Trying to Beat the Heat: Air-Conditioning and Learning

Mrinmoyee Chatterjee* Nolan G. Pope†

February 2, 2023

Abstract

Growing evidence demonstrates that heat impairs student learning. A potential policy solution is investing in air-conditioning. Using the staggered roll-out of AC across schools, we analyze the impact of a $135 million AC installation program undertaken by Chicago Public Schools between 2013-2017. We find no evidence AC installation improved students' end-of-year test scores or grade retention and suggestive evidence that attendance marginally improved. Even when measuring returns at the top of the 99 percent confidence interval, benefits to student achievement remain small. These results can help school districts better optimize their often limited budgets when striving to improve student performance.

We would like to thank Michael Gilraine, Joshua Goodman, Jisung Park, Richard Patterson, and Nathan Petek for helpful comments. We would also like to thank George Zuo for his valuable assistance with this project.

*University of Maryland, 3114 Tydings Hall, 7343 Preinkert Dr., College Park, MD 20742. Email: mrinchat@umd.edu

†University of Maryland, 3114 Tydings Hall, 7343 Preinkert Dr., College Park, MD 20742. Email: npope@umd.edu

1 Introduction

Many environmental factors such as temperature, noise, light, and pollution impact human performance (Echeverria, Barnes and Bittner, 1994). The negative effects of excessive heat has received particular attention due to its ubiquitous and widespread nature (Jokl, 1982; Ramsey, 1995; Barreca et al., 2016; Kjellstrom et al., 2016). High temperatures have been found to decrease productivity not just in physically demanding jobs such as agriculture, sports, or construction (Hancher and Abd-Elkhalek, 1998; Wendt, van Loon and Lichtenbelt, 2007; Yi and Chan, 2017) but also in sedentary work environments (Seppanen, Fisk and Lei, 2006; Kjellstrom, Holmer and Lemke, 2009; Heal and Park, 2016).

Similar to work environments, excess heat has also been shown to cause losses in productivity in learning environments (Cho, 2017; Park et al., 2020). Hot classrooms may prevent children from learning effectively, and teachers from teaching effectively, due to discomfort, exhaustion, or slowed cognition. High temperatures may also lead to increased absenteeism in schools (Randell and Gray, 2016, 2019). A potential policy solution to alleviate these learning losses is for schools to invest in air-conditioning (AC). However, estimating the causal impact of AC on student performance is difficult since AC installation is typically done in conjunction with other infrastructure spending in schools (Cellini, Ferreira and Rothstein, 2010; Neilson and Zimmerman, 2014). As such, the current literature is limited to providing correlations between AC coverage and student performance (Park et al., 2020) and there is little causal evidence as to whether installing AC in schools is an effective tool in improving student outcomes.

In 2013, then Mayor of Chicago, Rahm Emanuel announced that $135 million would be spent to install AC in all classrooms in Chicago Public Schools (Corley, 2013). The campaign was motivated by the sweltering summer temperatures in Chicago (which can reach 90F) as well as reports of inhumane classroom conditions cited by teachers during the district's lengthy teachers' union strike in 2012 (Strauss, 2012; Chambers, 2013). This announcement led to one of the largest ever investments in AC made by a public school district and installed AC in more than 200 schools over the next four years.

We exploit the roll-out of this campaign to study the impacts of AC installation on student performance. During this roll-out, AC was installed in schools over four different waves, starting in the school year 2013-14 and ending in 2016-17 (Chicago Public Schools Press Releases, 2016). We leverage the staggered timing of AC installation across schools using a difference-in-differences strategy to compare students exposed to AC to those that are not, before and after AC installation.

Despite costing $135 million, we find no evidence that the AC installation campaign in Chicago improved student achievement. Using our difference-in-differences design, we find that students whose schools received AC saw no significant improvements in their test scores compared to those whose schools did not. In addition to test scores, we find no significant impact of AC installation on the probability of being held back a grade. Since there may be disruption effects to concurrent test scores in the year of installation and students may only see potential gains in later years, we also look at the impact of AC installation on test scores for each year post treatment. We find there are no significant positive impacts of AC installation for students in the treated schools even several years after treatment. However, we find some evidence that average student attendance at the school level increased by approximately half a day per school year after AC installation.

One potential concern is that some treated schools already had existing AC infrastructure and the Chicago Public Schools campaign merely replaced or updated already functioning AC units. In this case, including schools with preexisting AC could attenuate the estimated effects of the program. To help account for this, we use data on preexisting AC infrastructure in each school that provides information on what fraction of the school was air-conditioned prior to the campaign. After accounting for prior AC infrastructure, we still find no evidence of significant positive impacts of AC installation on student test scores or the probability of being held back a grade.

Classroom AC is one of the many aspects of educational inequality. On top of being less likely to have AC in their schools, due to residential sorting, low-performing and low-income students also have fewer environmental amenities in their neighborhoods such as poorer air quality and hotter temperatures (Banzhaf and Walsh, 2008). Thus, they may face larger test score declines due to heat exposure in schools (Park et al., 2020). We analyze the impact of AC on low-performing students and find null results similar to those found in the full population of students.

Our results show no evidence that the installation of AC in Chicago Public schools had a positive impacts on student achievement and limited evidence of a positive impact on school-level attendance. This analysis covers a temperate region of the United States where temperatures can range from average lows of 17F in January to average highs of 85F in July (see Figure A.1) and where the typical year has 137 days over 70F and 76 days over 80F, of which approximately 77 and 35 days fall within the school year, respectively (see Figure A.2).[1] Estimating the causal effect of AC installation on student learning for this type of climate has both benefits and drawbacks. The major drawback is that we can-

[1]Monthly averages from 2000-2020 (Lawrimore et al., 2016), daily normals from 2000-2020 (Arguez et al., 2020).

not determine whether AC is an ineffective tool in combating the detrimental effects of heat in schools or whether there are no detrimental effects of heat on learning in temperate climates like Chicago.[2] On the other hand, this region is similar to other school districts that are on the margin of investing in air-conditioning. As such, our findings have important policy implications. Many large school districts in the US are not fully air-conditioned such as New York City, Philadelphia, Baltimore City, Denver, and Detroit and many are considering large-scale AC installation projects (Barnum, 2017). For example, Mayor DeBlasio announced in 2017 that the Department of Education would spend $29 million to air-condition every classroom in New York City by 2022 (NYC City Hall, 2017). Our results speak directly to the potential benefits (or lack thereof) of these expensive AC infrastructure projects on student learning.

Given the strict budget constraints faced by many public school districts (e.g. Chicago Public Schools cited a deficit of $1 billion in 2013 (Corley, 2013)), our results suggest that the $135 million investment in AC might have been better spent on other educational resources. Even when using estimates at the top of the 99 percent confidence interval, the AC installation program returned test-score gains of less than 0.03 standard deviations. Although test-score gains and other academic benefits may not be the only goal of AC installation, the results of this campaign compare poorly to other interventions whose mean positive test-score gains are substantially larger, such as high-dosage tutoring (Fryer Jr and Howard-Noveck, 2020) and making tenure decisions based on teacher value-added (Chetty, Friedman and Rockoff, 2014).

We outline the context of the AC installation program in Chicago and describe our primary sources of data in section 2. Section 3 details our methodology followed by a discussion of the results in section 4. Section 5 outlines the policy implications of our results and concludes.

2 Background and Data

To estimate the impact of AC installation on students' academic outcomes we leverage the roll-out of AC in Chicago Public Schools (CPS) from 2013 to 2017. CPS is the third-largest school district in the US (after New York City and Los Angeles) with 355,156 students enrolled across 642 schools in the 2018-19 school year (Chicago Public Schools, 2020). The public school system in Chicago serves an ethnically diverse student body, of which the largest proportion of students are Hispanic (46.6%)

[2] In our analysis, we use end-of-year test scores to measure student learning. As such, we cannot differentiate between the impact of AC on test scores due to changes in student learning accumulated throughout the school year or simply through changes in student performance on test day.

and the next largest are Black (35.9%). The district categorizes more than three quarters of the student population as coming from 'Economically Disadvantaged' households. In addition, the district has a history of poor academic performance. Since being called the "worst public school system in the nation" in 1988 by the U.S. Secretary of Education William Bennet, CPS has made vast improvements in high school graduation rates and test scores, but still fares poorly on college readiness nationally (Luppescu et al., 2011).

In 2012, the Chicago Teachers Union went on a nine-day strike to protest teacher evaluations, pay, and classroom conditions (Pearson and Yan, 2012). The issue of sub-optimal classroom conditions rose again during teacher strikes and protests in 2013 (Chambers, 2013; Ahmed-Ullah, 2013; Peralta, 2013). Partly in response to these concerns, then mayor of Chicago, Rahm Emanuel, announced that $135 million would be spent to install AC in all previously non air-conditioned schools (Chicago Public Schools Press Releases, 2016) – thus providing air conditioning to all students while learning in the classroom. This large expenditure on AC installation occurred despite CPS facing a looming $1 billion budget deficit which forced CPS to close 47 under-performing schools and provoked city-wide protests in 2013. In defence of these school closures, Mayor Emanuel highlighted that the funds recouped could be better spent on other programs such as "access to libraries, iPads, and air-conditioned classrooms" (Corley, 2013).

The campaign to install AC was implemented in four waves across 212 schools. Using CPS press releases we identify which schools received AC in each of the four waves. Of the 212 schools that received AC, 67 schools received AC during Wave 1 in which installation occurred while school was in session during the 2013-14 school year. In Wave 2, 56 schools received AC during the summer of 2014. In Wave 3, 29 schools received AC in October of 2014. In the fourth and final wave, 60 schools received AC during the 2016-17 school year but prior to spring of 2017. A full list of treated schools by wave of AC installation can be found in Appendix Table A.1.

To measure the academic performance of students, we obtain student-level test scores for math and English from school years ending in 2008 to 2017 for students in grades 3-8 for 603 Chicago schools from the Illinois State Board of Education. The test scores come from standardized tests administered at the end of the year for all students in Illinois.[3] This test is known as a "high stakes" test in the state

[3]Prior to 2015, the Illinois State Board of Education used the Illinois Standards Achievement Test for students in grades 3-8 in math and reading (which we refer to as English for the rest of the paper). Starting in 2015, the State Board mandated all schools to implement the Partnership for Assessment of Readiness for College and Careers test which was created to better reflect the new and updated Common Core standards and replace previous state-wide assessments for all students in grades 3-8 (Citizens For Public Schools, 2017). These are the test scores we use for years 2015-2017 for math and English

and is used both to help determine whether a student advances to the next grade and by administrators to evaluate school performance. We normalize student test scores by year and grade using the full Illinois state distribution of test scores. In addition to test scores, we obtain a measure of grade retention (i.e. 'Held Back' a grade) which is a binary variable equal to 1 if a student repeats the same grade. Finally, we also obtain a school-level measure of the average fraction of days students attend each year. .

Since test scores are only available for 3-8 grades, our analysis does not look at the impact of AC on high school students. Most students in Chicago attend an elementary school from kindergarten to 8th grade, followed by four years of high school. Thus, of the 212 schools that received AC, only the 183 elementary schools and 2 middle schools appear in our sample.[4] In addition, there are 417 'control' schools in our dataset that do not receive AC during this campaign.

In addition to student outcomes, we gather data on existing AC infrastructure in each school prior to the campaign roll-out. Between 2009 and 2011, the Energy Star Portfolio Manager system collected data on the percentage of school facilities that were air-conditioned and on other physical attributes of the schools (as required by the U.S. Environmental Protection Agency). Of the schools for which we have test score and AC installation data, the Energy Star System has information on approximately 60 percent of those schools. Table 1 shows the differences in physical attributes of these schools by treatment status.[5] We consider schools to be 'treated' if they receive AC as part of any of the four waves of AC installation between 2013 and 2017, while the remaining schools that never receive AC are designated as 'controls'. As can be seen in Table 1, treated schools are substantially less air conditioned than control schools. On average, treated schools had only one-third of their facilities air-conditioned by 2011 while control schools had more than two-thirds of their facilities air-conditioned. While most of the treated schools had little to no AC prior to the AC installation program, not all control schools were fully air-conditioned. To better illustrate the difference in preexisting AC infrastructure between treated and control schools, Figure 1 provides a histogram of the fraction of the school air-conditioned by treatment status. In addition to preexisting AC infrastructure, control schools are significantly newer and have a lower share of black and low income students. Also, students in control schools are less likely to be held back, have higher attendance rates, and have higher math and English test

Language Arts (which we also refer to as English).

[4]Of these 185 schools, 66 schools received AC during Wave 1, 50 schools in Wave 2, 29 schools in Wave 3, and 40 in Wave 4.

[5]Table A.2 shows the difference in physical attributes of these schools both by treatment status and separately for each wave. In addition, both Tables 1 and A.2 match the analysis sample and remove 46 schools as discussed in detail in the methodology section.

scores. In contrast to the discrepancies in AC, all schools are heated.

3 Methodology

The AC installation campaign in Chicago provides a natural experiment to measure the potential benefits of having AC in schools on student performance. In particular, the staggered roll-out of AC to schools allows for a straightforward difference-in-differences approach to identify the causal impact of AC on student performance. It also allows us to solely estimate the effect of AC, separate from any other concurrent infrastructure expenditure.

To estimate the effect of having AC in a school on student performance, we estimate a standard difference-in-differences model as follows:

$$y_{ist} = \alpha + \beta \mathit{Have\ AC}_{st} + \gamma_1 \mathit{Math}_{is,t-1} + \gamma_2 \mathit{English}_{is,t-1} + \mu_s + \lambda_t + \varepsilon_{ist} \tag{1}$$

where y_{ist} is the normalized test score (or held back indicator) of student i in school s in year t. *Have* AC_{st} is an indicator equal to one if school s has AC in year t. This variable is equal to one for control schools in all years and equal to one for treated schools starting in the year they receive AC (and zero before). In addition, we include controls for lagged math ($\mathit{Math}_{is,t-1}$) and English ($\mathit{English}_{is,t-1}$) test scores, school fixed effects (μ_s), and year fixed effects (λ_t). Including lagged math and English test scores allows us to measure the change in test scores from year to year instead of test score levels.[6] This allows us to measure the yearly value-added of having AC in a school on student achievement. Thus, the main coefficient of interest, β, measures the difference in the change in test scores before and after AC installation between students whose schools received AC versus those who did not. We also estimate the effect of AC on attendance. Since our attendance data is at the school level instead of the student level, we estimate equation 1 at the school level without including individual lagged test scores. For all estimates we cluster standard errors at the school level.

The main identifying assumption for this model is that the outcomes for treated and control groups would have parallel trends in the absence of treatment. In our setting, this assumption requires that had the treated schools not received AC, their scores would have moved in parallel with the control schools (which already had AC). While the counterfactual parallel trend assumption cannot be observed, we can test for parallel trends prior to the treatment. We plot the average test scores

[6] Appendix Table A.3 reports our main estimates without controls for lagged math and English test scores and find similar results.

of students for each year by treatment status in Figure 2 separately for each wave of treatment. Similar figures can be seen for being held back and attendance in Figure A.3. These figures show that the test scores and the probability of being held back of the treated and control schools appear to move in parallel prior to AC installation. However, for attendance there is some evidence of a pre-trend, particularly for wave 4 schools. To formally test for parallel pre-trends, Figure 3 and A.4 plots the coefficient on *Have* AC_{st} from Equation 1 interacted with each year. These figures show that there is no statistically significant difference in the trend between treated and control schools prior to treatment in each year for each wave for test scores and the probability of being held back. However, again there is a statistically significant pre-trend for attendance for wave 4 schools.

Additionally for the counterfactual parallel trends assumption to hold, there would need to be no other concurrent policy changes that would differently affect AC-receiving schools versus control schools. While that appears to be true for later waves, the AC installation in wave 1 schools coincided with the closure of 47 'under-performing or under-utilized' schools by CPS in the summer of 2013. Students who previously attended these closed schools were assigned by CPS to 48 'Welcoming Schools' (De la Torre et al., 2015). In our data, we observe 46 of the designated 48 'Welcoming Schools'. Of the 66 schools that received AC in wave 1, 33 were 'Welcoming Schools' and 33 were not (while only 13 of 417 control schools were 'Welcoming Schools'). As such, half of the schools treated in wave 1 were simultaneously impacted by being a 'Welcoming School', while few control schools were. Since most of the closed schools were under-performing, 'Welcoming Schools' saw a large influx of low test-score students to their school in 2013 and consequently saw large declines in their average test scores. Therefore, when estimating the impact of AC on student achievement in these 'Welcoming Schools', there will likely be a negative bias because the timing of AC installation coincides with welcoming new low-performing students from closed schools (see Appendix Figure A.5). To account for this potential bias, our main analysis omits these 46 assigned 'Welcoming Schools' from the sample.[7]

Equation 1 estimates the impact of AC on student performance based on schools undergoing a binary change from having no AC to being fully air-conditioned as part of the CPS installation program. However, we might be concerned that this change is not binary for each of the treated schools. To help address this concern we use the Energy Star data on existing AC infrastructure for 354 of the schools prior to the campaign roll-out. Figure 1 shows the distribution of AC for treated

[7] In Appendix Figures A.6, A.7 and Table A.4 we show the results for wave 1 for both 'Welcoming Schools' and 'Non-Welcoming Schools'. While we find null effects for 'Non-Welcoming Schools', the estimates for 'Welcoming Schools' show moderate negative effects on test scores of AC installation consistent with a negative bias due to simultaneously welcoming low-performing students.

and control schools in this sample. This figure shows that the modal treated school (32% of schools) had 10% of their school air-conditioned while the modal control school (43% of schools) had 100% of their school air-conditioned. However, 22% of treated schools had more than 50% of their school air-conditioned. Thus, most treated schools already had some non-zero percentage of AC in their school prior to the CPS installation. Hence using a binary variable for AC status in the difference-in-differences model could attenuate the estimates.

Therefore, we use an alternative specification to account for the prior AC infrastructure in treated schools:

$$y_{ist} = \alpha + \beta \mathit{Fraction\ AC}_{st} + \gamma_1 \mathit{Math}_{is,t-1} + \gamma_2 \mathit{English}_{is,t-1} + \mu_s + \lambda_t + \varepsilon_{ist} \tag{2}$$

where all variables are the same as in Equation 1 except the $\mathit{Fraction\ AC}_{st}$ variable which takes a value from 0 to 1 and is the fraction of the school that was air-conditioned prior to the treatment. For treated schools the value of $\mathit{Fraction\ AC}_{st}$ changes to 1 for all years after AC installation. As such, β measures the impact of a school moving from no AC to being fully air-conditioned on student outcomes. The results for the specifications in Equations 1 and 2 are reported in Table 2.

4 Results

4.1 Descriptive Results

Before directly estimating our difference-in-differences model, we first look at the trends in student outcomes between treated and control schools. This allows us to test for an effect of AC on student performance after AC installation in the raw data. If AC installation has a positive impact on students, we expect student outcomes to improve in treated schools after treatment relative to control schools. Therefore, in Figures 2 and A.3, we plot the average standardized test scores for math and English, held back, and attendance separately for each wave of treatment, by treatment status over each year. In each sub-graph, the dashed lines represent the treated schools and the solid lines represent the control schools. The vertical line marks when schools in each wave received AC.

In Figure 2, we see little evidence that AC installation improved student test scores. For all waves of treatment, we do not see the treated schools' standardized test scores converge post-treatment towards the control schools. In addition, there appears to be parallel trends prior to the treatment. In Figure A.3 we see little evidence that AC installation decreased the likelihood of being held back, however, there is some evidence of increased attendance for schools treated in wave 1. Overall, this evidence suggests that AC installation had little to no impact on student achievement while potentially improving attendance.

4.2 Difference-in-Differences

Next, we estimate the difference-in-differences model using Equation 1 and report the results in Panel A of Table 2. If installing AC provides better learning conditions for students and teachers, then we would expect positive impacts of AC installation in treated schools post-treatment.

In Panel A of Table 2, we find no evidence that students in treated schools saw their math or English test scores improve as compared to students in control schools after AC was installed. Students in treated schools saw statistically insignificant decreases of 0.007 standard deviations in their average math test scores and 0.001 standard deviations in their English test scores post AC installation as compared to control schools. While also statistically insignificant, we estimate that students in schools that received AC were 0.001 percentage points (or 5.3 percent) more likely to be held back after AC was installed. However, for attendance we find that treated schools saw a 0.003 percentage point (or 0.3 percent) increase in attendance. These results can rule out relatively modest positive impacts of AC installation on student test scores. When measuring returns at the top of the 99 percent confidence interval, the positive impact of AC installation would only increase math and English test scores by 0.023 and 0.027 standard deviations, respectively.

Park et al. (2020) find the beneficial impacts of AC penetration (as measured by survey data from high school counsellors) are larger for marginalized students. The most vulnerable students may be unable to counter the stress of heat at school by going home to an air-conditioned environment. Thus, any potential positive impacts of AC installation may be concentrated on the already low performing students. To test this, we estimate Equation 1 for students in the bottom quartile of the test score distribution in both math and English. These results are presented in Table A.5. We find nearly identical results for students in the bottom of the test score distribution as we do in our full sample. These results show no evidence that AC provides any positive impacts on academic performance – even for low-performing students who may be the most vulnerable to heat in schools.

One may potentially expect negative impacts of AC in the year that AC was installed due to disruption effects from the installation process or construction. Conversely, positive impacts of AC on student achievement could occur some years after AC was installed in schools. To investigate this heterogeneity by years post-treatment, Figures 3 plots the coefficients from Equation 1 for test scores while allowing them to vary flexibly by each year. For all waves we see that there are no statistically significant impacts after treatment (including no disruption effects in the year of installation), on either math or English test scores. In addition, there are no large differences in estimates before versus after the treatment occurs. These figures also confirm that for each wave we observe parallel pre-trends between treated and control schools, given by confidence intervals that overlap zero for all pre-period estimates. In addition, the lack of heterogeneity across years implies that yearly variation in temperature (at least for the 4 post years) appears to have a limited interactive effect.[8] Hence, even after breaking down the impacts of the AC program by years after installation, we find no evidence of positive impacts on student test scores.

Analogous to Figure 3, Figure A.4 shows the coefficients by year for held back and attendance. For attendance there are substantially different patterns by the prior characteristics of the treated schools. For schools treated in waves 2 and 3 – that have similar characteristics to the control schools (see Table A.2) – there are no statistically significant impacts after treatment. For schools treated in wave 1 and 4 – that are lower performing compared to control schools (see Table A.2) – their attendance begins to converge to control schools starting in 2013 (see Figure A.3). As such, for wave 4 schools who were treated in 2016, Figure A.4 shows a clear pre-trend. For wave 1 schools the trend occurs right after treatment with no abrupt discontinuity at the treatment year. If AC improves classroom conditions for students, we would likely see an abrupt increase in attendance post AC installation. However, for all waves there are no large differences in estimates right before versus after the treatment occurs and only wave 1 shows a differential trend post treatment. Overall, these results suggest taking the positive effects of AC installation on attendance found in Table 2 with caution. In addition, Figure A.4 show no statistically significant impact after treatment on the likelihood of being held back.

In addition to heterogeneity across years, there may also be heterogeneity by wave due to when different types of schools were assigned to receive AC. Thus, in Panel A of Table A.6 we report the results of Equation 1 separately for each wave. For all waves, we find no positive impacts of AC installation on standardized math or English test scores, or on the probability of being held back in the post-treatment years when compared to students in control schools that did not receive AC. For attendance we find positive effects of AC installation for schools in waves 1 and 4. However, due to the patterns seen in Figure A.4, these results on attendance should be taken with caution.

[8] For the period of sample, the number of high temperature days in Chicago remain fairly consistent with approximately 25% of school days with a temperature above 70F and less than 5% of school days with a temperature above 90F (see Figure A.2).

Lastly, we test for heterogeneity across grade. Park, Behrer and Goodman (2021) find negative effects of heat that are fourfold larger for students in grades 3-5 than grades 6-8. This would suggest there may be positive effects of AC on student performance for earlier grades but not later grades. In figure A.8, we show our main results from Equation 1 separately for each grade. For both math and English we find no distinguishable difference between the grades.

4.3 Energy Star Difference-in-Differences

As discussed in the Methodology section, the above results estimate the impact of AC on student performance based on schools undergoing a binary change from having no AC to being fully air-conditioned. However, as shown in Figure 1 a substantial number of treated schools already had some non-zero percentage of AC infrastructure in their schools prior to the AC installation campaign. To account for this, we estimate Equation 2 as outlined in the Methodology section, which does not just measure the impact of being assigned to a school that receives AC, but modulates the treatment by using information on prior AC infrastructure within the treated schools. Thus, this specification measures the impact of being at a treated school that goes from having no AC to being fully air-conditioned on student achievement. [9]

These results are reported in Panel B of Table 2. We find that the estimates are very similar to those in Panel A – although they are slightly more positive and have larger standard errors (as expected due to the reduced number of schools in the sample). Going from having no AC at all to being fully air-conditioned saw a statistically insignificant increase of 0.004 standard deviations on math test scores in post-treatment years for students in the treated schools as compared to control schools, and a statistically insignificant increase of 0.009 standard deviations on English test scores. In addition, column (3) shows no evidence that going from no AC to being fully air-conditioned impacted the likelihood of a student being held back. However, for attendance the effect sizes are nearly twice as large with a point estimate of 0.005 percentage points (or 0.5 percent). The impacts for the low-performing students are also similar to the full sample (see Figure A.5).[10] With the larger standard errors, when measuring returns at the top of the 99 percent confidence interval, going from having no AC to being fully air-conditioned would increase math and English test scores by 0.057 and 0.051 standard deviations, respectively.

[9] Alternatively, we also estimate Equation 1 restricting the sample of treated schools to only those that had less than 30% of the school air-conditioned prior to being treated. Similar to the full sample, we find null results when making this restriction (see Table A.8).

[10] The estimates by wave of treatment are similar to the full sample, and are reported in Panel B of Appendix Table A.6.

While our results show little to no evidence that the installation of AC had a positive impact on student achievement, we are unable to distinguish whether AC is an ineffective tool in combating the detrimental effects of heat in schools or whether there are no detrimental effects of heat on learning in temperate climates like Chicago. Ideally, we would like to directly estimate the impact of heat on student learning in Chicago over this time period. However, we only have weather variance in Chicago over the nine years in our data and annual end of year test scores for students. While this technically allows us to estimate the direct impact of heat on test scores, all estimates will be based off of this very small sample size. Additionally, over this nine year period there is minimal variation in the number of hot days during the school year (see Figure A.2). With this very limited data, we find in Table A.9 that the number of hot days in a school year does not significantly impact student test scores. While these results should be taken with an abundance of caution, they suggest that there is perhaps little detrimental effect of heat in Chicago and, therefore there is little to no margin for AC to be an effect policy tool in this type of temperate climate.

5 Conclusion

Although there are well-documented detrimental impacts of heat, our results demonstrate that the AC installation program in Chicago had little impact on students' academic performance. These results are robust to different specifications, sub-populations, and heterogeneity by years post-treatment.

Chicago Public Schools spent $135 million dollars in fixed costs on their AC installation program. This expense averaged to nearly $730,000 per school or $2,600 per student – not including the operational costs such as electricity and maintenance. While AC installation may have improved outcomes along other dimensions, our estimates demonstrate that the AC installation program resulted in high costs with no observable academic benefits as measured by end-of-year test scores. Even when measuring returns at the top of the 99 percent confidence interval, the $730,000 spent per school led to relatively small test score gains for students of 0.02 to 0.03 standard deviations for each future year that the AC unit remains operable (which may vary from 12-20 years depending on upkeep).

Compared to other policy interventions, the Chicago AC installation program compares poorly in terms of test-score improvements, even when we use the 99 percent confidence interval to estimate returns. A meta-study by Fryer Jr (2017) shows that the average returns to school-based educational interventions are 0.05 standard deviation improvements in math and 0.07 standard deviation improvements in English test scores for students. Chetty, Friedman and Rockoff (2014) show that an improvement in teacher value added by one standard deviation improves math test scores by 0.14 standard deviations and English scores by 0.1 standard deviations. Per Krueger (1999), decreasing student class sizes by one-quarter in Project STAR increased test scores by 0.2 standard deviations. Alternatively, if the policy goal is to improve racial or SES disparities in student test performance, interventions like high-dosage tutoring may be more effective (Fryer Jr and Howard-Noveck, 2020). While the AC installation program in Chicago may have improved the comfort of the learning environment for students and teachers and potentially increased attendance, this change in environment did not translate to test-score improvements as in other interventions.

Policymakers in Chicago intended to reduce infrastructural disparities between schools and as such improve student performance by installing AC in schools. However, the program had little to no effect in closing the student performance gap between treatment and control schools. Therefore, given Chicago Public Schools' $1 billion deficit (Corley, 2013), the limited funds may have been better spent on other educational interventions if test-score gains was their main objective.

While most schools in the southern United States already have AC installed in their classrooms, the question of AC installation is still being considered by many school districts in temperate climates such as New York City, Philadelphia, Baltimore City, Milwaukee, Denver, Hawaii, Detroit, Jefferson County, and Long Beach (Barnum, 2017). The results of Chicago's AC installation program from this paper can help guide other marginal school districts when making the expensive choice of whether or not to install AC in classrooms.

References

Ahmed-Ullah, Noreen S. 2013. "Protests held at Chicago school headquarters." *Chicago Tribune*.

Arguez, A, I Durre, S Applequist, M Squires, R Vose, X Yin, and R Bilotta. 2020. "NOAA's US Climate Normals (1981–2020) Daily Summaries: Chicago O Hare, NOAA National Centers for Environmental Information."

Banzhaf, H Spencer, and Randall P Walsh. 2008. "Do people vote with their feet? An empirical test of Tiebout." *American economic review*, 98(3): 843–63.

Barnum, Matt. 2017. "Exclusive: Too Hot to Learn: Records Show Nearly a Dozen of the Biggest School Districts Lack Air Conditioning." *the74million.org*.

Barreca, Alan, Karen Clay, Olivier Deschenes, Michael Greenstone, and Joseph S Shapiro. 2016. "Adapting to climate change: The remarkable decline in the US temperature-mortality relationship over the twentieth century." *Journal of Political Economy*, 124(1): 105–159.

Cellini, Stephanie Riegg, Fernando Ferreira, and Jesse Rothstein. 2010. "The value of school facility investments: Evidence from a dynamic regression discontinuity design." *The Quarterly Journal of Economics*, 125(1): 215–261.

Chambers, Sarah. 2013. "Chicago Teacher: Inhumane Working Conditions are Inhumane Learning Conditions." *Education Week*.

Chetty, Raj, John N Friedman, and Jonah E Rockoff. 2014. "Measuring the impacts of teachers I: Evaluating bias in teacher value-added estimates." *American Economic Review*, 104(9): 2593–2632.

Chicago Public Schools, cps.edu. 2020. "Stats and Facts."

Chicago Public Schools Press Releases, cps.edu. 2016. "Mayor Emanuel and CPS Announce Every Classroom Will Be Air Conditioned by Spring 2017." *Chicago Public Schools: Press Releases*.

Cho, Hyunkuk. 2017. "The effects of summer heat on academic achievement: a cohort analysis." *Journal of Environmental Economics and Management*, 83: 185–196.

Citizens For Public Schools, High-Stakes Testing. 2017. "PARCC Fact Sheet." *citizensforpublicschools.org*.

Corley, Cheryl. 2013. "Discord Grows Over Chicago's Planned School Closings." *NPR.org*.

De la Torre, Marisa, Molly F Gordon, Paul Moore, and Jennifer Cowhy. 2015. "School Closings in Chicago." Research Report. Consortium.

Echeverria, D, V Barnes, and A Bittner. 1994. "The impact of environmental conditions on human performance: A handbook of environmental exposures. Volume 1." Nuclear Regulatory Commission, Washington, DC (United States).

Fryer Jr, Roland G. 2017. "The production of human capital in developed countries: Evidence from 196 randomized field experiments." In *Handbook of Economic Field Experiments*. Vol. 2, 95–322. Elsevier.

Fryer Jr, Roland G, and Meghan Howard-Noveck. 2020. "High-dosage tutoring and reading achievement: Evidence from New York City." *Journal of Labor Economics*, 38(2): 421–452.

Hancher, Donn E, and Hersham A Abd-Elkhalek. 1998. "The effect of hot weather on construction labor productivity and costs." *Cost Engineering*, 40(4): 32.

Heal, Geoffrey, and Jisung Park. 2016. "Reflections—temperature stress and the direct impact of climate change: a review of an emerging literature." *Review of Environmental Economics and Policy*, 10(2): 347–362.

Jokl, MV. 1982. "The effect of the environment of human performance." *Applied Ergonomics*, 13(4): 269–280.

Kjellstrom, Tord, David Briggs, Chris Freyberg, Bruno Lemke, Matthias Otto, and Olivia Hyatt. 2016. "Heat, human performance, and occupational health: a key issue for the assessment of global climate change impacts." *Annual Review of Public Health*, 37: 97–112.

Kjellstrom, Tord, Ingvar Holmer, and Bruno Lemke. 2009. "Workplace heat stress, health and productivity–an increasing challenge for low and middle-income countries during climate change." *Global Health Action*, 2(1): 2047.

Krueger, Alan B. 1999. "Experimental estimates of education production functions." *The Quarterly Journal of Economics*, 114(2): 497–532.

Lawrimore, Jay, Ron Ray, Scott Applequist, Bryant Korzeniewski, and Matthew Menne. 2016. "Global Summary of the Month and Year, Version 1.0." *NOAA National Centers for Environmental Information*.

Luppescu, Stuart, Elaine Allensworth, Paul Moore, Marisa de la Torre, James Murphy, and Sanja Jagesic. 2011. "Trends In Three Eras Of CPS." *Consortium on Chicago School Research*.

Neilson, Christopher A, and Seth D Zimmerman. 2014. "The effect of school construction on test scores, school enrollment, and home prices." *Journal of Public Economics*, 120: 18–31.

NYC City Hall, Press Office. 2017. "Mayor de Blasio, Chancellor Fariña and City Council Announce Every Classroom Will Have Air Conditioning by 2022." *The Official Website of the City of New York*.

Park, R Jisung, A Patrick Behrer, and Joshua Goodman. 2021. "Learning is inhibited by heat exposure, both internationally and within the United States." *Nature human behaviour*, 5(1): 19–27.

Park, R Jisung, Joshua Goodman, Michael Hurwitz, and Jonathan Smith. 2020. "Heat and learning." *American Economic Journal: Economic Policy*, 12(2): 306–39.

Pearson, Michael, and Holly Yan. 2012. "Official: No deal yet between Chicago teachers and school system." *CNN.com*.

Peralta, Eydar. 2013. "In Chicago, Dozens Arrested As They Protest School Closures." *NPR.org*.

Ramsey, Jerry D. 1995. "Task performance in heat: a review." *Ergonomics*, 38(1): 154–165.

Randell, Heather, and Clark Gray. 2016. "Climate variability and educational attainment: Evidence from rural Ethiopia." *Global Environmental Change*, 41: 111–123.

Randell, Heather, and Clark Gray. 2019. "Climate change and educational attainment in the global tropics." *Proceedings of the National Academy of Sciences*, 116(18): 8840–8845.

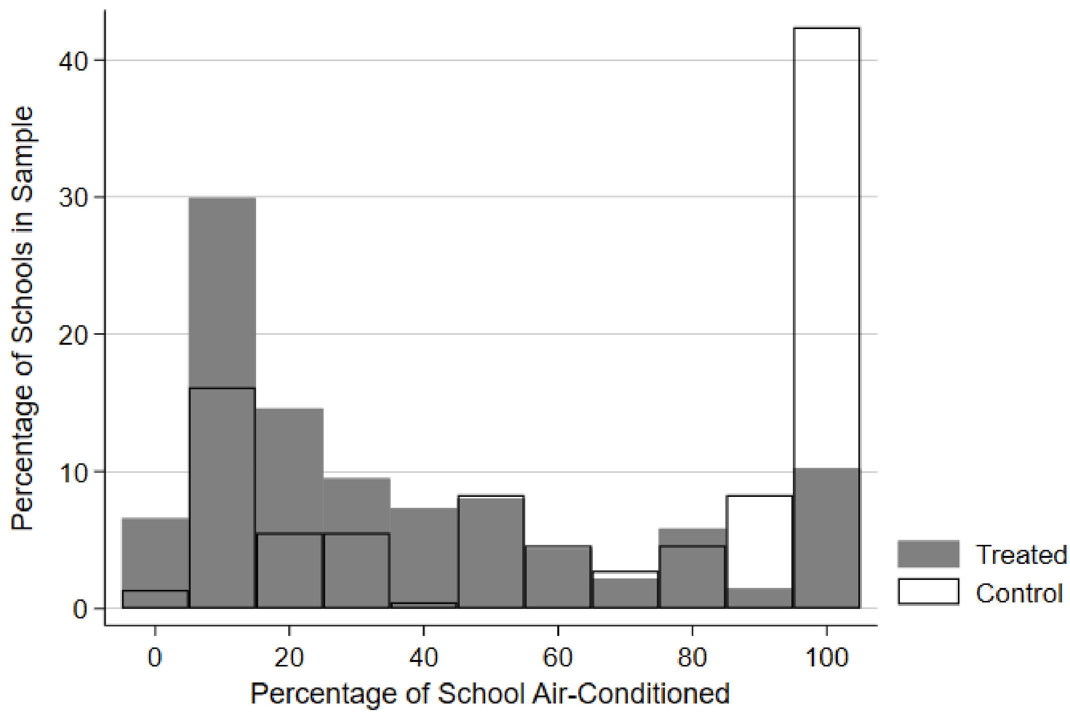
Seppanen, Olli, William J Fisk, and QH Lei. 2006. "Effect of temperature on task performance in office environment."

Strauss, Valerie. 2012. "Why shouldn't Chicago teachers ask for air conditioned schools?" *Washington Post*.

Wendt, Daniël, Luc JC van Loon, and Wouter D Marken Lichtenbelt. 2007. "Thermoregulation during exercise in the heat." *Sports Medicine*, 37(8): 669–682.

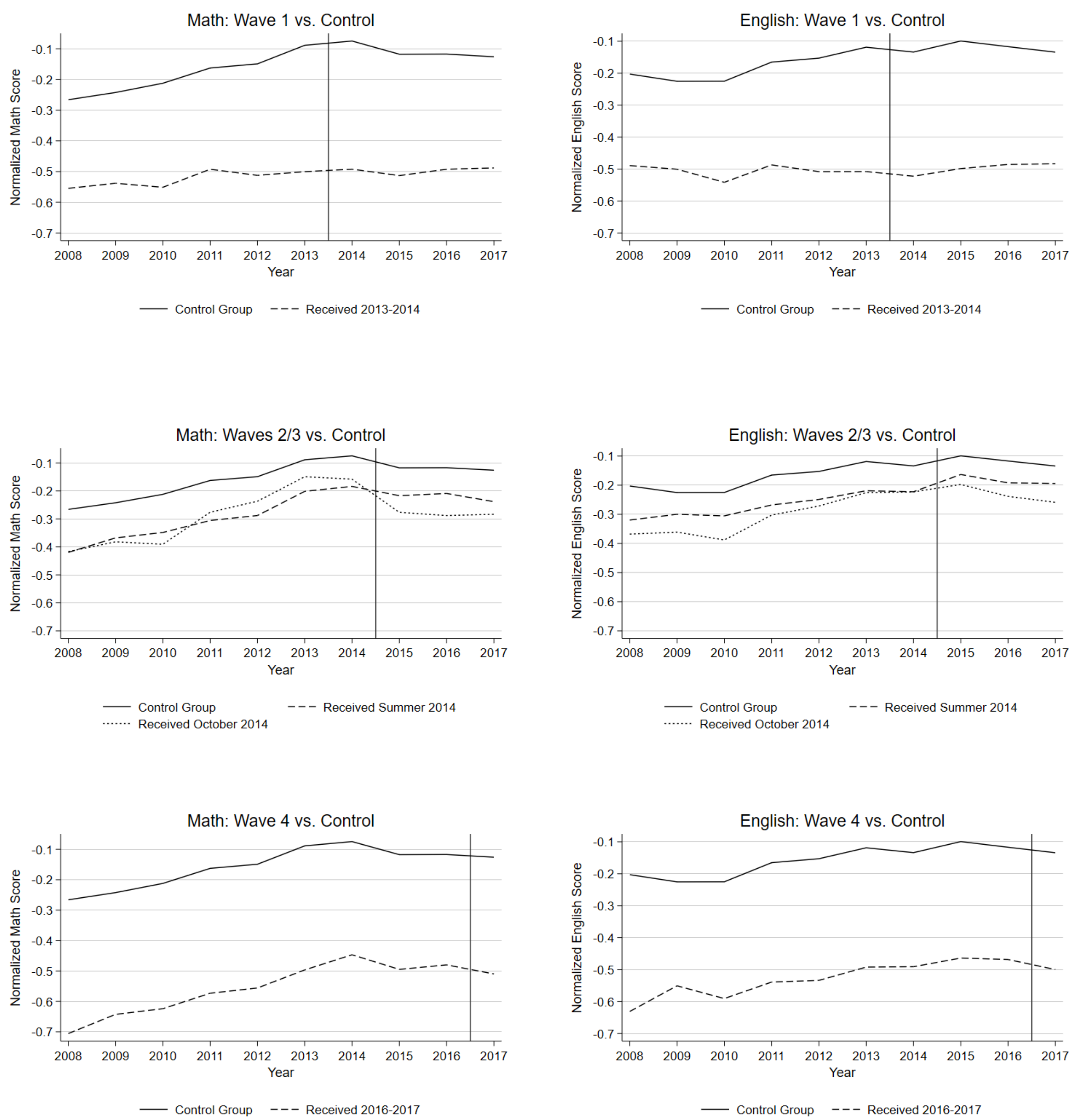
Yi, Wen, and Albert PC Chan. 2017. "Effects of heat stress on construction labor productivity in Hong Kong: a case study of rebar workers." *International Journal of Environmental Research and Public Health*, 14(9): 1055.

Figure 1: Percentage of School Air-Conditioned by Treatment Status



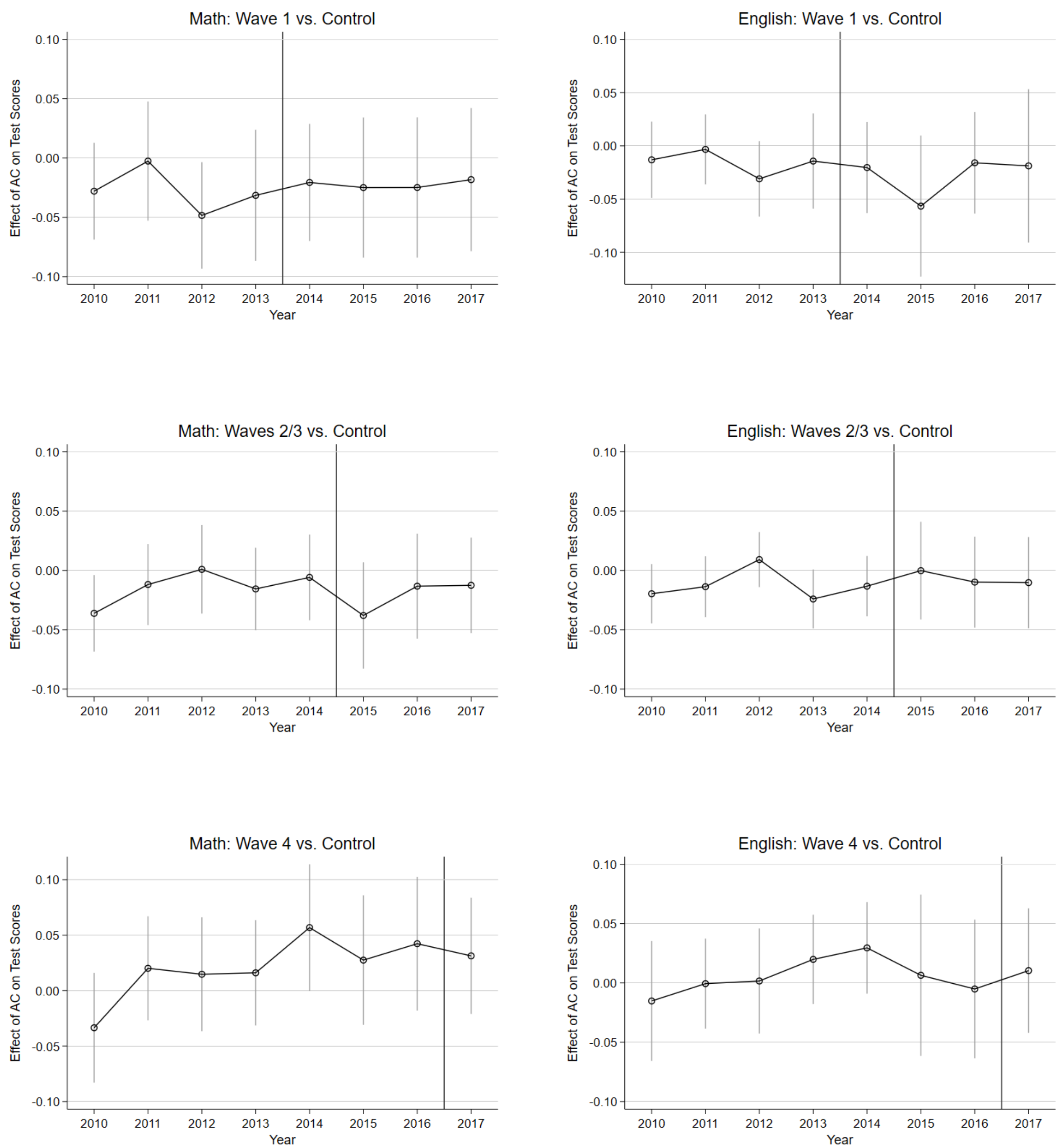
Notes: The figure shows the distribution of control and treated schools by decile for the percentage of the school that is air-conditioned prior to the AC installation program. A value of 100 implies the school is fully air-conditioned, while a value of 0 implies the school has no air-conditioning.

Figure 2: Average Test Scores by Year and Wave of Treatment



Notes: The figure reports average annual test scores for math and English for students in treated and control schools for each year from 2008 to 2017, by wave of treatment in the CPS AC installation campaign. Test scores are standardized by year and grade level using the full Illinois distribution of test scores. The vertical line marks treatment year for all sub-figures.

Figure 3: Effects of AC on Test Scores by Wave of Treatment



Notes: The figure reports difference-in-differences estimates for test score outcomes in math and English for treated and control schools from Equation 1 flexibly for each year from 2010 to 2017, by wave of treatment in the CPS AC installation campaign. Bars represent 95 percent confidence intervals. The vertical line marks treatment year for all sub-figures. Test scores are standardized by year and grade level using the full Illinois distribution of test scores. Equation 1 includes year FE, school FE, and controls for previous year's math and English scores. Robust standard errors are clustered at the school level.

Table 1: School-Level Summary Statistics by Treatment Status

	Control Mean (Std. Dev.)	Treated Mean (Std. Dev.)	Control-Treated Difference (T-Stat)
Panel A: Full Sample			
Math	-0.295	-0.405	0.110**
	(0.509)	(0.416)	(2.608)
English	-0.281	-0.395	0.114**
	(0.494)	(0.433)	(2.657)
Held Back	0.017	0.019	-0.002
	(0.051)	(0.015)	(-0.779)
Attendance	0.945	0.938	0.006*
	(0.027)	(0.029)	(2.093)
White	11.744	8.096	3.648*
	(18.758)	(15.124)	(2.077)
Black	39.310	54.694	-15.383***
	(41.089)	(42.951)	(-3.435)
Hispanic	43.482	32.496	10.986**
	(37.594)	(36.038)	(2.831)
Low Income	80.876	87.594	-6.718**
	(23.530)	(18.129)	(-3.122)
N	405	152	557
Panel B: Energy Star Sample			
Math	-0.164	-0.404	0.241***
	(0.536)	(0.426)	(4.674)
English	-0.168	-0.391	0.223***
	(0.535)	(0.446)	(4.241)
Held Back	0.013	0.019	-0.006***
	(0.013)	(0.014)	(-3.807)
Attendance	0.944	0.938	0.006
	(0.028)	(0.030)	(1.815)
White	11.811	8.498	3.314
	(18.624)	(15.408)	(1.797)
Black	39.088	53.578	-14.490**
	(40.935)	(42.975)	(-3.116)
Hispanic	43.571	33.003	10.568**
	(37.422)	(35.963)	(2.624)
Low Income	80.848	87.241	-6.392**
	(23.532)	(18.481)	(-2.816)
AC %	66.959	36.058	30.900***
	(36.514)	(31.257)	(8.481)
Year Built	19486	1931	17.255***
	(34.406)	(31.664)	(4.828)
Heated %	100.000	99.270	0.730
	(0.000)	(8.544)	(1.000)
N	217	137	354

Notes: Panel A contains information for the full sample of 557 schools. Panel B contains information on the 354 schools for which we have Energy Star data on AC penetration and other physical school characteristics.

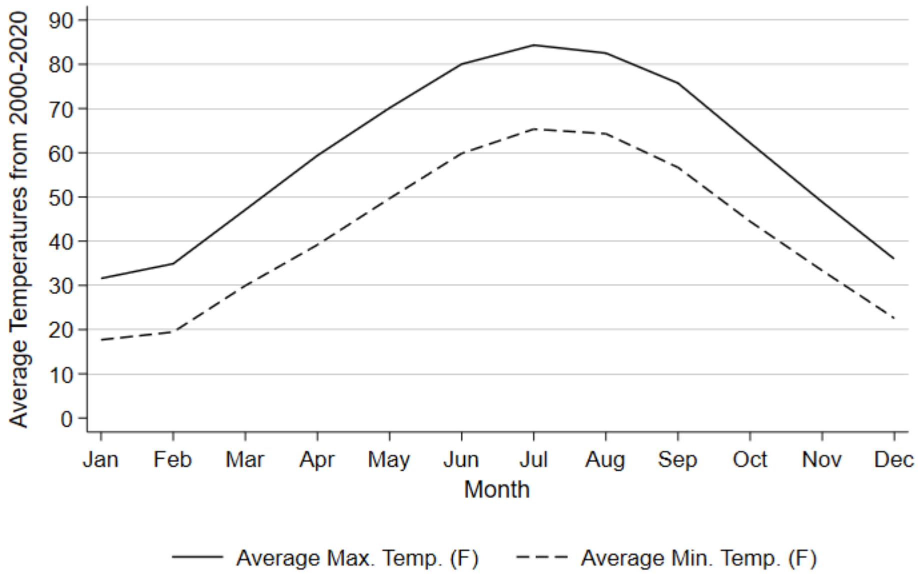
Table 2: Impact of AC From Difference-in-Differences

	Math	English	Held Back	Attendance
	(1)	(2)	(3)	(4)
Panel A: Full Sample				
Have AC	-0.0072	-0.0011	0.0010	0.0028**
	(0.0116)	(0.0108)	(0.0009)	(0.0013)
N	1,078,128	1,079,665	1,082,306	3,714
R^2	0.72	0.69	0.01	0.79
Panel B: Energy Star Sample				
Fraction AC	0.0041	0.0086	0.0002	0.0046**
	(0.0204)	(0.0164)	(0.0011)	(0.0020)
N	520,286	521,082	522,688	2,359
R^2	0.71	0.69	0.01	0.83

Notes: This table reports the estimated coefficients from the difference-in-differences model in Equation 1. The dependent variables in columns (1) and (2) are standardized math and English test scores, respectively. The dependent variable in column (3) is if a student is held back. The dependent variable in column (4) is average student attendance at the school-level, and therefore does not include lagged student test scores. In Panel A, *Have AC* is the main independent variable and is an indicator equal to one if a school has AC in a given year. In Panel B, *Fraction AC* is the main independent variable and is the fraction of the school that was air-conditioned prior to the AC installation campaign as reported in the 2011 Energy Star report. This variable is equal to 1 after a school receives AC. Robust standard errors clustered at the school level are in parentheses.

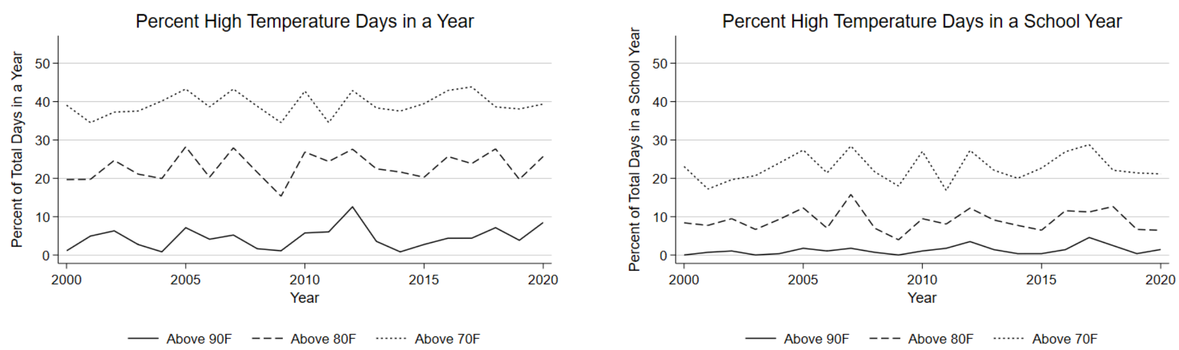
Appendix A

Figure A.1: Average Monthly Temperatures in Chicago (2000-2020)



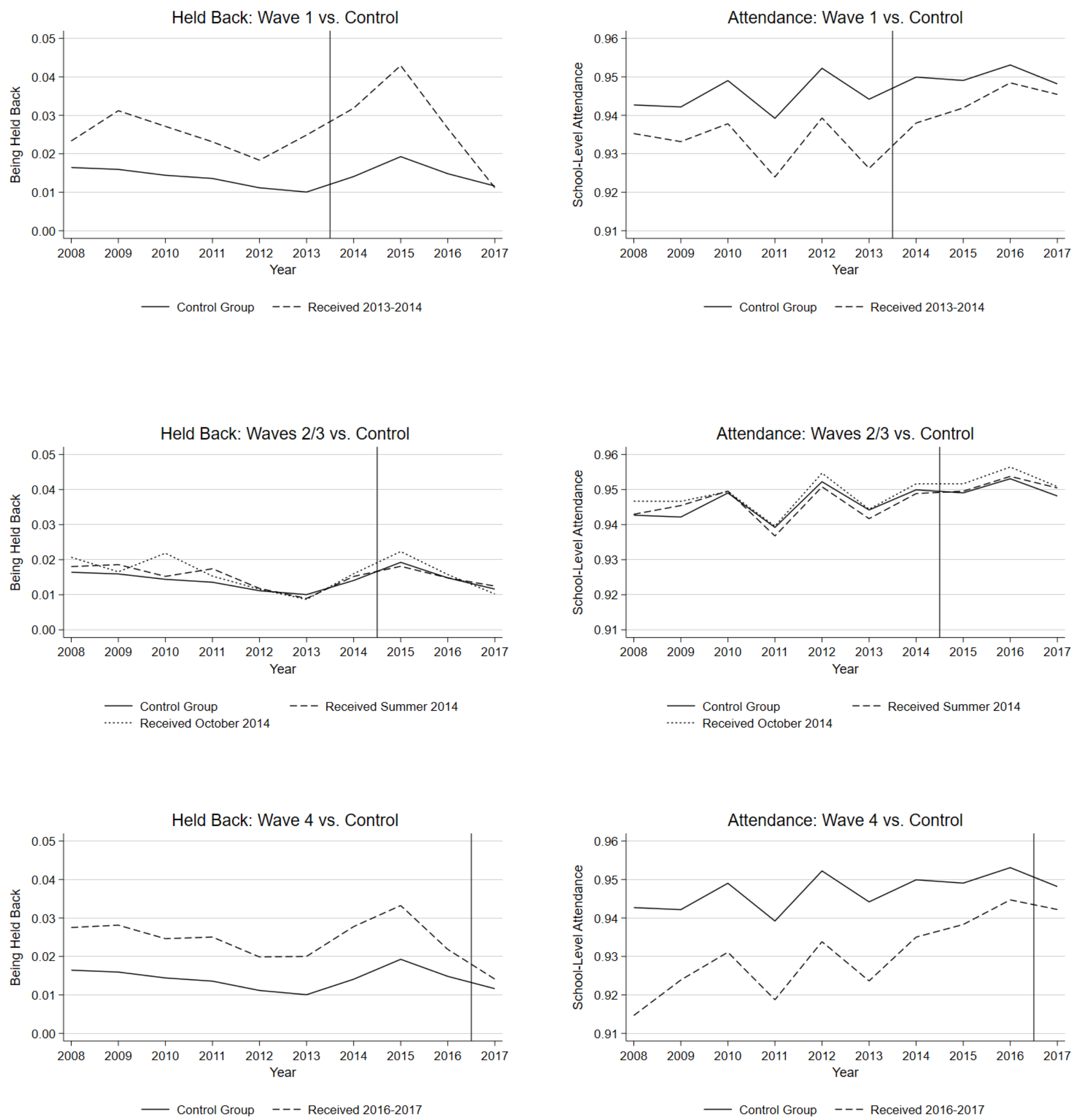
Notes: Average maximum and minimum temperatures each month in Chicago from 2000 to 2020 (Arguez et al., 2020).

Figure A.2: High Temperature Days in Chicago



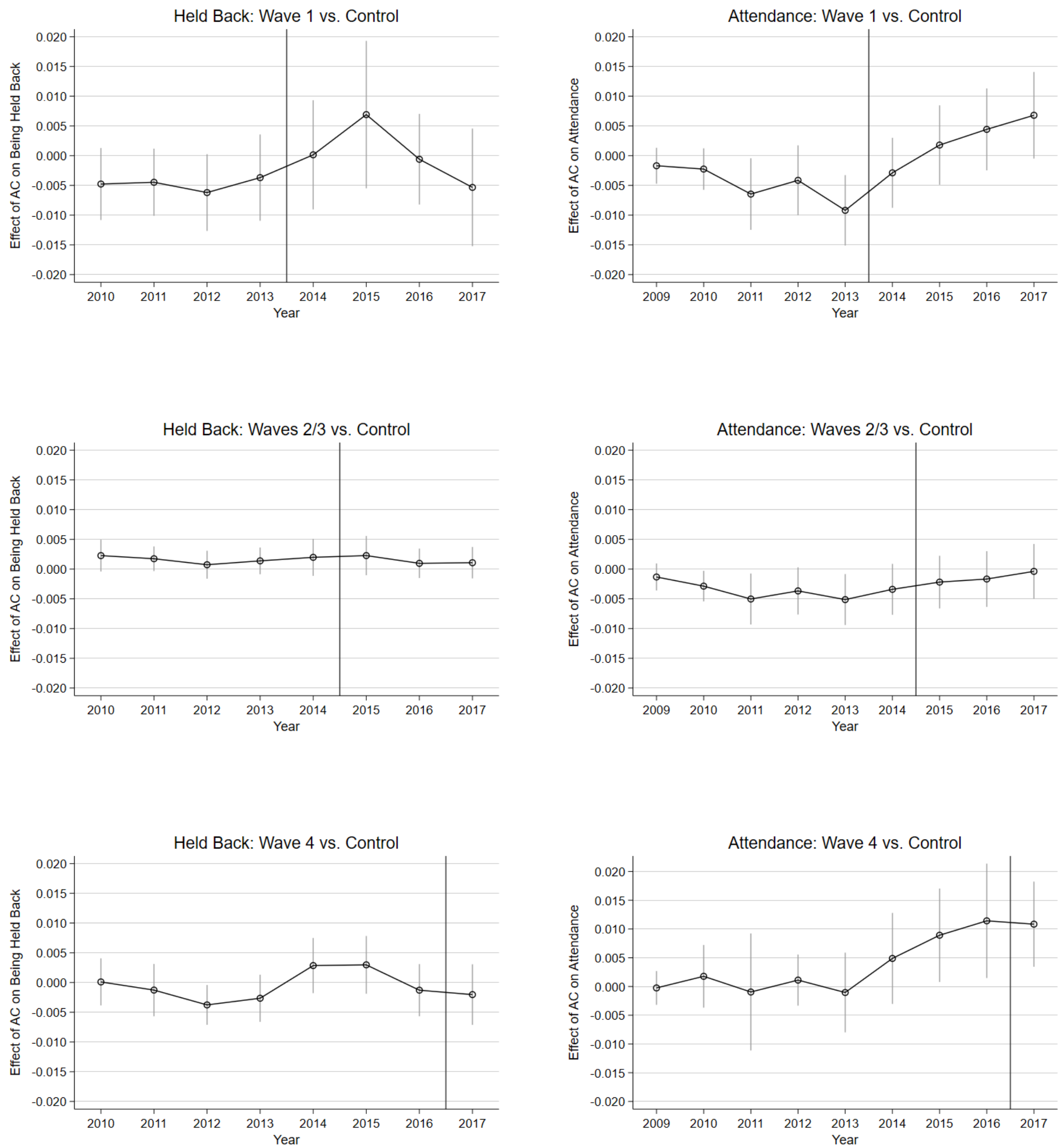
Notes: The figure on the left plots the percent of days in each year from 2000 to 2020 that have a maximum temperature above 70F, 80F, and 90F. The figure on the right plots the percent of school days in each school year that have a maximum temperature above 70F, 80F, and 90F. Daily normals are reported from the Chicago O Hare NOAA Station (Arguez et al., 2020).

Figure A.3: Average Grade Retention and Attendance by Year and Wave of Treatment



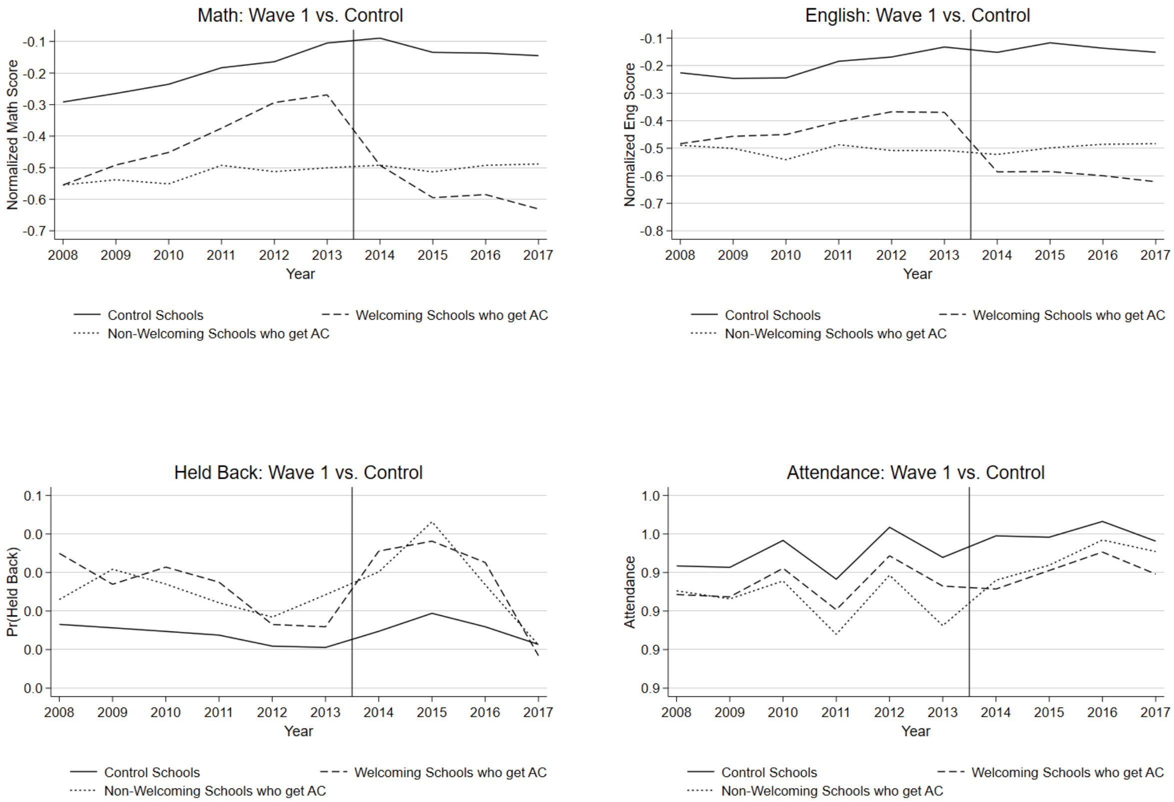
Notes: The figure reports the average annual likelihood of being held back for students in treated and control schools on the left and average school-level attendance for treated and control schools on the right by wave of treatment in the CPS AC installation campaign. The vertical line marks treatment year for all sub-figures.

Figure A.4: Effects of AC on Grade Retention and Attendance by Wave of Treatment



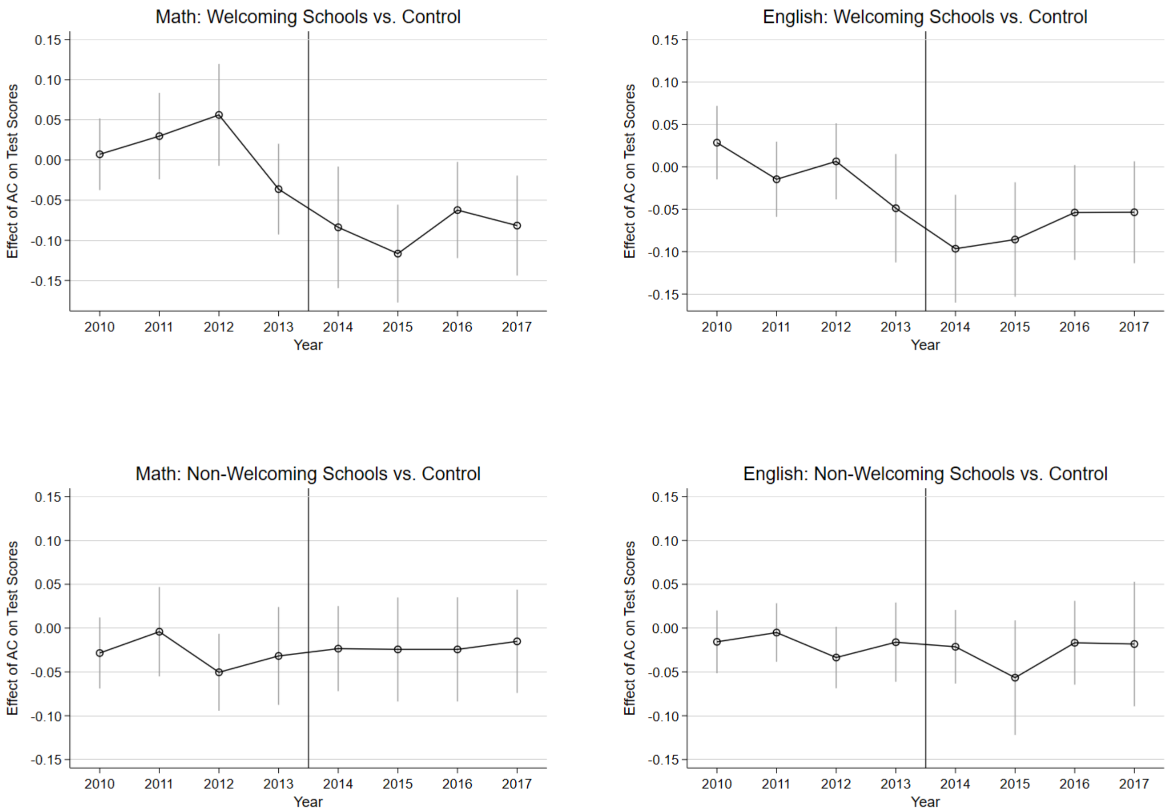
Notes: The figure reports difference-in-differences estimates of the probability of being held back for students in treated and control schools from Equation 1 on the left and the difference-in-differences estimates of school-level average student attendance in treated and control schools on the right by wave of treatment in the CPS AC installation campaign. Bars represent 95 percent confidence intervals. The vertical line marks the treatment year for all sub-figures. Equation 1 includes year FE, school FE, and controls for previous year's math and English test scores. However, lagged scores are not included for the attendance specifications since these data are at the school-year level. Robust standard errors are clustered at the school level.

Figure A.5: Average Test Scores, Grade Retention, and Attendance by Year For Wave 1, Welcoming and Non-Welcoming Schools



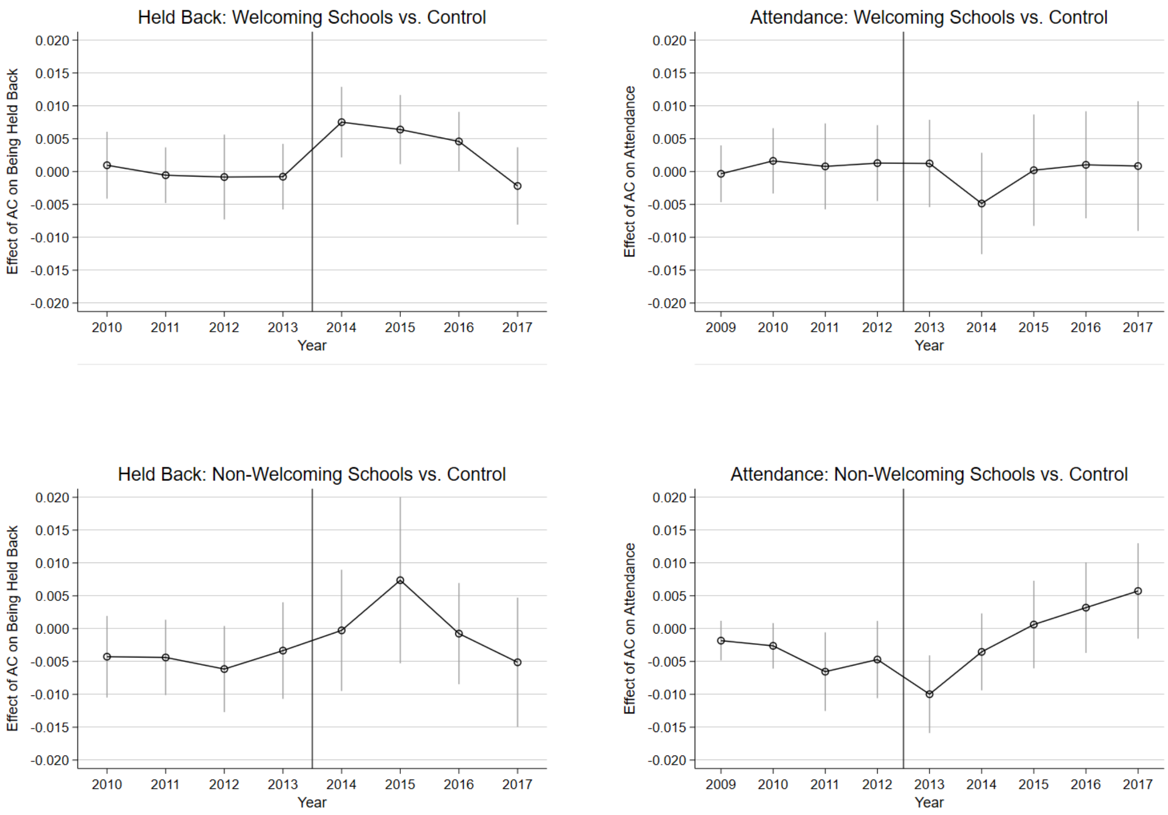
Notes: The figure shows the average annual test scores for math and English, the probability of being held back a grade, and the average school-level attendance in treated and control schools for Wave 1 of the CPS AC installation campaign by whether the school was a welcoming or non-welcoming school. Test scores are standardized by year and grade level using the full Illinois distribution of test scores. The vertical line marks treatment year, 2013-2014. The 'Welcoming Schools' sample includes 33 schools that received AC while also being designated to receive students from the 47 schools that were shut down by CPS that summer, while the 'Non-Welcoming Schools' sample includes 33 schools that received AC but were not designated by CPS to receive students from closed schools.

Figure A.6: Effects of AC on Test Scores for Wave 1, Welcoming and Non-Welcoming Schools



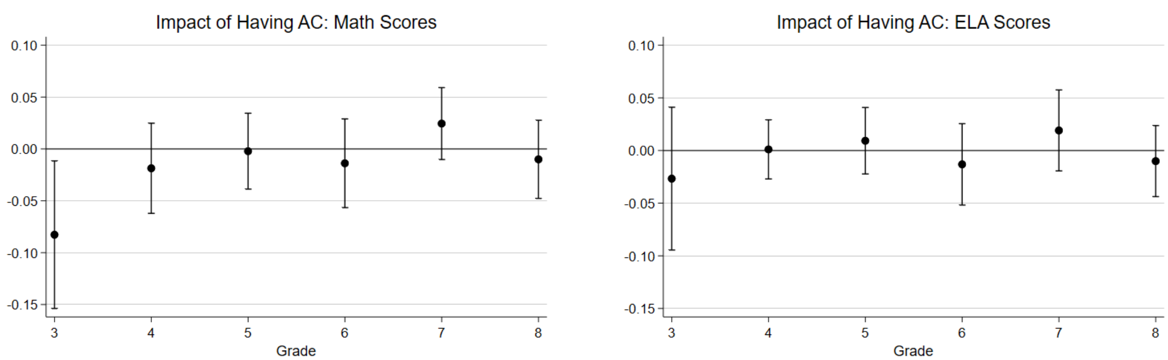
Notes: The figure reports difference-in-differences estimates for math and English test scores for treated and control schools from Equation 1 for Wave 1 of the CPS AC installation campaign by whether the school was a welcoming or non-welcoming school. Bars represent 95 percent confidence intervals. Vertical line marks treatment year, 2013-2014. Equation 1 includes year FE, school FE, and controls for previous year's math and English test scores. Robust standard errors are clustered at the school level. The 'Welcoming Schools' sample includes 33 schools that received AC while also being designated to receive students from the 47 schools that were shut down by CPS that summer, while the 'Non-Welcoming Schools' sample includes 33 schools that received AC but were not designated by CPS to receive students from closed schools.

Figure A.7: Effects of AC on Grade Retention and Attendance for Wave 1, Welcoming and Non-Welcoming Schools



Notes: The figure reports difference-in-differences estimates of the probability of being held back for students in treated and control schools from Equation 1 on the left and estimates for school-level average student attendance on the right, for wave 1 of the CPS AC installation campaign by whether the school was a welcoming or non-welcoming school. Bars represent 95 percent confidence intervals. The vertical line marks treatment year for all sub-figures. Equation 1 includes year FE, school FE, and controls for previous year's math and English test scores for grade retention. Prior math and English controls are not included for attendance because the attendance data is only available at the school level. Robust standard errors are clustered at the school level. The 'Welcoming Schools' sample includes 33 schools that received AC while also being designated to receive students from the 47 schools that were shut down by CPS that summer, while the 'Non-Welcoming Schools' sample includes 33 schools that received AC but were not designated by CPS to receive students from closed schools.

Figure A.8: Effect of AC on Test Scores by Grade



Notes: The figures reports difference-in-differences estimates for math and English test scores for treated and control schools from Equation 1 by grade. Bars represent 95 percent confidence intervals. Estimations includes year FE, school FE, and controls for previous year's math and English test scores. Robust standard errors are clustered at the school level.

Table A.1: Schools that Received AC by Wave of Treatment

Wave 1: 2013-2014	Wave 2: Summer 2014	Wave 3: October 2014	Wave 4: Spring 2017
Alex Haley ES (W)	Ambrose Plamondon ES	Albert R Sabin ES	Amundsen HS
Alice L Barnard ES	Arthur A Libby ES	Carl von Linne ES	Bennett ES
Benjamin E Mays ES (W)	Betty Shabazz – Sizemore	John G Whittier ES	Bogan HS
Bowen HS	Burnside ES	Alcott Humanities HS	Bouchet ES
Bret Harte ES	Charles H Wacker ES	Alexander Hamilton ES	Chicago Tech HS
Burnham Inclusive ES (W)	Charles Kozminski ES	Anna R. Langford ES	Clark G R ES
Carrie Jacobs Bond ES	Charles N Holden ES	Brighton Park ES	Cook ES
Charles Evans Hughes ES (W)	Christian Fenger HS	Cesar E Chavez ES	Cooper ES
Charles G Hammond ES	Christopher Columbus ES	Charles P Caldwell ES	Crown Fine Arts ES
Charles Sumner ES	Daniel Boone ES Daniel	Webster ES	Daniel Hale Williams HS
Clara Barton ES	Ella Flagg Young ES	DeWitt Clinton ES	Darwin ES
Daniel S Wentworth ES (W)	Fairfield ES	Edgebrook ES	Dunbar Vocational HS
Dewey ES of Fine Arts	Fernwood ES	Ernst Prussing ES	Epic Charter HS
Edmond Burke ES	Frank L Gillespie ES	Foster Park ES	Field ES
Ellen Mitchell ES	Frank W Gunsaulus ES	Frank W Reilly ES	Foreman HS
Esmond ES	Friedrich Ludwig Jahn ES	Franklin Art ES	Gage Park HS
Fort Dearborn ES	George B McClellan ES	Henry H Nash ES	Gale ES
Frederic Chopin ES (W)	George M Pullman ES	James Hedges ES	Graham A ES
Genevieve Melody ES (W)	Gurdon S Hubbard HS	Joseph Jungman ES	Harlan Community HS
George Leland ES (W)	Harold Washington ES	Joshua D Kershaw ES	Hirsch Metropolitan HS
George Manierre ES	Harriet Beecher Stowe ES	Mark Sheridan ES	Kelly HS
George W Curtis ES (W)	Helge A Haugan ES	Orville T Bright ES	Kilmer HS
George W Tilton ES (W)	Henry R Clissold ES	Phillip D Armour ES	King ES
George Washington Carver PS	Hiram H Belding ES	Richard J Oglesby ES	Lake View HS
Helen M Hefferan ES (W)	Inter-American Magnet ES	Rowe ES	Lasalle II ES
Ida B Wells Prep ES (W)	James N Thorp ES	Sauganash ES	Lincoln Park HS
Ira F Aldridge ES	James R Doolittle ES	Washington HS	Lovett ES
Irvin C Mollison ES (W)	Johann W Von Goethe ES	William E B Dubois ES	Lowell ES
Isabelle C O'Keeffe ES	John Barry ES	Wolfgang A Mozart ES	Madison ES
James B McPherson ES (W)	John Hay ES		Manley Career HS
James Otis ES (W)	Jonathan Burr ES		Mann ES

Notes: ES: Elementary School. MS: Middle School. HS: High School. (W) : 'Welcoming Schools' that were dropped from our main sample.

Wave 1: 2013-2014	Wave 2: Summer 2014	Wave 3: October 2014	Wave 4: Spring 2017
Jensen ES (W)	Kate S Kellogg ES		Marshall Metropolitan HS
Jesse Sherwood ES (W)	Louis Nettelhorst ES		Mason ES
John B Drake ES (W)	Lyman A Budlong ES		North Lawndale – Christiana
John Fiske ES (W)	Marvin Camras ES		Parkside ES
John Foster Dulles ES (W)	Melville W Fuller ES		Peace & Education HS
John Harvard ES (W)	Newton Bateman ES		Perez ES
John J Pershing ES Magnet (W)	Norman A Bridge ES		Perspectives Leadership HS
John M Smyth ES	North River ES		Perspectives Math Sci HS
John Milton Gregory ES (W)	Park Manor ES		Phillips Academy HS
Jose De Diego ES (W)	Patrick Henry ES		Phoenix Military HS
Laura S Ward ES (W)	Rachel Carson ES		Piccolo Specialty ES
Lawndale ES	Ravenswood ES		Richards Career HS
Leif Ericson ES	Spencer Technology ES		Roosevelt HS
Lorenz Brentano ES	Stephen Decatur ES		Ruggles ES
Ludwig Van Beethoven ES	Stephen K Hayt ES		Shoop Math Sci Tech ES
Mancel Talcott ES	Talman ES		Stagg ES
Maria Saucedo ES	Theodore Herzl ES		Suder Magnet ES
Mary E Courtenay ES (W)	Thomas A Hendricks ES		Sullivan HS
Michael Faraday ES (W)	Thomas J Waters ES		Tanner ES
Mount Vernon ES	Velma F Thomas Center		Tilden Career HS
Nicholson Tech Academy (W)	Washington D Smyser ES		Till Math Sci ES
Northwest MS	William Bishop Owen ES		Univ of Chicago – Donoghue
Owens Community ES (W)	William C Goudy ES		Univ of Chicago – Woodlawn
Paul Revere ES	William J Onahan ES		Urban Prep HS – West
Perkins Bass ES (W)	William Rainey Harper HS		Warren ES
Robert Nathaniel Dett ES (W)			Wells Community HS
Rosario Castellanos ES (W)			Whistler ES
Salmon P Chase ES			Woodson South ES
Scott Joplin ES			Yates ES
South Shore Academy (W)			
Thurgood Marshall MS			
Walter Q Gresham ES			
William C Reavis ES			
William H Ray ES			
William H Ryder ES (W)			
William W Carter ES			

Notes: ES: Elementary School. MS: Middle School. HS: High School. (W) : 'Welcoming Schools' that were dropped from our main sample.

Table A.2: School-Level Summary Statistics by Wave of Treatment

	Control Mean (Std. Dev.)	Wave 1 Mean (Std. Dev.)	Waves 2 & 3 Mean (Std. Dev.)	Wave 4 Mean (Std. Dev.)	Control-Wave 1 Difference (T-Stat)	Control-Waves 2 & 3 Difference (T-Stat)	Control-Wave 4 Difference (T-Stat)
Panel A: Full Sample							
Math	-0.295	-0.510	-0.292	-0.544	0.215**	-0.004	0.249***
	(0.509)	(0.335)	(0.446)	(0.353)	(3.377)	(-0.067)	(4.057)
English	-0.281	-0.500	-0.266	-0.563	0.219***	-0.015	0.282***
	(0.494)	(0.278)	(0.442)	(0.448)	(4.020)	(-0.265)	(3.763)
Held Back	0.015	0.026	0.028	0.022	-0.011***	0.002	-0.007*
	(0.015)	(0.013)	(0.111)	(0.017)	(-4.592)	(0.646)	(-2.598)
Attendance	0.945	0.936	0.946	0.922	0.008*	-0.001	0.022**
	(0.027)	(0.016)	(0.022)	(0.044)	(2.493)	(-0.464)	(2.846)
White	11.744	2.263	12.835	2.695	9.481***	-1.091	9.049***
	(18.758)	(4.932)	(18.659)	(6.267)	(6.345)	(-0.446)	(5.546)
Black	39.310	73.790	41.295	67.439	-34.479***	-1.985	-28.129***
	(41.089)	(39.783)	(42.368)	(36.985)	(-4.586)	(-0.360)	(-4.038)
Hispanic	43.482	20.417	39.711	27.376	23.065**	3.772	16.107*
	(37.594)	(35.798)	(35.808)	(33.732)	(3.402)	(0.794)	(2.534)
Low Income	80.876	92.250	82.955	93.906	-11.374***	-2.079	-13.030***
	(23.530)	(10.151)	(22.268)	(7.484)	(-4.834)	(-0.702)	(-6.504)
N	404	33	80	40	437	484	444
Panel B: Energy Star Sample							
Math	-0.164	-0.519	-0.280	-0.586	0.355***	0.116	0.423***
	(0.536)	(0.352)	(0.449)	(0.340)	(4.754)	(1.833)	(6.089)
English	-0.168	-0.509	-0.252	-0.604	0.341***	0.084	0.436***
	(0.535)	(0.292)	(0.445)	(0.456)	(5.236)	(1.334)	(4.993)
Held Back	0.013	0.026	0.015	0.024	-0.013***	-0.001	-0.010**
	(0.013)	(0.013)	(0.012)	(0.017)	(-5.074)	(-0.653)	(-3.230)
Attendance	0.944	0.936	0.946	0.922	0.008*	-0.002	0.022**
	(0.028)	(0.016)	(0.022)	(0.045)	(2.233)	(-0.646)	(2.726)
White	11.811	2.463	13.337	2.774	9.348***	-1.526	9.037***
	(18.624)	(5.146)	(18.866)	(6.351)	(5.846)	(-0.601)	(5.303)
Black	39.088	71.280	41.073	66.453	-32.192***	-1.985	-27.365***
	(40.935)	(41.020)	(42.468)	(37.133)	(-3.964)	(-0.349)	(-3.831)
Hispanic	43.571	22.435	39.216	28.212	21.136**	4.355	15.358*
	(37.422)	(37.065)	(35.565)	(33.922)	(2.876)	(0.894)	(2.353)
Low Income	80.848	92.331	82.414	93.790	-11.483***	-1.566	-12.941***
	(23.532)	(10.371)	(22.553)	(7.573)	(-4.563)	(-0.508)	(-6.158)
AC %	66.959	34.483	34.933	40.000	32.476***	32.025***	26.959***
	(36.514)	(32.248)	(31.295)	(30.923)	(5.011)	(7.308)	(4.549)
Year Built	1948	1934	1925	1941	13.817*	22.856***	7.546
	(34.406)	(32.746)	(28.251)	(35.997)	(2.121)	(5.697)	(1.128)
Heated %	100.000	100.000	100.000	96.970	0.000	0.000	3.030
	(0.000)	(0.000)	(0.000)	(17.408)	(.)	(.)	(1.000)
N	217	29	75	33	246	292	250

Notes: Panel A contains information for the full sample of 557 schools. Panel B contains information on the 354 schools for which we have Energy Star data on AC penetration and other physical school characteristics.

Table A.3: Impact of AC From Difference-in-Differences in Levels (Without Lagged Scores)

	Full Sample			Low-Performing Students		
	Math	English	Held Back	Math	English	Held Back
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Full Sample						
Have AC	-0.0126	-0.0054	0.0006	-0.0119	0.0051	0.0011
	(0.0182)	(0.0183)	(0.0015)	(0.0129)	(0.0136)	(0.0027)
N	1,570,976	1,566,628	1,577,349	172,765	173,020	173,817
R^2	0.19	0.17	0.01	0.05	0.04	0.01
Panel B: Energy Star Sample						
Fraction AC	-0.0169	-0.0071	0.0004	-0.0006	0.0316	0.0016
	(0.0269)	(0.0270)	(0.0020)	(0.0194)	(0.0208)	(0.0032)
N	822,858	821,551	826,652	83,086	83,188	83,644
R^2	0.20	0.19	0.01	0.04	0.04	0.01

Notes: This table reports the estimated coefficients from the difference-in-differences model in Equation 1 not including lagged student test scores. The dependent variables in columns (1) and (2) are standardized math and English test scores, respectively. The dependent variable in column (3) is if a student is held back. Columns (4), (5), and (6) are analogous to the first three columns but restrict the sample to students performing in the bottom quartile of both the math and English test score distributions. In Panel A, *Have AC* is the main independent variable and is an indicator equal to one if a school has AC in a given year. In Panel B, *Fraction AC* is the main independent variable and is the fraction of the school that was air-conditioned prior to the AC installation campaign as reported in the 2011 Energy Star report. This variable is equal to 1 after a school receives AC. Robust standard errors clustered at the school level are in parentheses.

Table A.4: Impact of AC From Difference-in-Differences for Wave 1 Schools, if Welcoming School or Not

	Welcoming Schools				Not Welcoming Schools			
	Math	English	Held Back	Attendance	Math	English	Held Back	Attendance
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Full Sample								
Have AC	-0.0980***	-0.0692***	0.0046***	-0.0015	0.0004	-0.0143	0.0039*	0.0058**
	(0.0229)	(0.0207)	(0.0015)	(0.0030)	(0.0178)	(0.0182)	(0.0023)	(0.0027)
N	871,517	872,943	875,005	2,786	876,721	878,098	880,334	2,786
R^2	0.71	0.69	0.01	0.75	0.72	0.69	0.01	0.76
Panel B: Energy Star Sample								
Fraction AC	-0.1343***	-0.0802**	0.0068***	-0.0057*	0.0150	0.0060	0.0079**	0.0112**
	(0.0401)	(0.0340)	(0.0026)	(0.0031)	(0.0429)	(0.0371)	(0.0031)	(0.0049)
N	390,621	391,349	392,473	1,674	397,614	398,286	399,594	1,723
R^2	0.71	0.69	0.01	0.82	0.71	0.69	0.01	0.82

Notes: Panel A of the table reports the estimated coefficient on Have AC from the difference-in-differences outlined in Equation 1. Similarly, Panel B of the table reports the estimated coefficient on Fraction AC from the difference-in-differences model outlined in Equation 2. Columns (1)-(4) reports estimates using only the 33 *Welcoming Schools* treated in wave 1, while columns (5)-(8) reports estimates using only the 33 *Non-Welcoming Schools* in wave 1. Robust standard errors clustered at the school level are in parentheses.

Table A.5: Impact of AC From Difference-in-Differences, Low-Performing Students

	Math	English	Held Back
	(1)	(2)	(3)
Panel A: Full Sample			
Have AC	-0.0147	-0.0011	0.0012
	(0.0112)	(0.0117)	(0.0027)
N	172,638	172,898	173,687
R^2	0.16	0.22	0.01
Panel B: Energy Star Sample			
Fraction AC	-0.0064	0.0151	0.0014
	(0.0174)	(0.0186)	(0.0031)
N	82,990	83,094	83,544
R^2	0.13	0.20	0.01

Notes: This table reports the estimated coefficients from the difference-in-differences model in Equation 1 for students in the bottom of both the math and English test score distributions. The dependent variables in columns (1) and (2) are standardized math and English test scores, respectively. The dependent variable in column (3) is if a student is held back. In Panel A, *Have AC* is the main independent variable and is an indicator equal to one if a school has AC in a given year. In Panel B, *Fraction AC* is the main independent variable and is the fraction of the school that was air-conditioned prior to the AC installation campaign as reported in the 2011 Energy Star report. This variable is equal to 1 after a school receives AC. Robust standard errors clustered at the school level are in parentheses.

Table A.6: Impact of AC From Difference-in-Differences by Wave of Treatment

	Wave 1				Waves 2 & 3				Wave 4			
	Math	English	Held Back	Attendance	Math	English	Held Back	Attendance	Math	English	Held Back	Attendar
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Full Sample												
Have AC	-0.0007	-0.0156	0.0041*	0.0065**	-0.0101	0.0036	0.0001	0.0016	0.0149	0.0060	-0.0016	0.0080**
	(0.0178)	(0.0184)	(0.0023)	(0.0027)	(0.0154)	(0.0135)	(0.0008)	(0.0015)	(0.0241)	(0.0236)	(0.0019)	(0.0027
N	848,371	849,685	851,787	2,656	958,072	959,540	961,618	3,096	843,445	844,854	846,741	2,634
R^2	0.72	0.69	0.01	0.77	0.72	0.69	0.01	0.76	0.72	0.69	0.01	0.81
Panel B: Energy Star Sample												
Fraction AC	0.0122	0.0033	0.0080***	0.0119**	0.0038	0.0063	-0.0013	0.0029	-0.0093	0.0250	-0.0039	0.0093*
	(0.0427)	(0.0371)	(0.0030)	(0.0049)	(0.0254)	(0.0195)	(0.0010)	(0.0021)	(0.0404)	(0.0348)	(0.0025)	(0.0046
N	385,639	386,285	387,510	1,646	456,723	457,544	458,715	1,954	384,612	385,287	386,327	1,645
R^2	0.72	0.69	0.01	0.83	0.71	0.69	0.01	0.83	0.71	0.69	0.01	0.85

Notes: This table reports the estimated coefficients from the difference-in-differences model in Equation 1 separately by each wave of AC installation. In Panel A, *Have AC* is the main independent variable and indicator equal to one if a school has AC in a given year. In Panel B, *Fraction AC* is the main independent variable and is the fraction of the school that was air-conditioned prior to the AC installation campai reported in the 2011 Energy Star report. This variable is equal to 1 after a school receives AC. Wave 1 schools received AC in 2013-14, wave 2 in Summer 2014, wave 3 in October 2014, and wave 4 in 2016-17. R standard errors clustered at the school level are in parentheses.

Table A.7: Impact of AC From Difference-in-Differences by Wave of Treatment in Levels (Without Lagged Scores)

	Wave 1			Waves 2 & 3			Wave 4		
	Math	English	Held Back	Math	English	Held Back	Math	English	Held Back
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Full Sample									
Have AC	-0.0525	-0.0611**	0.0032	0.0024	0.0170	0.0008	0.0520	0.0127	-0.0113*
	(0.0326)	(0.0274)	(0.0027)	(0.0223)	(0.0231)	(0.0018)	(0.0365)	(0.0324)	(0.0063)
N	1,229,844	1,226,925	1,234,935	1,392,397	1,388,484	1,397,759	1,224,627	1,221,647	1,229,571
R^2	0.20	0.18	0.01	0.19	0.18	0.01	0.20	0.18	0.01
Panel B: Energy Star Sample									
Fraction AC	-0.0416	-0.0500	0.0047	-0.0102	0.0030	0.0005	0.0247	0.0269	-0.0133
	(0.0547)	(0.0416)	(0.0037)	(0.0331)	(0.0354)	(0.0023)	(0.0375)	(0.0455)	(0.0110)
N	607,891	607,099	610,766	718,691	717,611	721,789	606,090	605,311	608,771
R^2	0.21	0.20	0.01	0.19	0.19	0.01	0.20	0.20	0.01

Notes: This table reports the estimated coefficients from the difference-in-differences model in Equation 1 not including lagged student test scores. In Panel A, *Have AC* is the main independent variable and is an indicator equal to one if a school has AC in a given year. In Panel B, *Fraction AC* is the main independent variable and is the fraction of the school that was air-conditioned prior to the AC installation campaign as reported in the 2011 Energy Star report. This variable is equal to 1 after a school receives AC. Wave 1 schools received AC in 2013-14, wave 2 in Summer 2014, wave 3 in October 2014, and wave 4 in 2016-17. Robust standard errors clustered at the school level are in parentheses.

Table A.8: Impact of AC From Difference-in-Differences for Schools with Lowest Prior AC Coverage

	Math (1)	English (2)	Held Back (3)	Attendance (4)
Have AC	0.0147	0.0131	0.0009	0.0030**
	(0.0214)	(0.0172)	(0.0011)	(0.0013)
N	436,584	437,335	438,576	2,394
R^2	0.71	0.69	0.01	0.83

Notes: This table reports the estimated coefficients from the difference-in-differences model in Equation 1 while restricting the sample of treated schools to only those that had less than 30% of the school air-conditioned prior to being treated. The dependent variables in columns (1) and (2) are standardized math and English test scores, respectively. The dependent variable in column (3) is if a student is held back. The dependent variable in column (4) is average student attendance at the school-level, and therefore does not include lagged student test scores. *Have AC* is the main independent variable and is an indicator equal to one if a school has AC in a given year. Robust standard errors clustered at the school level are in parentheses.

Table A.9: Impact of Temperature on Test Scores

	Days Above 70F		Days Above 80F		Days Above 90F	
	Math	English	Math	English	Math	English
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Using Lagged Test Scores						
School Days Above 70F	-0.0010	-0.0015**				
	(0.0006)	(0.0006)				
School Days Above 80F			-0.0000	-0.0013		
			(0.0009)	(0.0009)		
School Days Above 90F					-0.0011	-0.0017
					(0.0021)	(0.0015)
N	1,078,128	1,079,665	1,078,128	1,079,665	1,078,128	1,079,665
R^2	0.72	0.69	0.71	0.69	0.71	0.69
Panel B: Using Student Fixed Effects						
School Days Above 70F	0.0003	0.0001				
	(0.0010)	(0.0011)				
School Days Above 80F			0.0028	0.0019		
			(0.0017)	(0.0021)		
School Days Above 90F					0.0024	0.0017
					(0.0032)	(0.0032)
N	1,471,988	1,468,802	1,471,988	1,468,802	1,471,988	1,468,802
R^2	0.85	0.84	0.85	0.84	0.85	0.84

Notes: This table reports the estimated coefficients from a regression of achievement outcomes on the total number of school days above a certain temperature. The dependent variables in columns (1), (3) and (5) are the standardized math test scores, and in columns (2), (4) and (6) are the standardized English test scores. The main independent variable is the total number of days above a certain temperature in the school year. Controls in Panel A include lagged student test scores in the prior year and school fixed effects. Controls in Panel B include student fixed effects and school fixed effects. Errors are clustered by year.