the effect of >80°F temperatures on behavioral referrals are illustrated in the Figure 5. Results indicate that referrals of Hispanic students are more responsive to temperature than referrals of either white or Black students.[34] 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

[33]The full set of coefficient estimates from race-specific regressions is illustrated in Figure A13

[34]Referrals of Black students are imprecisely estimated for all temperature bins. When focusing just on temperatures exceeding 90°F,

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.

5.5 Sensitivity to heat varies by category of behavior

The types of behavior affected by heat and cold are illustrated in Figures A11 and A12. While patterns are only suggestive, disruptive behavior appears to be the most responsive to hot (>80°F) temperatures.[35] 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.

6 Student Behavior and Climate Change

Climate change is expected to result in an increase in the number of school days with moderately and very hot temperatures. Estimates from an RCP6.0 scenario suggest that by 2050, the average school year in the LUSD will be characterized by 60% more days with a maximum temperature exceeding 80°F than in 2000, and twice as many >90°F days.[36]

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 a 18% decrease in the number of days with a maximum temperature below 30°F. This lack of symmetry in changes in hot and cold conditions may be due to increased variability in temperature. 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.[37] Changes in precipitation events, air pollution from wildfires, and other forms of extreme weather may also affect student behavior, although modeling these directly is challenging.

To predict how student behavior will be affected by climate change, I rely on temperature projections developed by Rasmussen et al. (2016), who provide annual county-level temperature projections and probability weights from a set of general circulation (GCM)

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

[36] These percent changes represent differences between 20-year average temperatures (1990-2010 and 2040-2060) taken from the RCP6.0 modeled temperatures.

[37] 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."

models. I use these data to assign each school day in the 1990-2010 and 2040-2060 school years to a temperature bin. I then use the model specified in equation (1) to compare absences and behavioral referrals in 2040-2060 (2050 20-year normal) to 1990-2010 (2000 20-year normal). For simplicity, I make two changes to the specification. First, rather than making assumptions about non-temperature environmental conditions, I exclude all non-environmental controls from the model, effectively assuming that whatever environmental conditions typically accompany a day with a certain maximum temperature will continue to do so. Second, due to the challenges of predicting the attendance of each individual student, I rely on a model predicting the disciplinary referrals of all enrolled students, rather than all present students. The data and prediction process are described in greater detail in Appendix C.

Relative to 1990-2010, behavioral referrals in the the first 30 days of the school year are expected to increase by 3% in 2040-2060, which represents a nearly doubling of the number of temperature-induced incidents during this period (from 3.7% to 6.2%). Over the full school year (excluding the last two weeks of school), there are expected to be 70% more temperature induced incidents in 2050 relative to 2000.[38]

Unlike behavioral referrals, absences are highly responsive to both cold temperatures and snow, so the response of attendance to future climate is highly dependent on how snowfall responds to warming conditions. Preserving the current temperature-snowfall relationship implies that while temperature-induced absences rise slightly (4%) in the first 30 days of the school year, about 1% fewer absences can be expected over the full school year, which translates to a 10% decrease in temperature-induced absences.[39]

7 Discussion and Conclusion

This paper explores the impact of extreme temperatures on student attendance and disciplinary referrals, two components of student behavior which may be disruptive to learning and affect later life well-being. To study this question, I link a data set of daily student-level behavioral outcomes from a large urban school district with environmental data and school and residential air conditioning information. I then leverage this data set to estimate the

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

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

short-term response of student behavioral outcomes to temperature. My empirical strategy exploits between-year variation in temperature, while controlling for the exact day of the school year as well as time-invariant student and school characteristics. This research design as well as my rich data set of student, school, and neighborhood characteristics, allows for a nuanced exploration of heterogeneity in this relationship.

I find that both hot and cold temperatures have a causal, statistically significant impact on student attendance. The attendance of both minority and low-income students is more affected by cold, and, to a lesser extent, by heat. Results indicate that, relative to temperate days with an outdoor maximum temperature between 60-70°F, days with a temperature between 80-90°F and exceeding 90°F result in an estimated 9% and 15% increase in absences. Very cold conditions, those with temperatures below 30°F, result in a 34% increase in absences.

I further find that behavioral referrals increase in response to heat. This response is driven by students attending schools that lack air conditioning and is largest among low-income and Hispanic students, who are the least likely to have access to air conditioning at home. In schools without air conditioning, behavioral referrals are 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.

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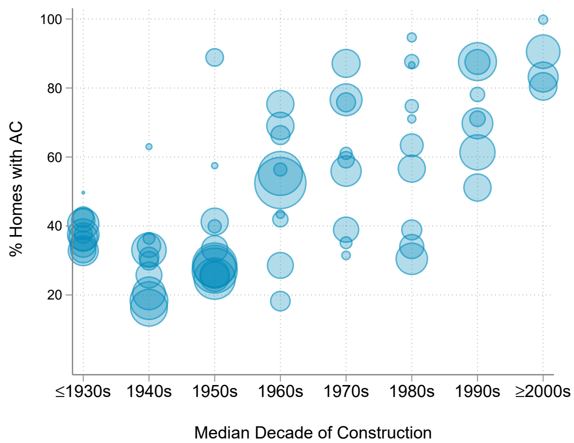
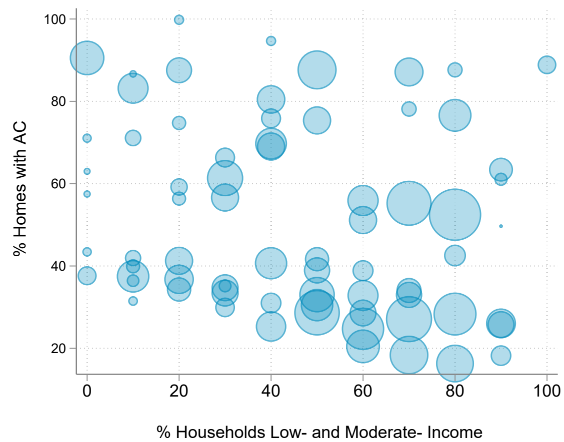
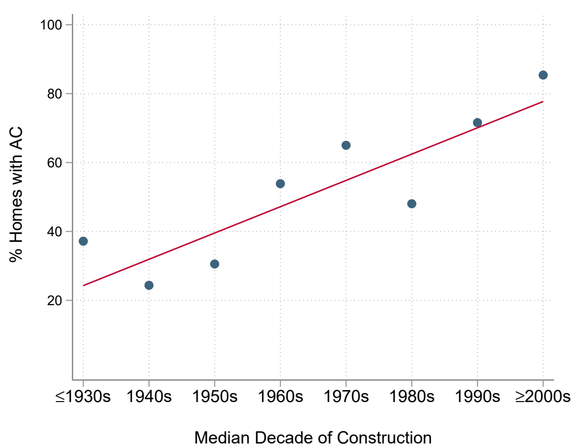
Appendix A: Additional Figures



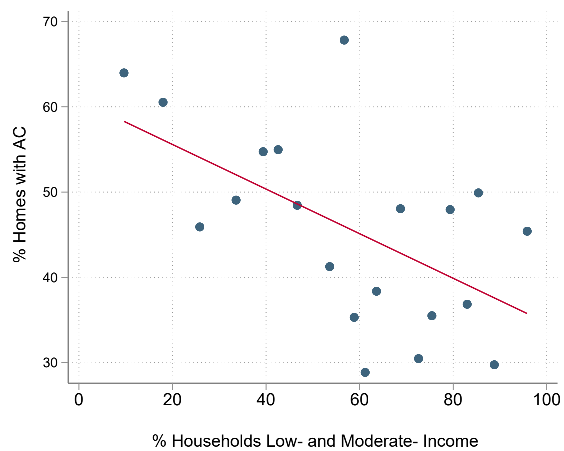
(A) Home AC by Neighborhood Age



(B) Home AC by Neighborhood Income



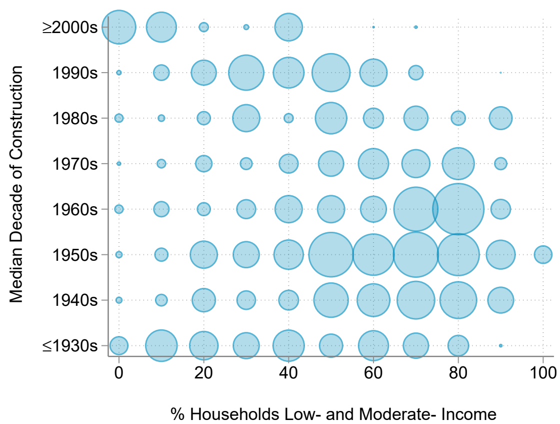
(C) Home AC by Neighborhood Age



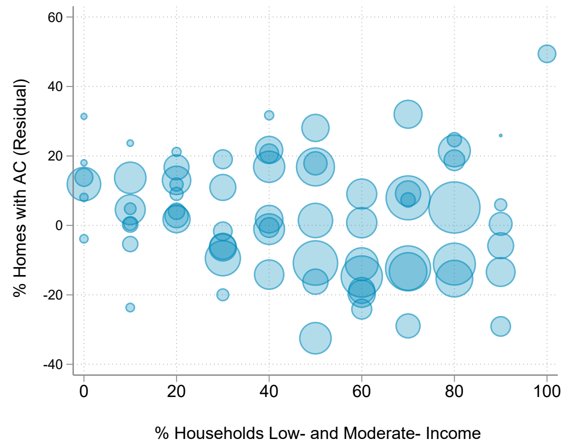
(D) Home AC by Neighborhood Income

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

Figure A1: Association between home air conditioning penetration and (A) neighborhood housing stock age and (B) percent low or moderate income



(A) Home AC by Neighborhood Age



(B) Home AC by Neighborhood Income

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

FIGURE A2: Association between home air conditioning penetration and (A) neighborhood housing stock age and (B) percent low or moderate income

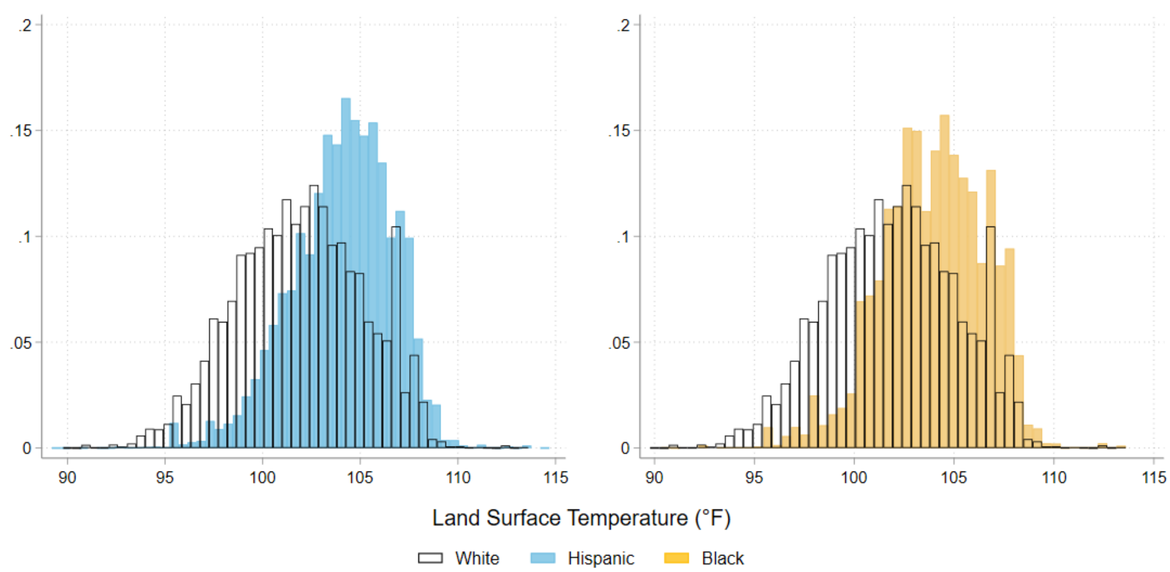
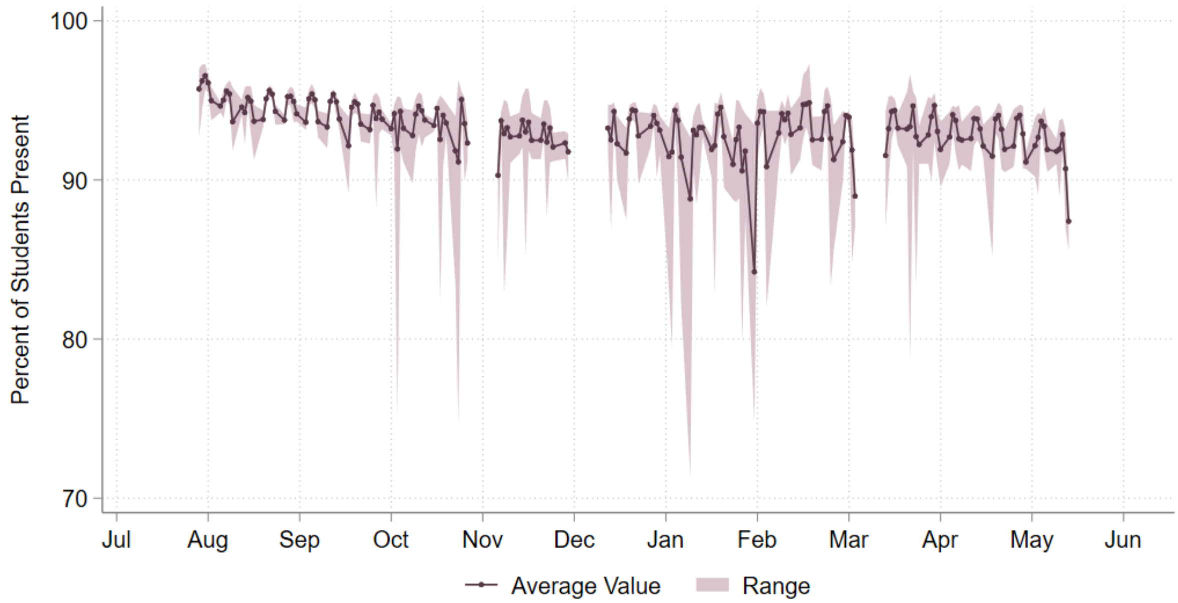
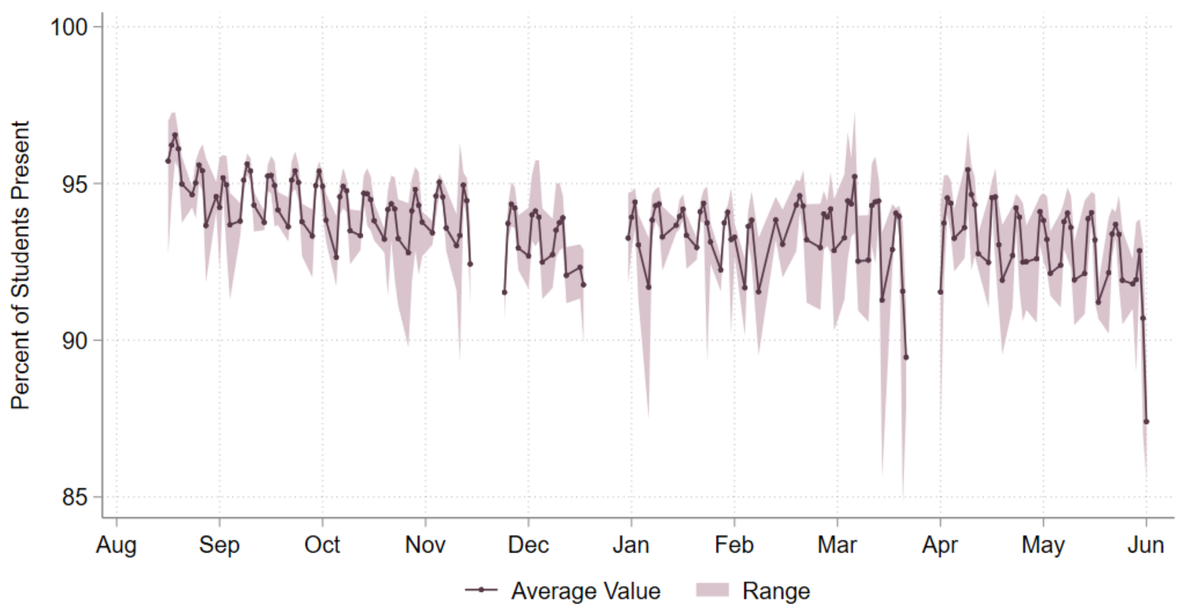


FIGURE A3: Distribution of summer land surface temperature by race for the three most common races.



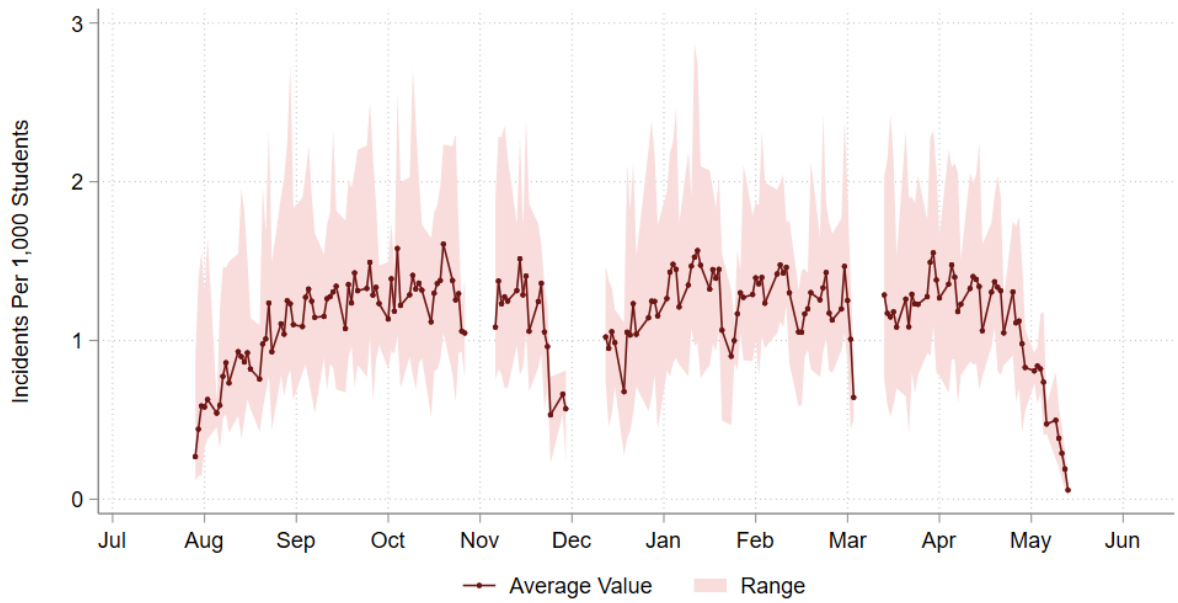
(A) All School Days



(B) All School Days, Excluding Known Anomalies

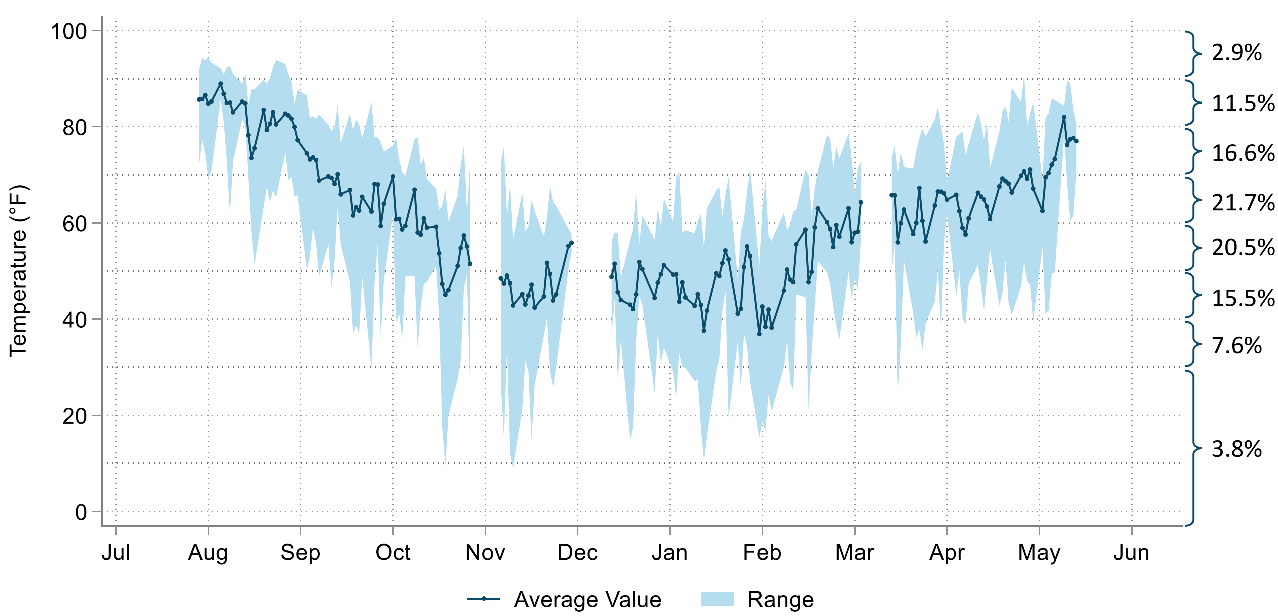
Notes: For the purpose of this image, the annual school year is shifted so that weekends are aligned. Blank spaces represent school breaks. In Panel B, days were excluded when absences were high due snowfall or an identifiable, non-environment related reason (Super Bowl parade, the "Day Without Immigrants"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

FIGURE A4: Percent of student body present, grades K-12, 2011/12-2018/19.



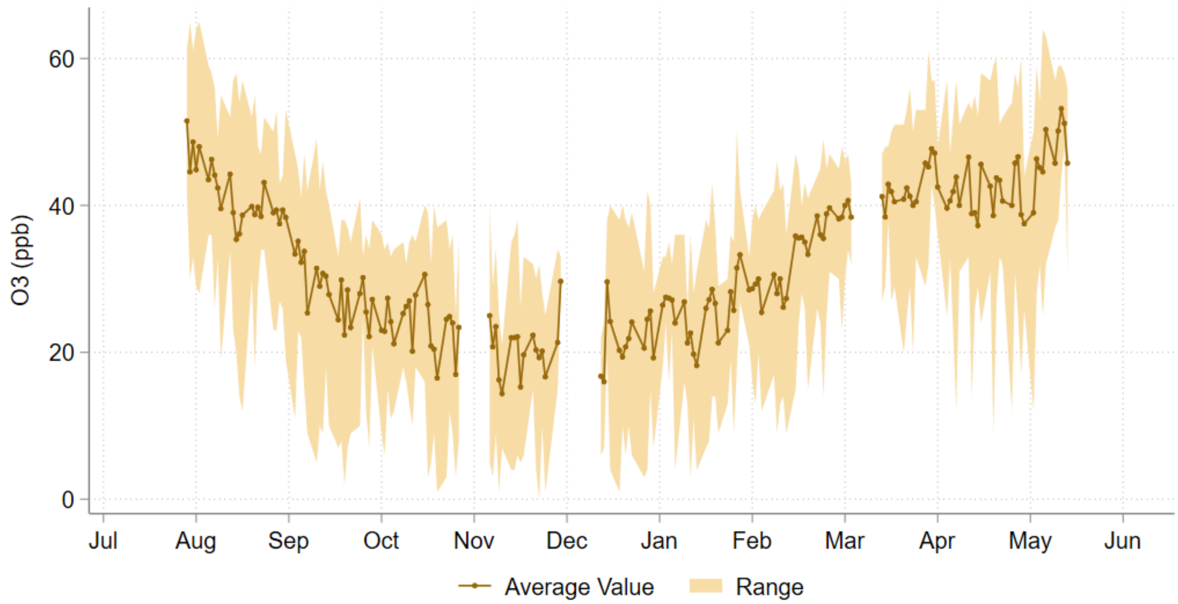
Notes: In this image, the academic school year is shifted to align weekends. Temperature values from the realigned data are displayed for a given day if it corresponds to a school day in at least two academic years. Blank spaces represent school breaks. Disciplinary referrals are presented per 1,000 present students.

FIGURE A5: Within-year trends in referrals per 1,000 present students (2011/12-2018/19).

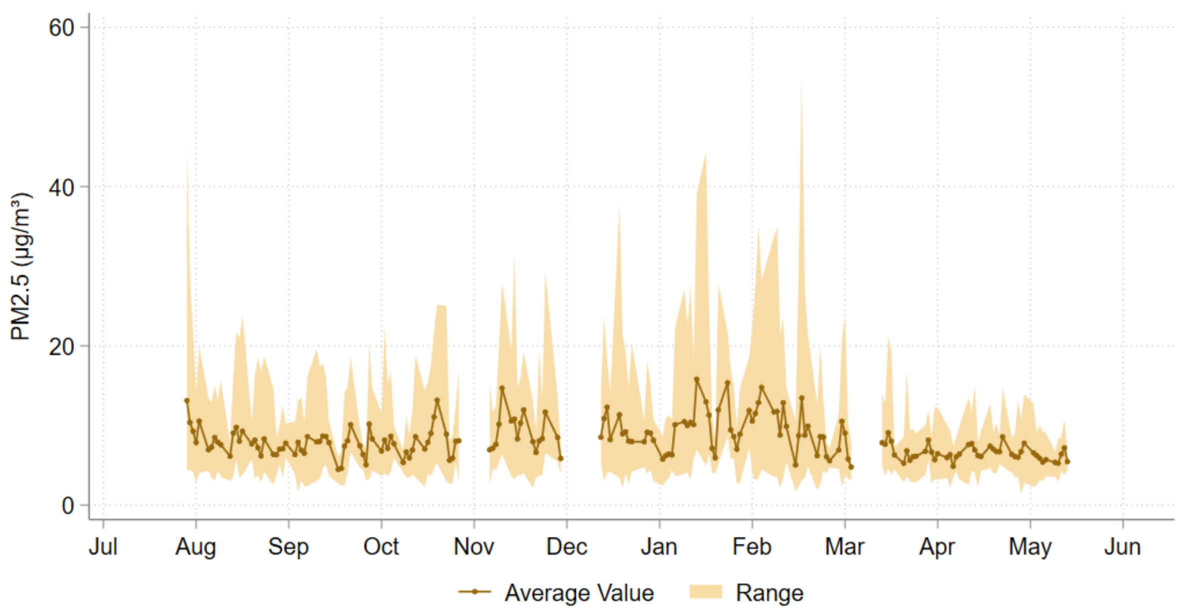


Notes: District-wide maximum temperature is calculated for all school days by averaging the outdoor temperature at all school locations. In this image, the academic school year is shifted to align weekends. Temperature values from the realigned data are displayed for a given day if it corresponds to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

FIGURE A6: Within-year trends in maximum daily temperature (2011/12-2018/19.)

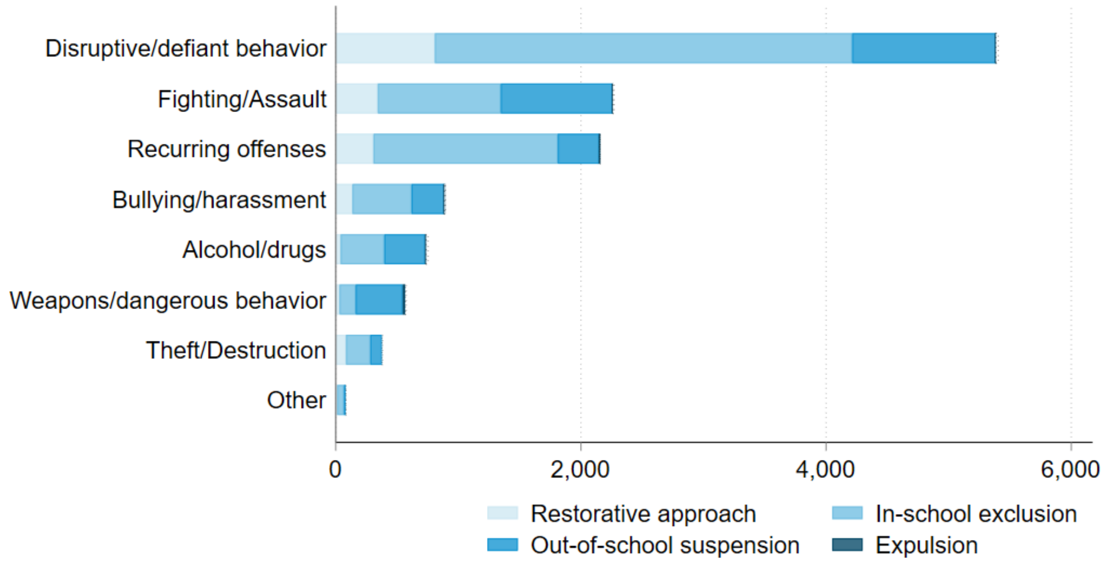


(A) Ambient Levels of Ground Level Ozone (O_3)



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

FIGURE A7: 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 B4 and B5 respectively. This figure shows only school-level discipline; referrals to law enforcement (police or fire) are not displayed here.

FIGURE A8: Behavioral referrals in an average year, by category and disciplinary outcome (2014/15-2018/19).

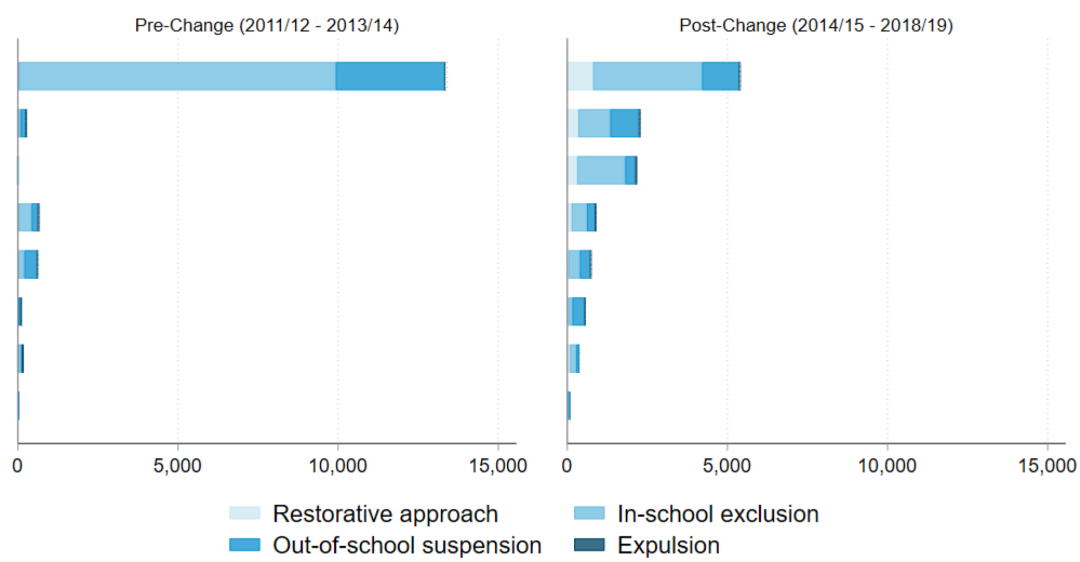
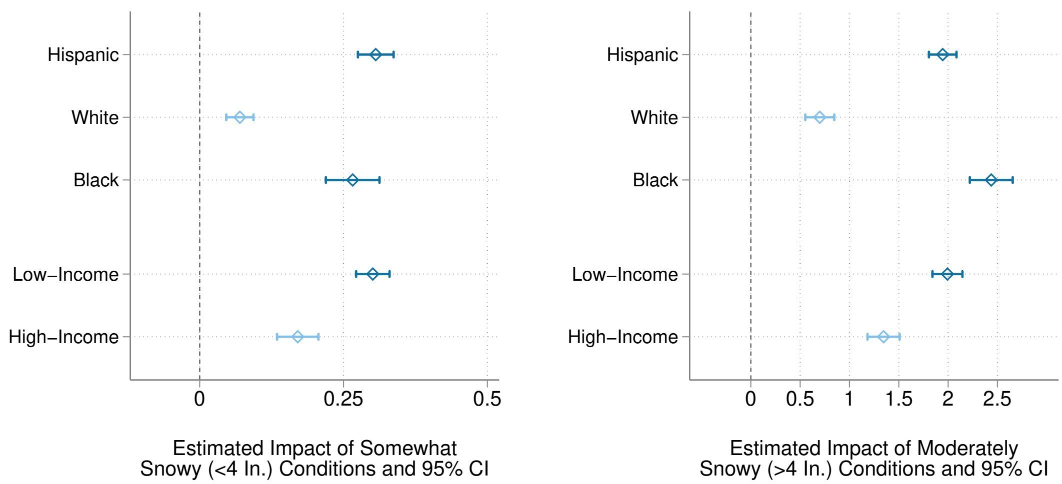
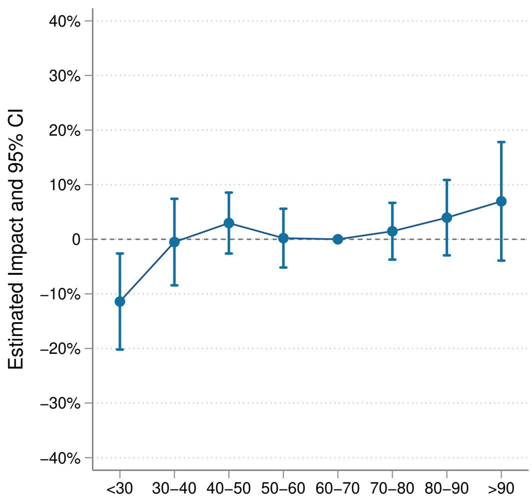


FIGURE A9: Behavioral incidents in an average year before and after reporting policy change, by category and disciplinary outcome.

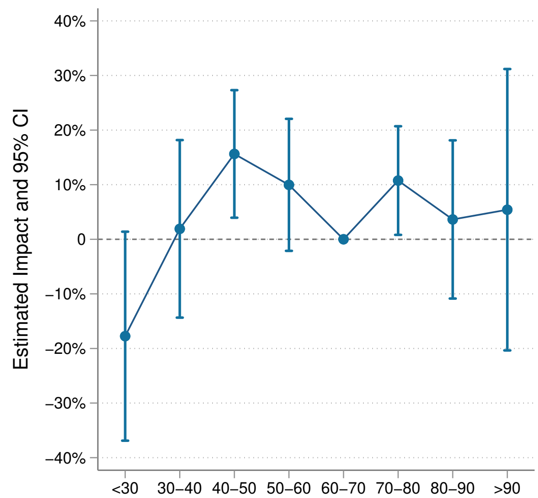


Notes: Coefficient estimates are taken from linear regressions modeling daily, student-level absences on indicators for binned temperature for the 2011/12-2016/17 academic years for students in schools without AC. Estimates are expressed as absences per 15 students, which is approximately equivalent to normalizing by the mean, district-wide daily absent rate (6.5%). 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.

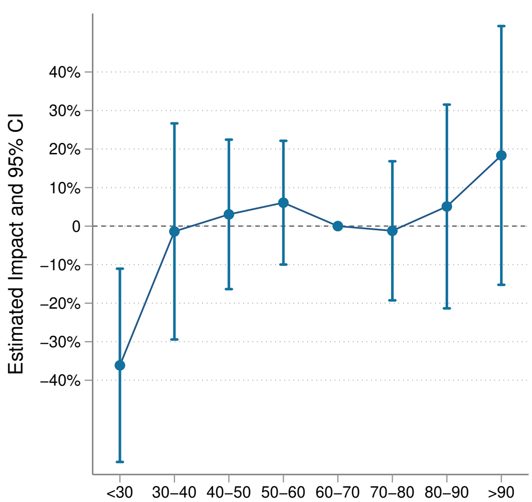
FIGURE A10: Coefficient estimates of the effect of somewhat snowy (< 4 in) and moderately snowy (>4 in) conditions on absences relative to a day with a 60-70°F max temperature that does not have snow, by student and neighborhood characteristics in schools without air conditioning (2011/12-2016/17).



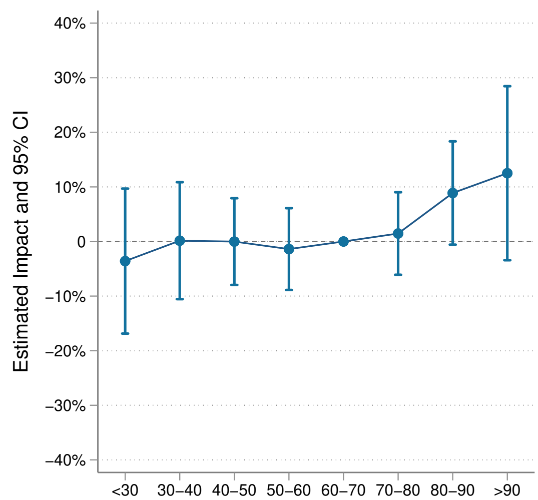
(A) All Types (2014/15-2018/19)



(B) Fighting/Assault



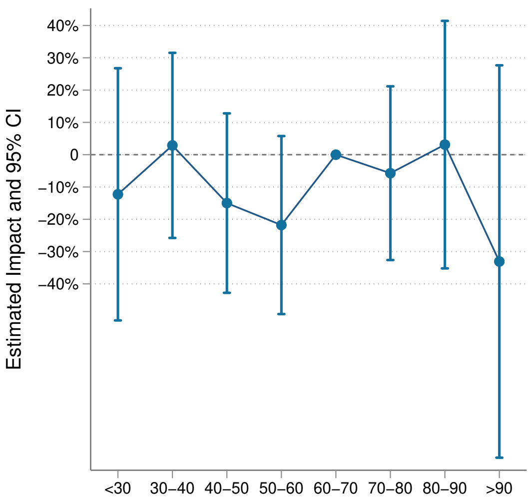
(C) Bullying/Harassment



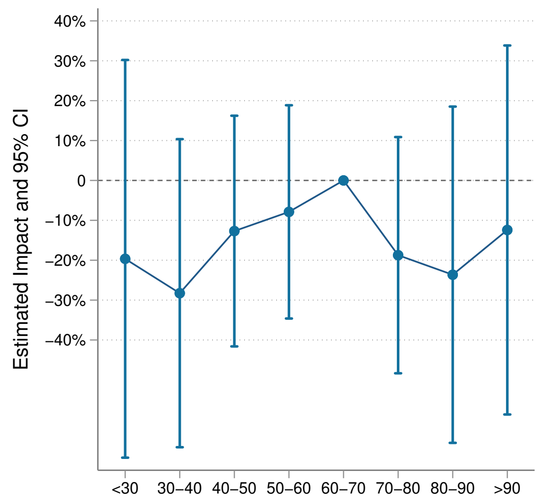
(D) Disruptive/Defiant Behavior

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.

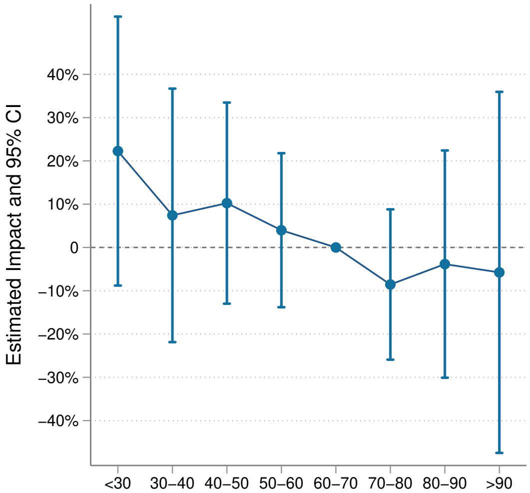
FIGURE A11: Effect of temperature on referrals (separated by type of incident) relative to a day with a maximum temperature between 60-70°F.



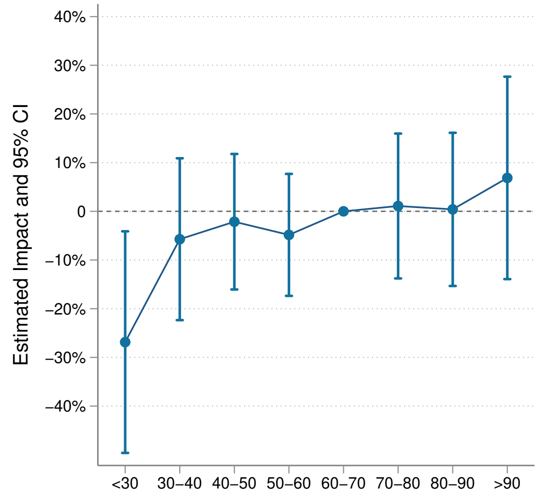
(A) Weapons/Danger



(B) Theft/Destruction



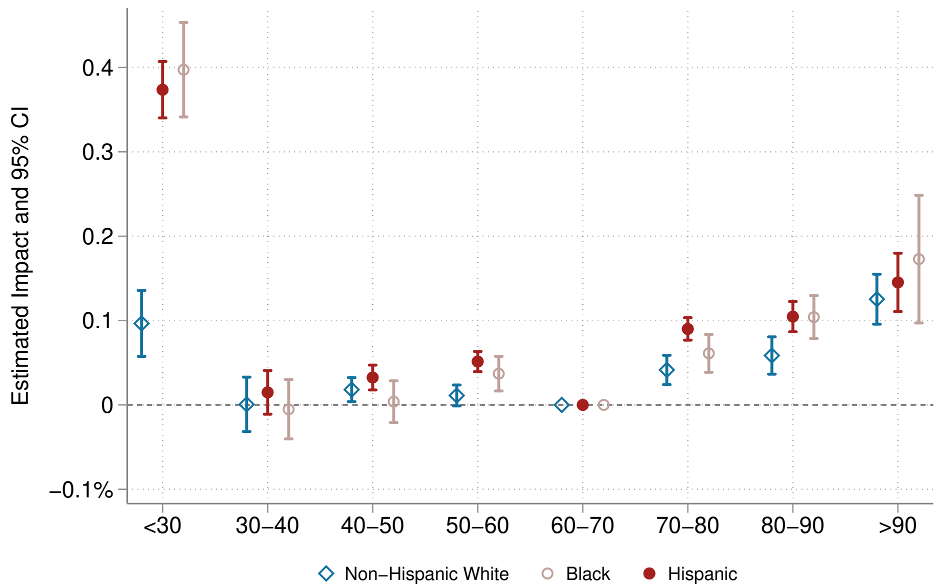
(C) Alcohol/Drugs



(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 A12: 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 A13: 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 B1: Predictors of Neighborhood 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.

Table B2: Student characteristics by home air conditioning status.

	High AC Neighborhoods			Low AC Neighborhoods		
	All	School AC	No School AC	All	School AC	No School AC
Student Characteristics						
Share of Enrollment (%)	34	19	15	65	24	41
% with School AC	55	–	–	37	–	–
% English Language Learners	40	43	38	44	50	41
Average % VLI or LMI	54	52	57	60	62	58
Average % Built <1950	19	10	29	56	40	66
% Living in Hottest 25th Pct of Neighborhoods	36	42	28	19	29	13
Race/Ethnicity						
Black (%)	20	21	18	13	16	11
White (%)	23	21	26	17	11	21
Hispanic (%)	47	47	46	63	67	60
Grade Level						
Elementary (%)	52	59	43	48	49	48
Middle (%)	24	23	24	24	27	22
High School (%)	24	18	32	28	24	30

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

Table B3: Student and facility characteristics by air conditioning status.

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

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

Table B4: 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 B5: 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 B6: 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.

Table B7: Effect of temperature on absences relative to a day with a maximum temperature between 60-70°F.

	(1) Linear	(2) Poisson	(3) No School AC	+ With AC
Max Temp.				
<30F	0.323***	0.253***	0.304***	0.044
	(0.014)	(0.010)	(0.016)	(0.029)
30-40F	0.004	-0.001	0.006	-0.003
	(0.008)	(0.008)	(0.012) (0.015)	
40-50F	0.024***	0.031***	0.024***	-0.000
	(0.004)	(0.004)	(0.005)	(0.008)
50-60F	0.040***	0.045***	0.039***	0.002
	(0.004)	(0.004)	(0.005)	(0.008)
60.temp	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
70-80F	0.078***	0.072***	0.073***	0.013
	(0.005)	(0.005)	(0.007)	(0.009)
80-90F	0.090***	0.089***	0.092***	-0.004
	(0.006)	(0.007)	(0.008)	(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	–
Pre-2017/18	X	X	X	–
Day of Year FE	X	X	X	–
School FE	X		X	–
Student X Year FE		X		–

Notes: Coefficient estimates are from linear regressions modeling daily, student-level absences 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 3-4, 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%). Asterisks indicate coefficient significance level (2-tailed): *** p<.01; ** p<.05; * p<.10.

Table B8: Effect of temperature on behavioral referrals relative to a day with a maximum temperature between 60-70°F.

	(1)	(2)	(3)	(4)	
	Linear	All Enrolled	Poisson	No School AC	+ With AC
Max Temp.					
<30F	-0.118**	-0.179***	-0.165***	-0.161**	0.100
	(0.046)	(0.048)	(0.043)	(0.064)	(0.092)
30-40F	0.007	0.002	-0.000	-0.003	0.025
	(0.034)	(0.034)	(0.028)	(0.045)	(0.068)
40-50F	-0.005	-0.024	-0.018	-0.019	0.035
	(0.025)	(0.024)	(0.021)	(0.034)	(0.049)
50-60F	-0.007	-0.019	-0.011	-0.015	0.017
	(0.022)	(0.023)	(0.020)	(0.029)	(0.044)
60-70F	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
70-80F	-0.005	-0.019	-0.014	-0.009	0.009
	(0.024)	(0.025)	(0.022)	(0.033)	(0.048)
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 and poisson regressions modeling daily, student-level behavioral referrals on indicators for binned temperature and 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. Specifications 1, 2, and 4 include school and demographic (grade, race, gender, "English learner") fixed effects. Specification 3 includes student-by-year fixed effects. 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 the 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 referral rate (0.13%). Asterisks indicate coefficient significance level (2-tailed): *** p<.01; ** p<.05; * p<.10.

Appendix C: Climate Projections

I estimate the impact of future climate change using temperature projections provided by Rasmussen et al. (2016). Their data provide annual county-level projections of the number of days that fall within each 1°F bin from 1981 to 2100 for each county within the continental United States. 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.

Using data from RCP6.0 for the county, I count the projected number of days falling within each temperature bin for each year between 1990-2010 and 2040-2060. I then assign temperatures to individual days within the school year by (1) using 2011-2019 observed temperature data to estimate the average temperature rank of each day compared to other days within the year (hottest day, second hottest day, etc.) and (2) preserving that rank order when assigning temperatures to days for each year within 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.

To predict behavioral referrals and absences using modeled temperature, I estimate equation (1) for the 2011/12-2017/18 school years. I focus on non-air conditioned schools to better capture the unmitigated effect of warming conditions on student behavior. Several non-temperature environmental conditions also affect student behavior, but rather than attempting to predict these conditions (rain, snow, pollution) on each day, I instead estimate equation (1) without any non-temperature environmental controls. This effectively assumes that whatever environmental conditions typically accompany a day with a certain maximum temperature would continue to accompany that day in the future. Changes in precipitation (conditional on temperature), wildfires, and pollution are therefore not included in this analysis.

I use the resulting estimated coefficients and the projected temperature data to estimate the number of absences and behavioral referrals for each year from 1990-2010 and 2040-2060. I then compare the average rate of behavioral referrals and absences for the 1990-2010 period to the 2040-2060 period.