Trying to Beat the Heat: Air-Conditioning and Learning

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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 find marginal improvements in attendance. When measuring returns at the top of the 95 percent confidence interval, benefits to student achievement remain relatively modest. These results can help school districts better optimize their often limited budgets when striving to improve student performance.

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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).[1] 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

[1] Alternatively, Johnston et al. (2021) show that in Australia additional cold days significantly reduce student test scores.

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 little evidence that AC installation impacted 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. We do 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. Even upon restricting our sample to schools that had the lowest AC penetration prior to the campaign, we do not find gains in test scores for students.

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 do not have data on student socio-economic status but upon analyzing the impact of AC on low-performing students, we 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 impact 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).[2] 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 cannot 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 where less than a third of the school days are above 70F and less than 20% are above 80F.[3] 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 several of those 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. When using estimates at the top of the 95 percent confidence interval, the AC installation program returned test-score gains are typically less than 0.03 standard deviations, although test-score gains may not be the only goal of AC installation.

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 323,291 students enrolled across 642 schools in the 2023-24 school year (Chicago Public Schools, 2023). The public school system in Chicago serves an ethnically diverse student body, of which the largest proportion of students are Hispanic (46.9%)

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

[3] 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 (35.0%). The district categorizes more than two thirds 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 and statewide (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 students in every 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.[4] This test is known as a "high stakes" test in the state

[4]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 school 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.[5] 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 scores 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.[6] 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 either. 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

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

[5]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.

[6]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.

and English test scores. In contrast to the discrepancies in AC, treated and control schools are both nearly fully 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:

$$y_{ist} = \alpha + \beta \textit{Have AC}_{st} + \theta_i + \mu_s + \lambda_t + \varepsilon_{ist} \tag{1}$$

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, student fixed effects (θ_i), school fixed effects (μ_s), and year fixed effects (λ_t) are included.[7] The main coefficient of interest, β, measures the difference in test scores before and after AC installation for 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 student fixed effects. 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 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. Figure 2 shows that the test

[7] Appendix Table A.3 reports our main estimates that control for students' lagged math and English test scores instead of including student fixed effects and find similar and more precise results.

scores in the treated and control schools appear to move in parallel prior to AC installation. However, for attendance and the probability of being held back a grade, there is some evidence of a pre-trend for wave 4 schools in Figure A.3. To formally test for parallel pre-trends, Figure 3 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 test scores and attendance. However, there are strong and significant pre-trends for being held back a grade.[8]

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, the '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.[9]

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

[8]When we repeat our test for pre-trends using lagged student test scores instead of student fixed effects in Figure A.4, we do not see significant pre-trends for test scores, attendance or the probability of being held back a grade.

[9]In Appendix Figures A.6, A.7, A.8, A.9 and Tables A.4 and A.5 we show the results for Wave 1 for both 'Welcoming Schools' and 'Non-Welcoming Schools' separately. While we find mostly null effects for 'Non-Welcoming Schools', the estimates for 'Welcoming Schools' show a significant decline in test scores after AC installation, consistent with a negative bias due to simultaneously welcoming low-performing students. The differences between Welcoming and Non-Welcoming schools in the impacts of AC on the probability of being held back a grade and average school attendance are less disparate.

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 did have more than 50% of their school air-conditioned. Thus, some 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:

$$y_{ist} = \alpha + \beta \mathit{Fraction\ AC}_{st} + \theta_i + \mu_s + \lambda_t + \varepsilon_{ist} \tag{2}$$

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 appear to be parallel trends prior to the treatment. In Figure A.3 we see possible evidence that AC installation decreased the likelihood of being held back in Wave 4 schools, as well as 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 other outcomes.

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 0.013 standard deviations in their average math test scores and 0.005 standard deviations in their English test scores post AC installation as compared to control schools (similar results can be seen in Appendix Table A.3 when lagged student test score are used instead of student fixed effects in Equation 1). These effects are close to zero and are in the opposite direction as would be predicted if AC was beneficial for student test scores. We estimate that students in schools that received AC were 0.61 percentage points less likely to be held back after AC was installed. While this effect on being held back is statistically significant, there appear to be strong pretrends when the estimation is done dynamically (see Figure 3) suggesting this estimated effect may not be due to AC installation. In fact, when using the lagged test score specification shown in Appendix Table A.3 for which there are no pre-trends, the effect on being held back goes to zero. For attendance, we find that treated schools saw a 0.003 percentage point (or 0.3 percent) increase in attendance.

Panels B, C, and D show that the results are very similar when taking into account potential time-varying heterogeneous treatment effects. Panel B accounts for potential time-varying heterogeneous treatment effects using methods from Borusyak, Jaravel and Spiess (Forthcoming). Similarly, Panel C and D use methods from De Chaisemartin and d'Haultfoeuille (2020) and Callaway and Sant'Anna (2021), respectively. Similar to the two-way fixed effect results in Panel A, there is no evidence that AC installation had a significant positive effect on student test scores. These results can rule out relatively modest positive impacts of AC installation on student test scores. When measuring returns at the top of the 95th percent confidence interval, the most positive estimate for the impact of AC installation would only increase math and English test scores by less than 0.04 standard deviations.

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.6 and Table A.7. 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 and to better examine potential pre-trends, Figures 3 plots the coefficients from Equation 1 while allowing them to vary flexibly by each year (similar figures are shown using lagged test score controls instead of student fixed effects in Appendix Figure A.4). For both math and English test scores we see that there are no statistically significant impacts after treatment (including no disruption effects in the year of installation). In addition, there are no large differences in estimates in the years just before versus just after the treatment occurs. These figures also confirm that for test scores 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.[10] Hence, even after breaking down the impacts of the AC program by years after installation, we find little evidence of positive impacts on student test scores.

Another way to test for the possible negative disruptions of AC installation during the school year would be to re-estimate Equation 1 after dropping observations of test scores and outcomes from the year in which AC was installed in treated schools. On doing this in Table A.8 we find that there are still no significant positive impacts of AC installation on test scores or the probability of being held back a grade.[11]

In addition to test scores, Figure 3 shows the coefficients by year for held back and attendance.

[10] For the period of our 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).

[11] Estimating this specification with lagged student test scores instead of student fixed effects in Table A.9 leads us to the same conclusion.

In the probability of being held back a grade, there are large and significant pre-trends. In addition, there is no large difference in the estimates around the year of AC installation. This suggests that the beneficial effect of AC on being held back found in Table 2 is driven by pre-trends. When lagged test scores are used instead of student fixed effects as seen in Figure A.4 there are no pre-trends in the possibility of being held back a grade and the estimated difference-in-difference coefficients are indistinguishable from zero (see Table A.3). There do not appear to be any pre-trends for attendance. Similar to test scores, there is not an abrupt discontinuity at the treatment year, however, there is an increase in attendance three and four years after the AC installation. If AC improves classroom conditions for students, we would likely see an increase in attendance sooner after AC installation. However, there are no large differences in estimates right before versus after the treatment occurs. Overall, these results suggest taking the positive effects of AC installation on attendance found in Table 2 with caution.

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.10 we report the results of Equation 1 separately for each wave. For all waves, we find no statistically positive impact of AC installation on standardized math or English test scores. While the specification with student fixed effects finds a reduction in the likelihood of being held back, this is again likely due to pre-trends and becomes positive or insignificant when using lagged student test scores (see Appendix Table A.11). For attendance we find positive effects of AC installation for schools in waves 1 and 4. When plotting the coefficients of Equation 1 allowing the impacts of AC to vary flexibly by wave and year, we see that both math and English test scores in Wave 1 see a decline in the years prior to AC installation in Figure A.10 and the probability of being held back sees significant negative pre-trends in Waves 1 and 4 in Figure A.11.[12]

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.14, 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.[13]

[12]When replicating the figures using lagged student test scores instead of student fixed effects in Figures A.12 and A.13, we only see statistically significant pre-trend in attendance during Wave 4, and not on the test scores or the probability of being held back a grade.

[13]The results in estimating the equation with lagged student test scores instead of student fixed effects in Appendix Figure A.15 also shows no distinguishable differences between the impacts of air-conditioning by grade.

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.[14]

These results are reported in Panel II of Table 2. We find that the estimates are very similar to those in Panel A – although they 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 0.015 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 decrease of -0.019 standard deviations on English test scores. These effects are even more negative when using De Chaisemartin and d'Haultfoeuille (2020) to account for heterogeneous treatment effects. In addition, columns (3) and (4) show similar-sized effects of going from no AC to being fully air-conditioned impacted on the likelihood of a student being held back and attendance. The impacts for the low-performing students are also similar to the full sample (see Table A.6).[15] When using methods from De Chaisemartin and d'Haultfoeuille (2020), the estimates for both held back and attendance are closer to zero.

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 the annual end of year test scores for students. While this

[14] 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 Tables A.12 and A.13).

[15] The estimates by wave of treatment are similar to the full sample but have larger standard errors.

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.14 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. In addition, the average electricity cost due to air conditioning is approximately $204 per student per year.[16] 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. In fact, if taken at face value, the point estimates on test scores typically suggest negative effects on test scores. Alternatively, we could measure the upper end of the possible range of returns by using the top of the 95 percent confidence interval (see Table 2 and Table A.3). Using either the student fixed effects or lagged test score specification, the gains on test scores for students would be below 0.036 and 0.021 standard deviations, respectively. When using the smaller Energy Star sample where the estimates are less precise, the top of the confidence intervals are roughly 50 percent larger. Overall, this would suggest relatively modest increases in test scores even at the top of the confidence interval.

Compared to other policy interventions, the Chicago AC installation program compares fairly poorly in terms of test-score improvements. 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

[16] These estimates come from reports from the Chicago Public Schools on their electricity usage. See https://www.cps.edu/strategic-initiatives/energy-sustainability/programs/energy-efficiency/ and https://www.ameresco.com/portfolio-item/chicago-public-schools/.

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). However, while the AC installation had a high fixed cost the average cost per student per year could be as low as $500 dollars assuming no maintenance costs for 10 years. Therefore, if the returns for the AC installation are at the top of the 95 percent confidence interval the cost-benefit ratio would be fairly low. For example, Jackson and Mackevicius (Forthcoming) find that on average a $1,000 increase in per pupil expenditure for four years increases test scores by 0.031 standard deviations. While some of the confidence intervals could reject this size of an effect, not all the confidence intervals, especially when using the smaller Energy Star data in Equation 2, could reject this size of an effect. However, while the AC installation program in Chicago may have improved the comfort of the learning environment for students and teachers, our point estimates show that this change in environment did not appear to translate to significant test-score improvements unlike 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. On the other hand, the slow improvements we see in school-level attendance two or more years after AC installation could point to possible gains along non-test score outcomes. It could be useful to re-evaluate this and other AC installation programs on other non-test score student outcomes, especially given the evidence that test scores may typically understate the larger, longer-term benefits of education interventions (Card and Krueger, 1992; Krueger, 1999; Jackson, 2018; Beuermann et al., 2023).

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.

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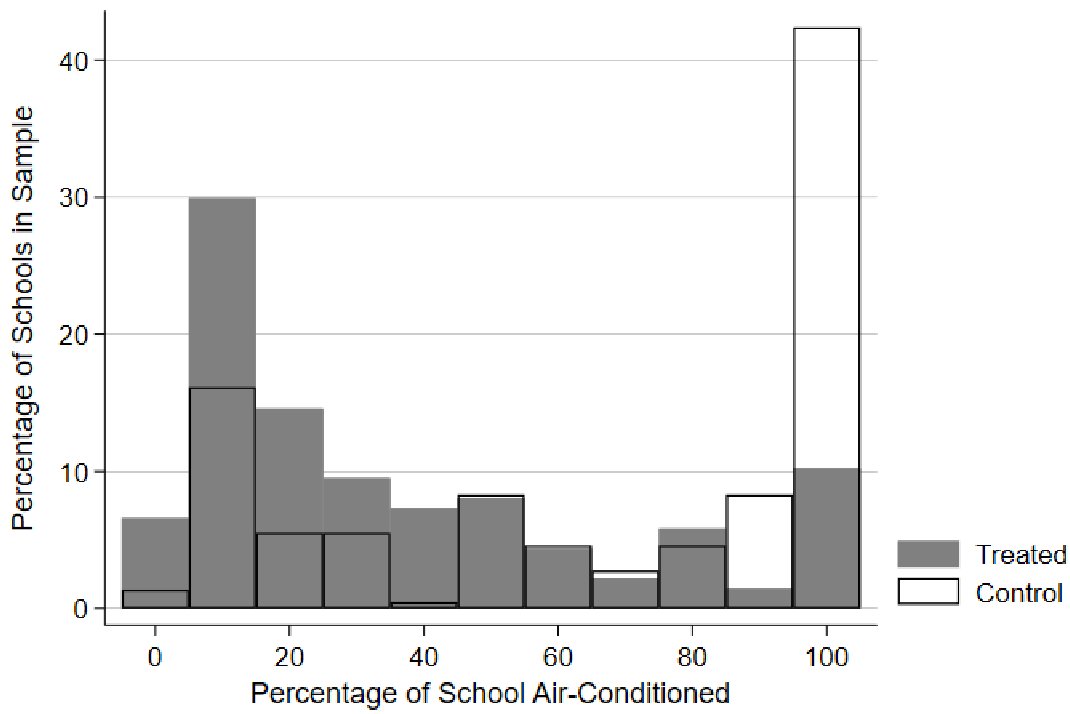
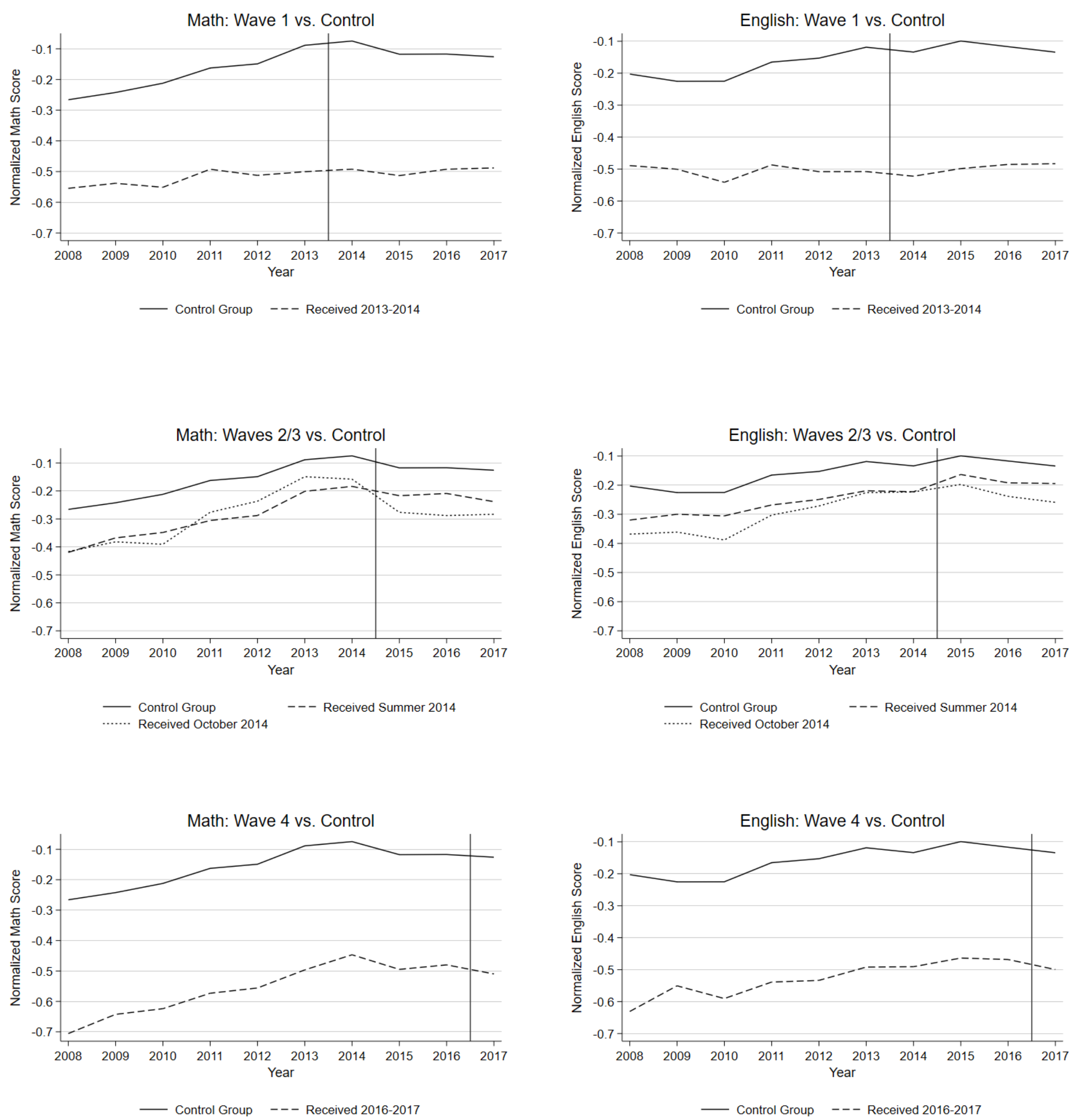
Figure 1: Percentage of School Air-Conditioned by Treatment Status



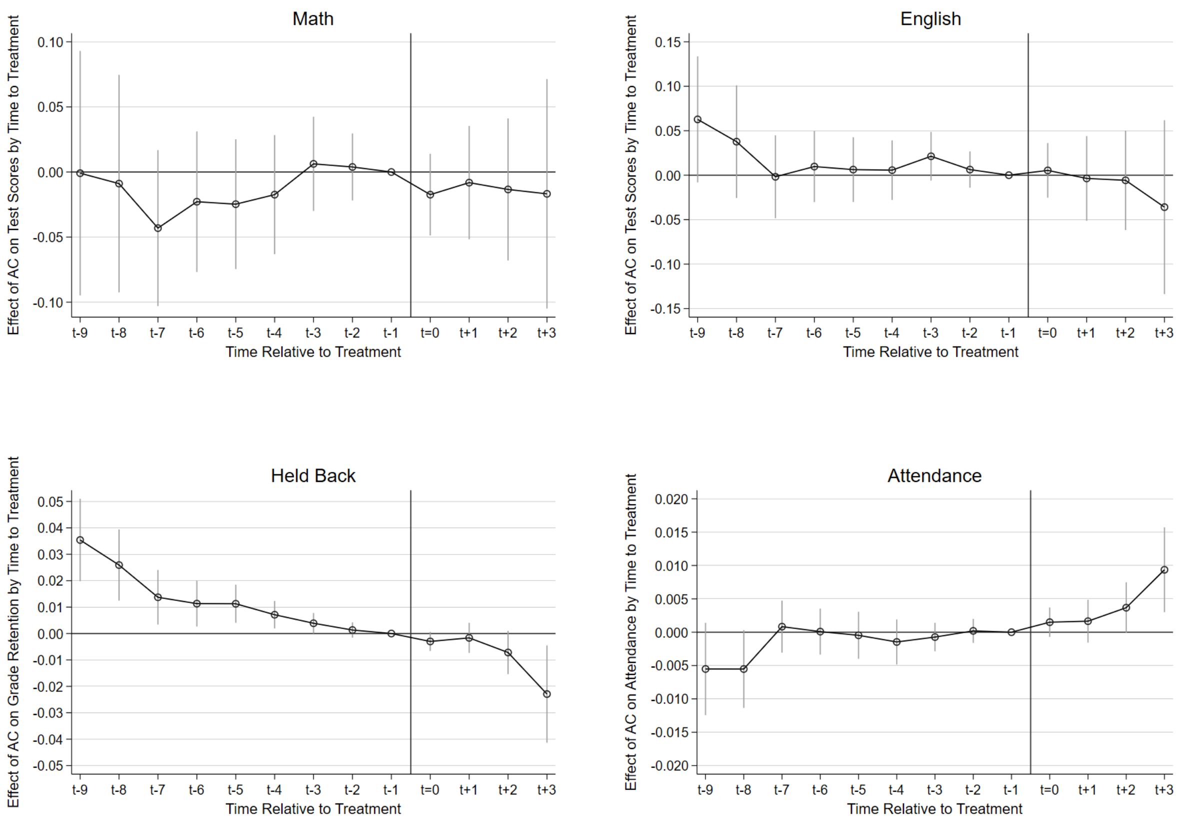
Notes: The figure shows the distribution of control and treated schools by decile for the percentage of the school that is air-conditioned prior to the AC installation program. A value of 100 implies the school is fully air-conditioned, while a value of 0 implies the school has no air-conditioning.

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, Grade Retention, and Attendance



Notes: The figure reports difference-in-differences estimates of time relative to receiving AC on math test scores, English test scores, the probability of being held back for students, and on school-level average student attendance. The omitted year is *t-1*, where *t* is the treatment year. Bars represent 95 percent confidence intervals. The vertical line marks the treatment year for all sub-figures. The estimating equation includes year FE, school FE, and student FE. Student fixed effects 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.

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	1948	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.

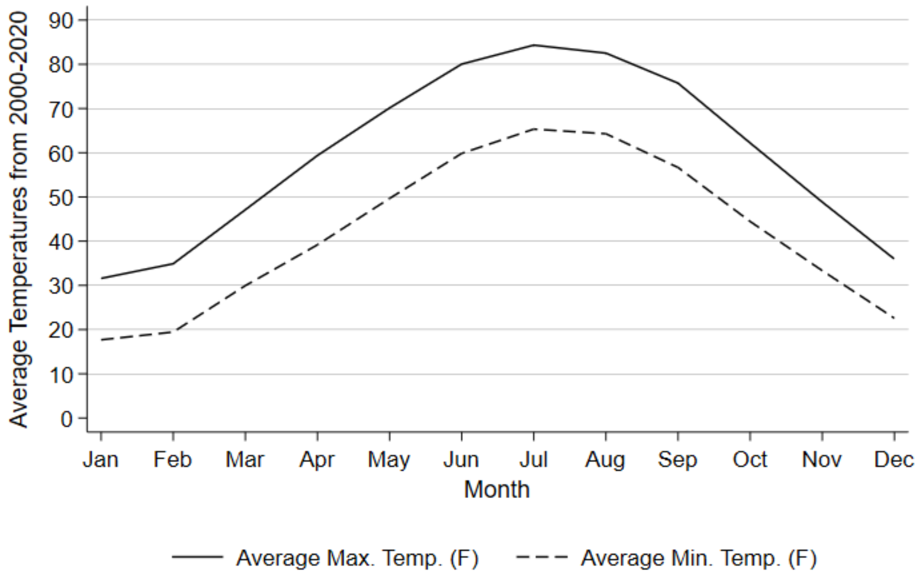
Table 2: Impact of AC From Difference-in-Differences

	Math	English	Held Back	Attendance
	(1)	(2)	(3)	(4)
I. Full Sample				
Panel A: Two-Way Fixed Effects				
Have AC	-0.0128	-0.0048	-0.0061**	0.0028**
	(0.0190)	(0.0208)	(0.0025)	(0.0013)
N	1,471,988	1,468,802	1,478,591	3,714
R^2	0.85	0.84	0.25	0.79
Panel B: Borusyak, Jaravel and Spiess (Forthcoming)				
Have AC	-0.0036	0.0188	-0.0112***	0.0030**
	(0.0174)	(0.0181)	(0.0026)	(0.0014)
N	1,529,145	1,525,410	1,535,235	3,720
Panel C: De Chaisemartin and d'Haultfoeuille (2020)				
Have AC	-0.0172	-0.0022	0.0037**	-0.0010
	(0.0145)	(0.0102)	(0.0028)	(0.0017)
N	974,407	972,883	980,372	244
Panel D: Callaway and Sant'Anna (2021)				
Have AC	-0.0090	0.0072	-0.0056**	0.0044***
	(0.0177)	(0.0163)	(0.0024)	(0.0015)
N	1,420,625	1,418,276	1,427,744	3,714
II. Energy Star Sample				
Panel E: Two-Way Fixed Effects				
Fraction AC	0.0154	-0.0189	-0.0061	0.0029
	(0.0282)	(0.0298)	(0.0040)	(0.0019)
R^2	0.86	0.85	0.27	0.82
N	1,129,833	1,126,856	1,135,000	3,366
Panel F: De Chaisemartin and d'Haultfoeuille (2020)				
Fraction AC	-0.0488*	-0.0287	-0.0036	0.0016
	(0.0233)	(0.0193)	(0.0033)	(0.0016)
N	817,018	815,501	822,518	536

Notes: This table reports the estimated coefficients from the difference-in-differences model in Equation 1 with the full sample in Part I, and from Equation 2 in Part II. 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. In Panels A, B, C, and D, the main independent variable is *Have AC* which is an indicator equal to one if a school has AC in a given year. In Panels E and F, *Fraction AC* is the main independent variable which 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. The specifications in Panels A and E include student, year, and school fixed effects, whereas specifications in Panels B, C, D and F only contain student and year fixed effects. Column (4) never includes student fixed effects since the attendance data is at the school level, and always has school and year fixed effects only. Robust standard errors clustered at the school level are in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

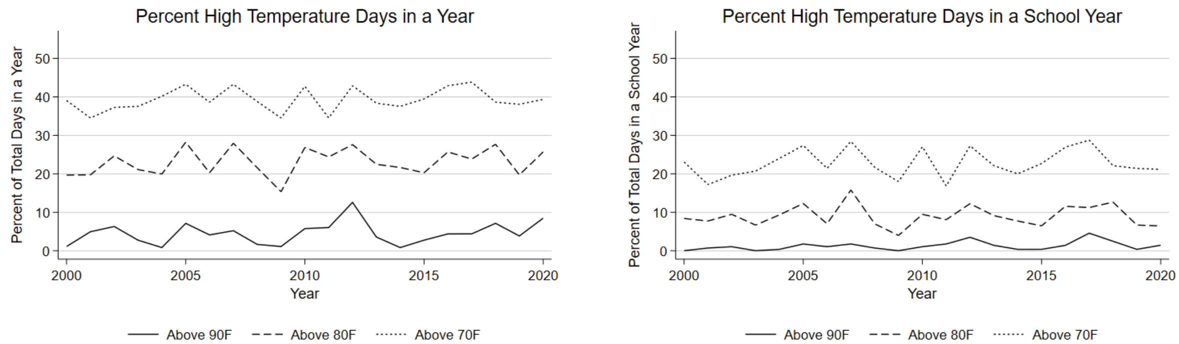
Appendix A

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



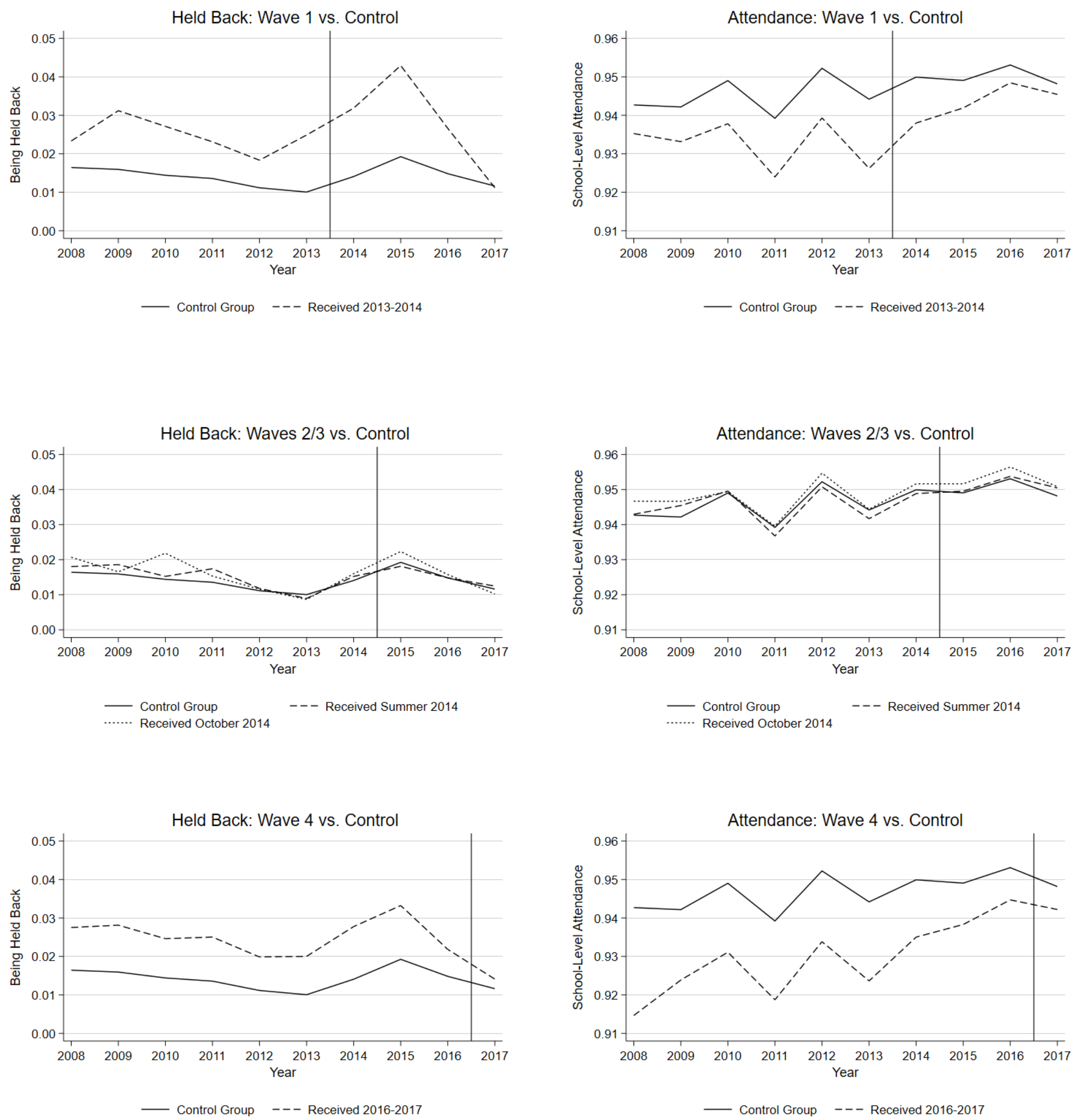
Notes: Average maximum and minimum temperatures each month in Chicago from 2000 to 2020 (Arguez et al., 2020).

Figure A.2: High Temperature Days in Chicago



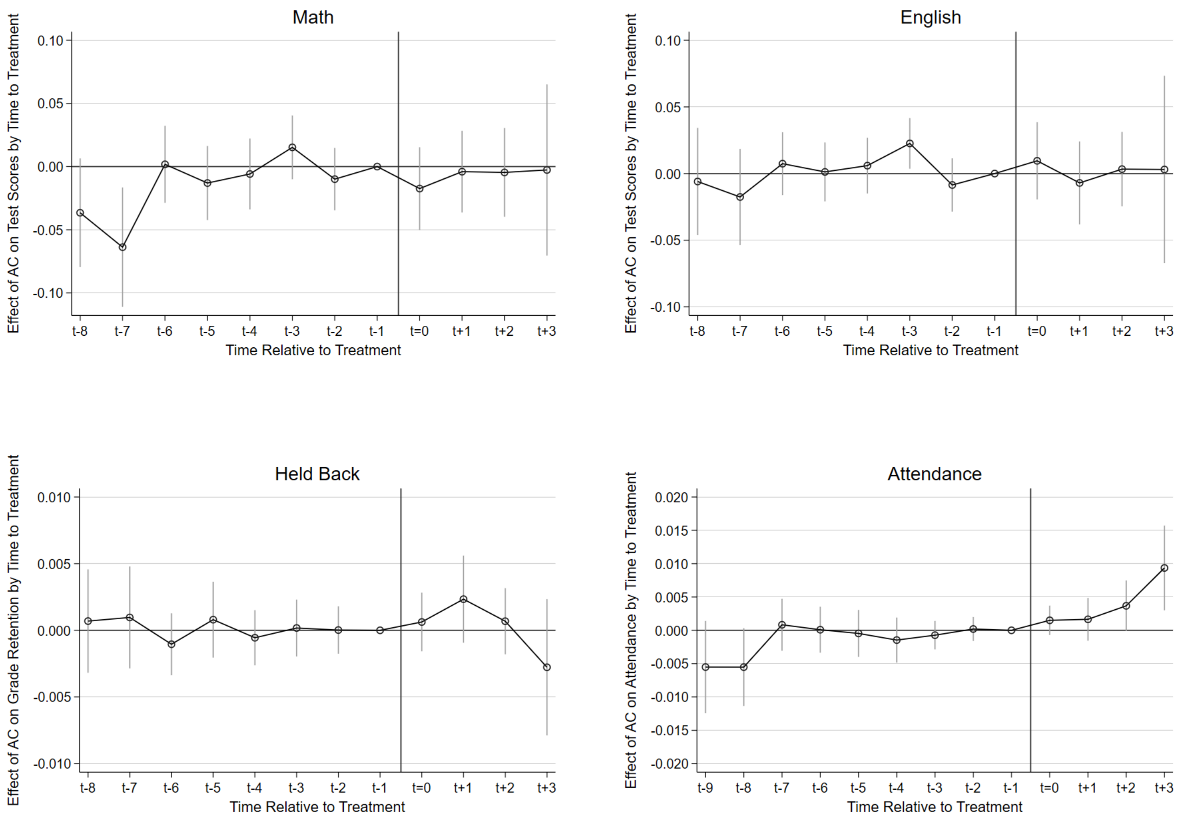
Notes: The figure on the left plots the percent of days in each year from 2000 to 2020 that have a maximum temperature above 70F, 80F, and 90F. The figure on the right plots the percent of school days in each school year that have a maximum temperature above 70F, 80F, and 90F. Daily normals are reported 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



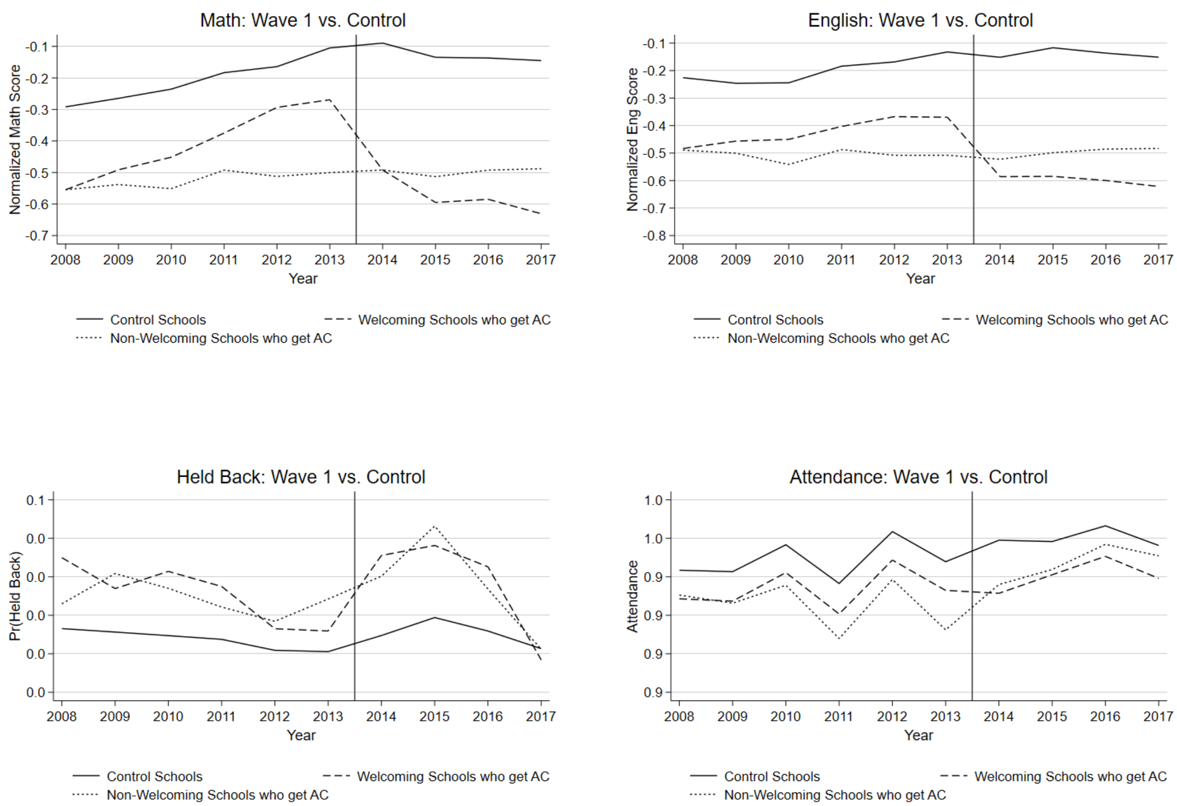
Notes: The figure reports the average annual likelihood of being held back for students in treated and control schools on the left and the average school-level attendance for treated and control schools on the right by wave of treatment in the CPS AC installation campaign. The vertical line marks the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

Figure A.4: Effects of AC on Test Scores, Grade Retention, and Attendance, Using Lagged Test Scores



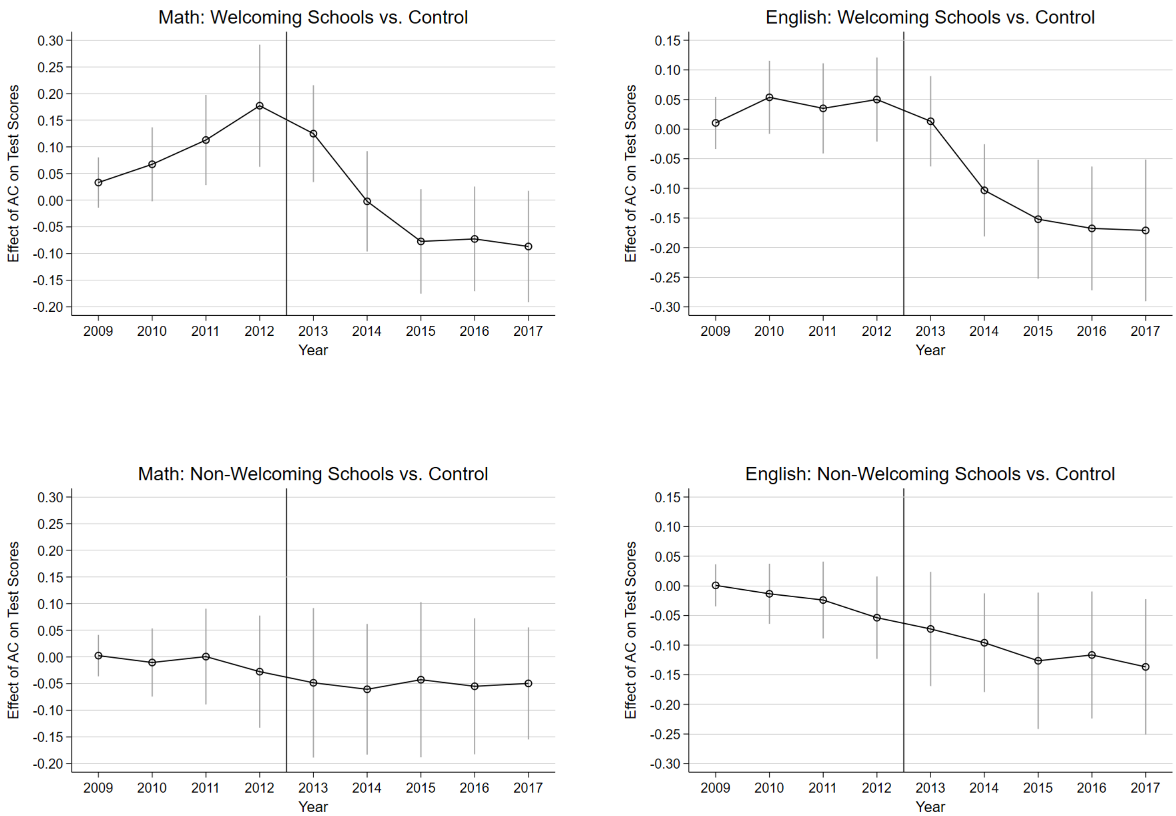
Notes: The figure reports difference-in-differences estimates of time relative to receiving AC on math test scores, English test scores, the probability of being held back for students, and on school-level average student attendance. The omitted year is *t-1*, where *t* is the treatment year. Bars represent 95 percent confidence intervals. The vertical line marks the treatment year for all sub-figures. The estimating equation includes includes year FE, school FE, and controls for the prior year's test scores. Lagged test scores 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.

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



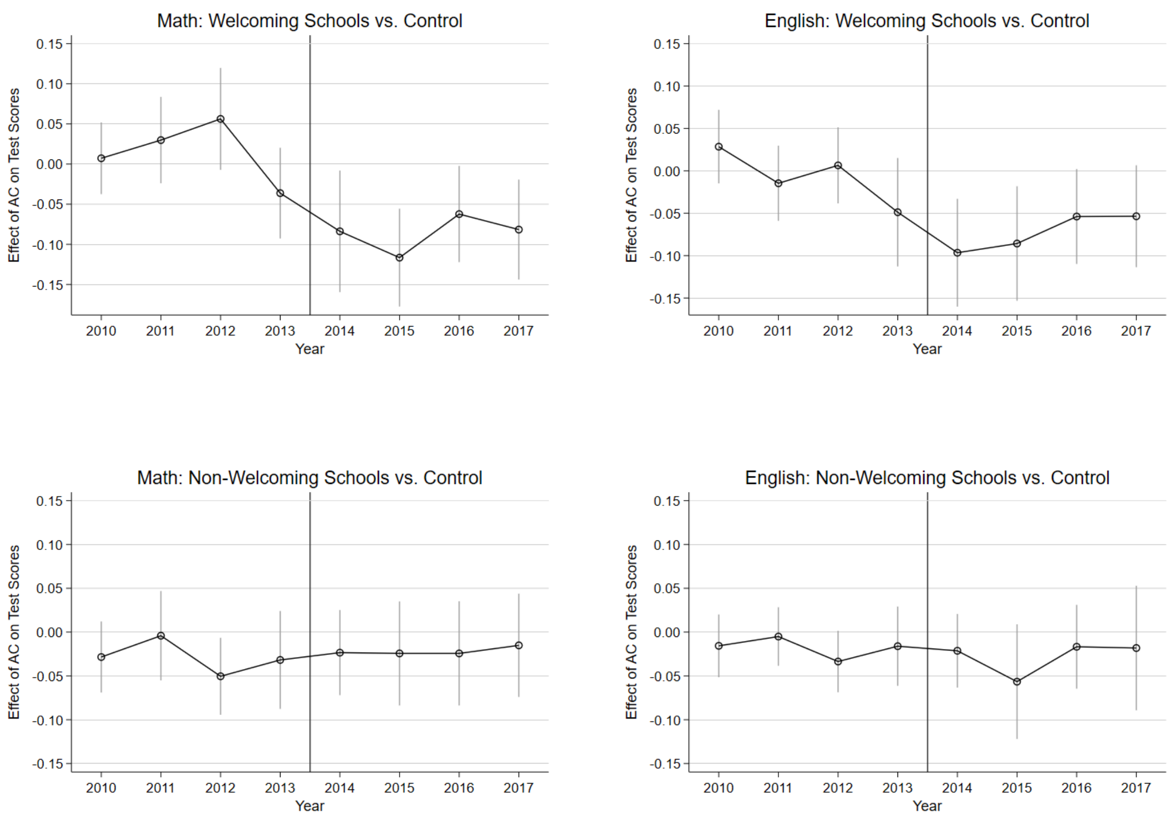
Notes: The figure shows the average annual test scores for math and English, the probability of being held back a grade, and the average school-level attendance in treated and control schools for Wave 1 of the CPS AC installation campaign by whether the school was a welcoming or non-welcoming school. 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, Using Student Fixed Effects



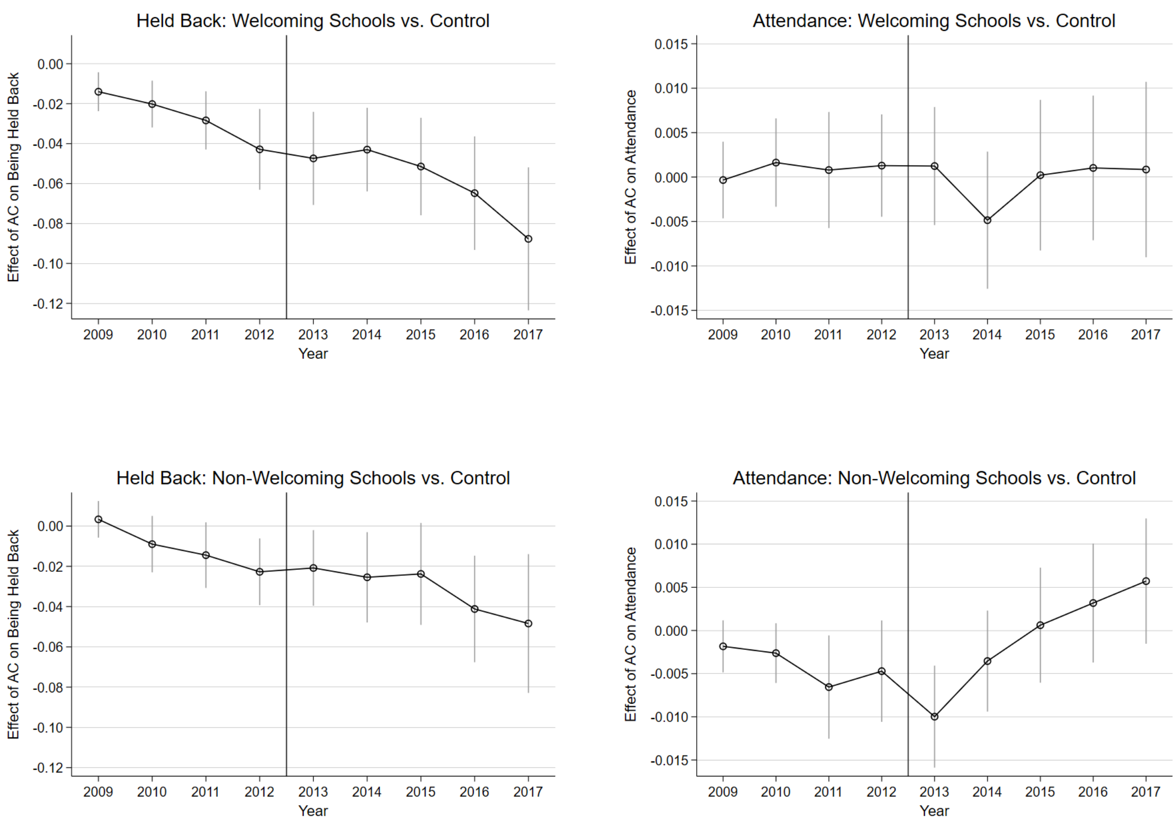
Notes: The figure reports difference-in-differences estimates for math and English test scores for treated and control schools from Equation 1 for Wave 1 of the CPS AC installation campaign by whether the school was a welcoming or non-welcoming school. The omitted year for the figures is 2008. Bars represent 95 percent confidence intervals. Vertical line marks treatment year, 2013-2014. Equation 1 includes year FE, school FE, and student FE. 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 Test Scores for Wave 1, Welcoming and Non-Welcoming Schools, Using Lagged Test Scores



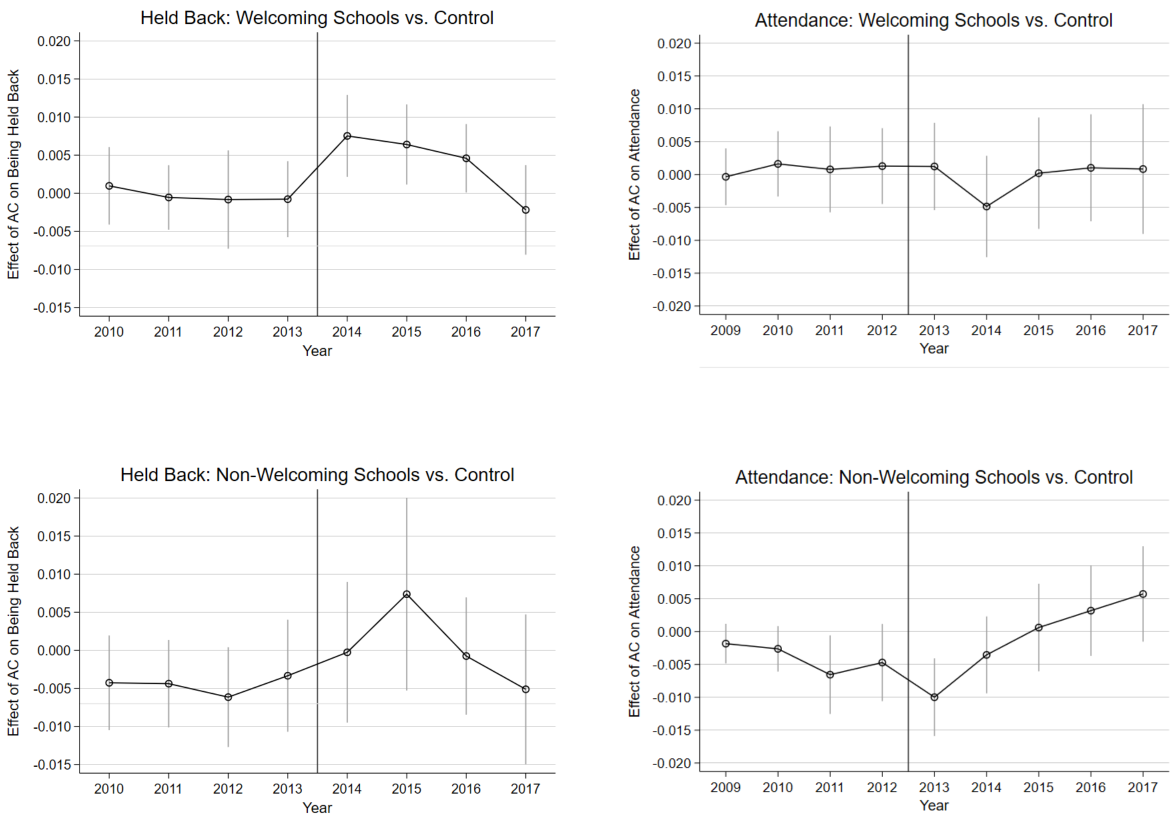
Notes: The figure reports difference-in-differences estimates for math and English test scores for treated and control schools from a variation of Equation 1 for Wave 1 of the CPS AC installation campaign by whether the school was a welcoming or non-welcoming school. The omitted year for the figures is 2009 (since this specification uses lagged test scores we have one less year of observations). Bars represent 95 percent confidence intervals. Vertical line marks treatment year, 2013-2014. This variation of 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.8: Effects of AC on Grade Retention and Attendance for Wave 1, Welcoming and Non-Welcoming Schools, Using Student Fixed Effects



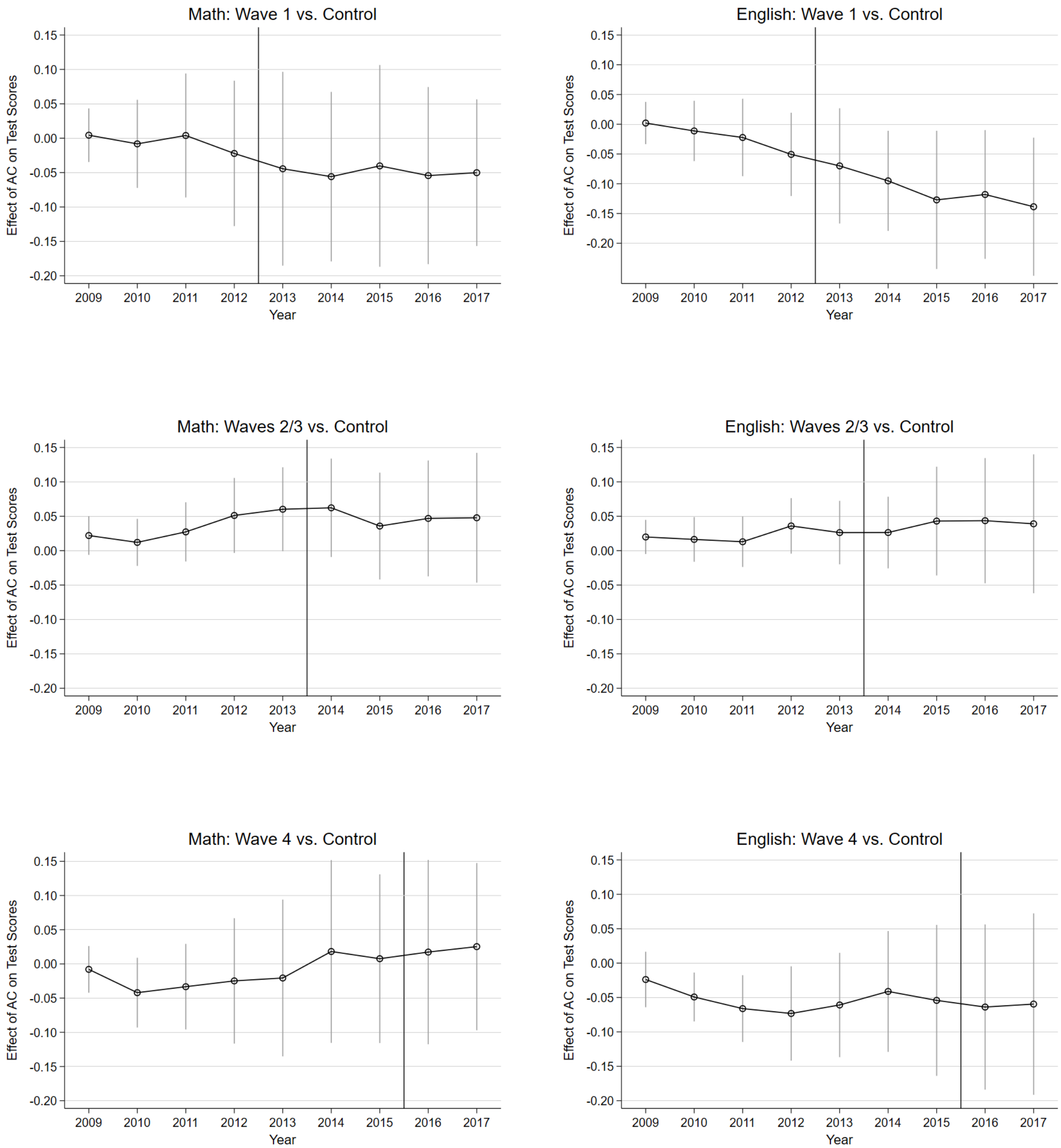
Notes: The figure reports difference-in-differences estimates of the probability of being held back for students in treated and control schools from Equation 1 on the left and estimates for school-level average student attendance on the right, for wave 1 of the CPS AC installation campaign by whether the school was a welcoming or non-welcoming school. The omitted year for the figures is 2008. Bars represent 95 percent confidence intervals. The vertical line marks treatment year for all sub-figures. Equation 1 includes year FE, school FE, and student FE for grade retention. Student fixed effects 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.9: Effects of AC on Grade Retention and Attendance for Wave 1, Welcoming and Non-Welcoming Schools, Using Lagged Test Scores



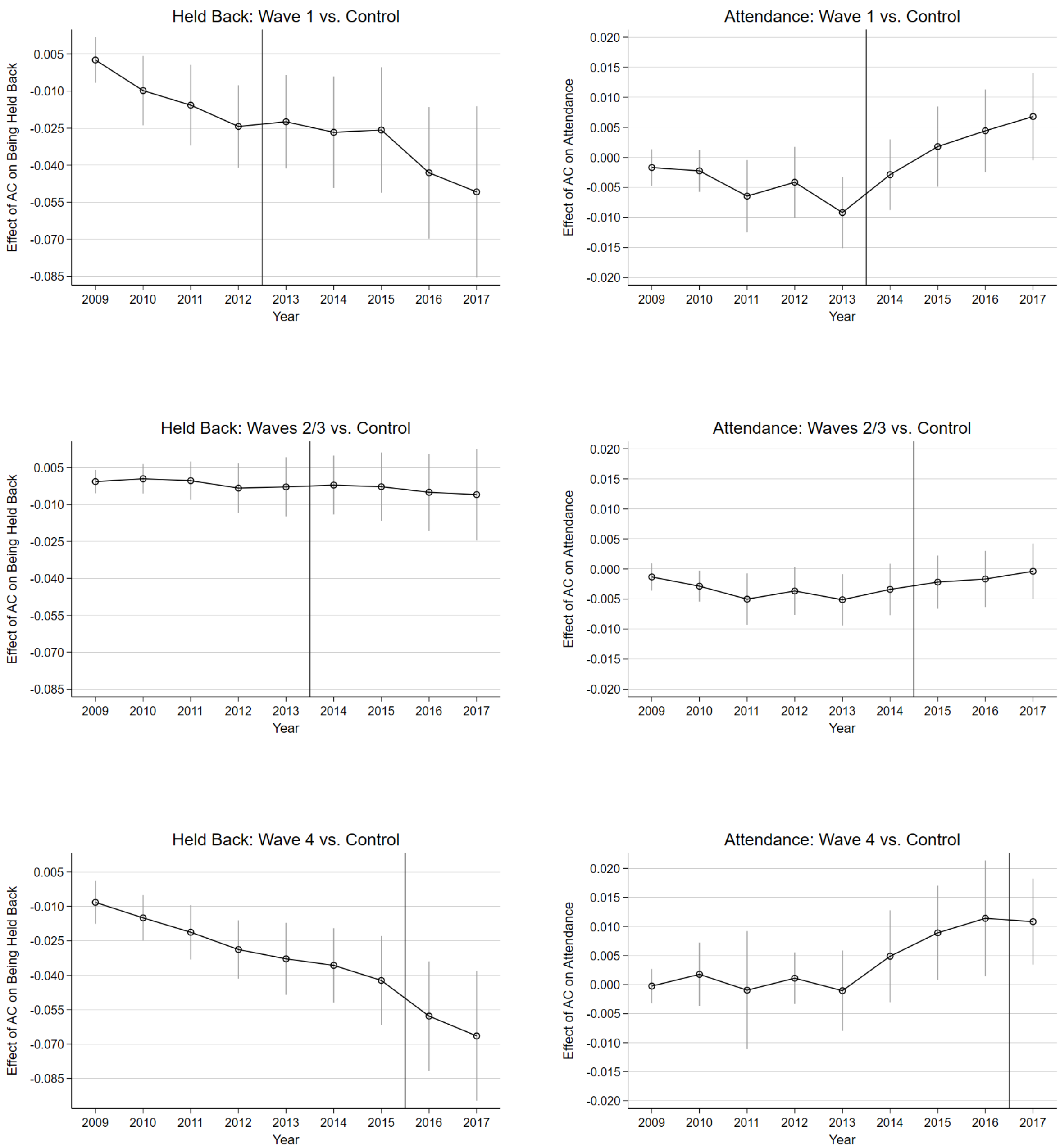
Notes: The figure reports difference-in-differences estimates of the probability of being held back for students in treated and control schools from a variation of Equation 1 on the left and estimates for school-level average student attendance on the right, for wave 1 of the CPS AC installation campaign by whether the school was a welcoming or non-welcoming school. The omitted year for the figures on the left is 2009 (since this specification uses lagged test scores we have one less year of observations), and for the figures on the right is 2008. Bars represent 95 percent confidence intervals. The vertical line marks treatment year for all sub-figures. This variation of 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.10: Effects of AC on Test Scores by Wave of Treatment, Using Student Fixed Effects



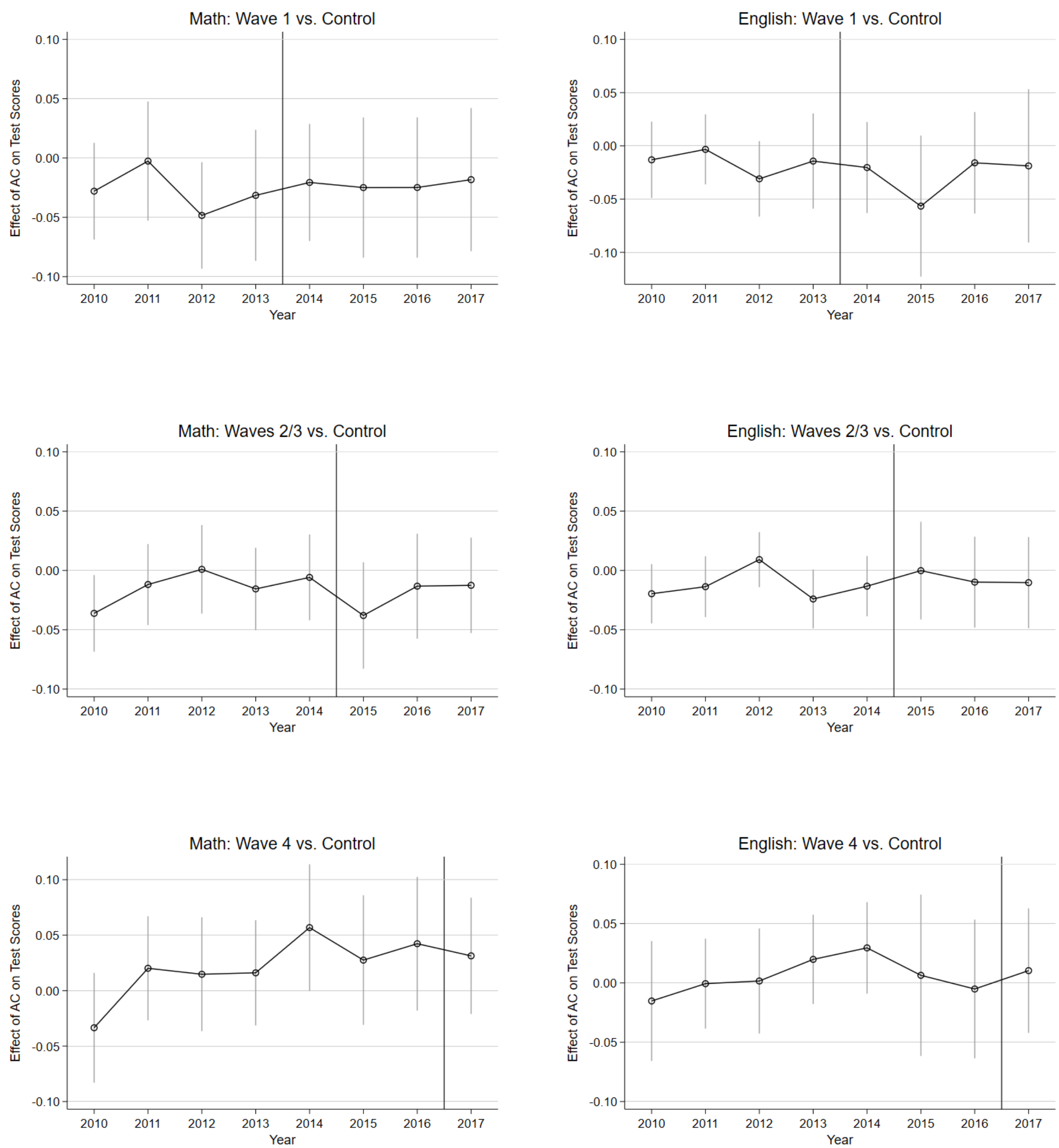
Notes: The figure reports difference-in-differences estimates for test score outcomes in math and English for treated and control schools from Equation 1 flexibly for each year from 2010 to 2017, by wave of treatment in the CPS AC installation campaign. The omitted year for the figures is 2008. Bars 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 student FE. Robust standard errors are clustered at the school level.

Figure A.11: Effects of AC on Grade Retention and Attendance by Wave of Treatment, Using Student Fixed Effects



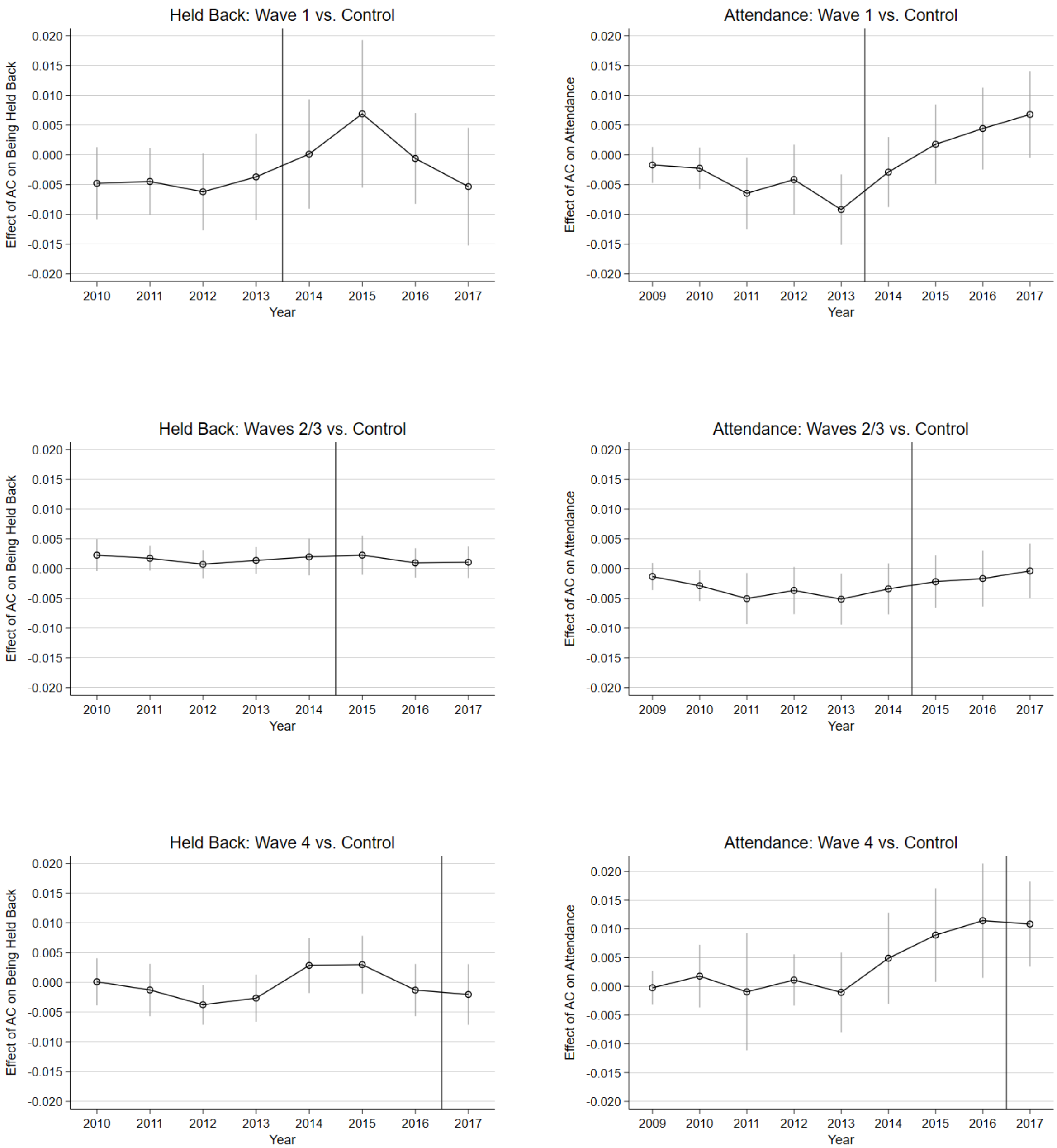
Notes: The figure reports difference-in-differences estimates of the probability of being held back for students in treated and control schools from Equation 1 on the left and the difference-in-differences estimates of school-level average student attendance in treated and control schools on the right by wave of treatment in the CPS AC installation campaign. The omitted year for the figures is 2008. 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 student FE. However, student fixed effects 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.12: Effects of AC on Test Scores by Wave of Treatment, Using Lagged Test Scores



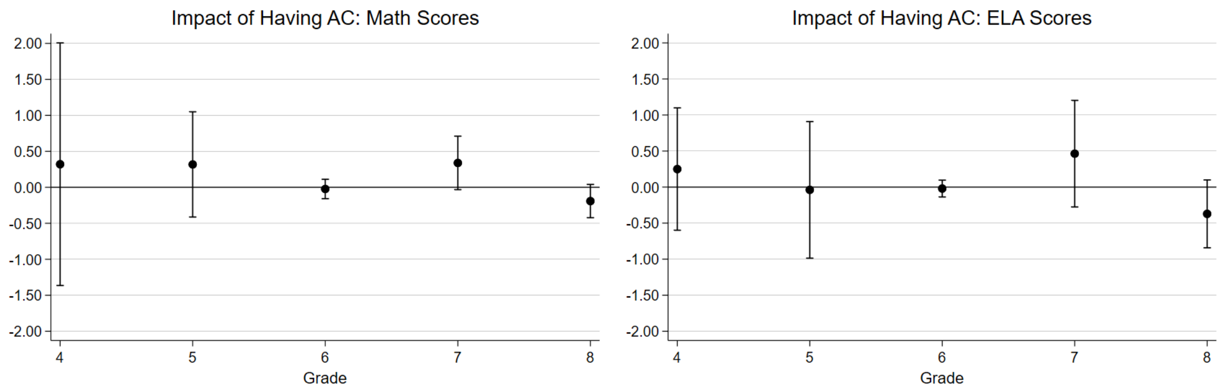
Notes: The figure reports difference-in-differences estimates for test score outcomes in math and English for treated and control schools from a variation of Equation 1 flexibly for each year from 2010 to 2017, by wave of treatment in the CPS AC installation campaign. The omitted year for all figures is 2009 (since this specification uses lagged test scores we have one less year of observations). 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. This variation of 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.

Figure A.13: Effects of AC on Grade Retention and Attendance by Wave of Treatment, Using Lagged Test Scores



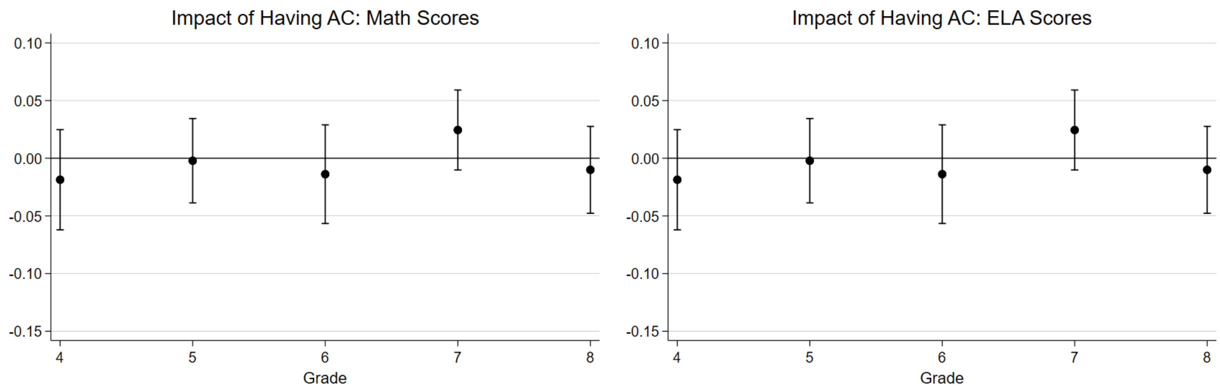
Notes: The figure reports difference-in-differences estimates of the probability of being held back for students in treated and control schools from a variation of Equation 1 on the left and the difference-in-differences estimates of school-level average student attendance in treated and control schools on the right by wave of treatment in the CPS AC installation campaign. The omitted year for the figures on the left is 2009 (since this specification uses lagged test scores we have one less year of observations), and for the figures on the right is 2008. Bars represent 95 percent confidence intervals. The vertical line marks the treatment year for all sub-figures. This variation of 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.14: Effect of AC on Test Scores by Grade, Using Student Fixed Effects



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

Figure A.15: Effect of AC on Test Scores by Grade, Using Lagged Test Scores



Notes: The figures reports difference-in-differences estimates for math and English test scores for treated and control schools from a variation of Equation 1 separately by grade. Bars represent 95 percent confidence intervals. This variation of 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.

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	Wave 1	Waves 2 & 3	Wave 4	Control-Wave 1	Control-Waves 2 & 3	Control-Wave 4
	Mean	Mean	Mean	Mean	Difference	Difference	Difference
	(Std. Dev.)	(Std. Dev.)	(Std. Dev.)	(Std. Dev.)	(T-Stat)	(T-Stat)	(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. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table A.3: Impact of AC From Difference-in-Differences, Using Lagged Test Scores

	Math (1)	English (2)	Held Back (3)	Attendance (4)
I. Full Sample				
Panel A: Two-Way Fixed Effects				
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: Borusyak, Jaravel and Spiess (Forthcoming)				
Have AC	-0.0037	-0.0004	0.0009	0.0030**
	(0.0118)	(0.0107)	(0.0009)	(0.0014)
N	1,077,554	1,079,096	1,081,732	3,720
Panel C: De Chaisemartin and d'Haultfoeuille (2020)				
Have AC	-0.0268	-0.0040	0.0017	-0.0010
	(0.0147)	(0.0143)	(0.0020)	(0.0017)
N	633,984	634,951	636,453	244
Panel D: Callaway and Sant'Anna (2021)				
Have AC	-0.0179	0.0038	0.0021	0.0044***
	(0.0180)	(0.0173)	(0.0013)	(0.0015)
N	959,417	961,195	963,320	3,714
II. Energy Star Sample				
Panel E: Two-Way Fixed Effects				
Fraction AC	0.0020	-0.0026	0.0001	0.0029
	(0.0183)	(0.0167)	(0.0013)	(0.0019)
R^2	0.72	0.70	0.01	0.82
N	812,894	814,118	816,033	3,366
Panel F: De Chaisemartin and d'Haultfoeuille (2020)				
Fraction AC	-0.0784***	-0.0441**	0.0022	0.0016
	(0.0276)	(0.0220)	(0.0022)	(0.0016)
N	519,212	520,239	521,436	536

Notes: This table reports the estimated coefficients from the difference-in-differences model in a variation of 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. In Panels A, B, C, and D, the main independent variable is *Have AC* which is an indicator equal to one if a school has AC in a given year. In Panels E and F, *Fraction AC* is the main independent variable which 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. The specifications in Panels A and E include year, and school fixed effects alongside controls for the previous year's test scores, whereas specifications in Panels B, C, D and F contain student and year fixed effects in addition to the lagged test scores as controls. Column (4) does not have the lagged student test scores since the attendance data is at the school level. Robust standard errors clustered at the school level are in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

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

	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	-0.1562***	-0.1631***	-0.0190***	-0.0015	-0.0277	-0.0664***	-0.0138**	0.0058**
	(0.0420)	(0.0377)	(0.0049)	(0.0030)	(0.0238)	(0.0230)	(0.0058)	(0.0027)
N	1,163,068	1,161,119	1,168,339	2,786	1,170,573	1,168,525	1,176,029	2,786
R^2	0.85	0.84	0.27	0.75	0.86	0.84	0.27	0.76
Panel B: Energy Star Sample								
Fraction AC	-0.2081***	-0.2055***	-0.0095	-0.0035	-0.0317	-0.0944**	-0.0154	0.0076*
	(0.0699)	(0.0629)	(0.0070)	(0.0038)	(0.0368)	(0.0378)	(0.0111)	(0.0041)
N	826,553	824,745	830,337	2,388	846,268	844,363	850,327	2,458
R^2	0.86	0.85	0.28	0.80	0.86	0.85	0.28	0.81

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 for Wave 1 Schools, if Welcoming School or Not, Using Lagged Test Scores

	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	-0.1364***	-0.1005***	0.0061***	-0.0035	0.0004	-0.0198	0.0062*	0.0076*
	(0.0383)	(0.0336)	(0.0023)	(0.0038)	(0.0325)	(0.0319)	(0.0035)	(0.0041)
N	604,607	605,706	607,019	2,388	619,068	620,118	621,660	2,458
R^2	0.72	0.70	0.01	0.80	0.73	0.70	0.01	0.81

Notes: Panel A of the table reports the estimated coefficient on Have AC from the difference-in-differences using a variation of Equation 1 with lagged student test scores instead of student fixed effect. Similarly, Panel B of the table reports the estimated coefficient on Fraction AC from the difference-in-differences model using the same variation of 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.6: Impact of AC From Difference-in-Differences, Low-Performing Students, Using Student Fixed Effects

	Math	English	Held Back
	(1)	(2)	(3)
Panel A: Full Sample			
Have AC	-0.0349*	-0.0172	0.0049
	(0.0205)	(0.0213)	(0.0060)
N	129,157	129,375	130,088
R^2	0.55	0.60	0.33
Panel B: Energy Star Sample			
Fraction AC	-0.0397	-0.0256	-0.0011
	(0.0335)	(0.0325)	(0.0091)
N	94,374	94,540	95,017
R^2	0.55	0.61	0.33

Notes: This table reports the estimated coefficients from the difference-in-differences model in Equation 1 in Panel A and for Equation 2 in Panel B 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.7: Impact of AC From Difference-in-Differences, Low-Performing Students, Using Lagged Test Scores

	Math	English	Held Back
	(1)	(2)	(3)
Panel A: Full Sample			
Have AC	-0.0144	0.0004	0.0009
	(0.0112)	(0.0115)	(0.0027)
N	172,671	172,942	173,724
R^2	0.16	0.22	0.01
Panel B: Energy Star Sample			
Fraction AC	-0.0178	-0.0095	0.0006
	(0.0172)	(0.0173)	(0.0035)
N	130,231	130,401	130,977
R^2	0.16	0.23	0.01

Notes: This table reports the estimated coefficients from a variation of the difference-in-differences model in Equation 1 in Panel A and Equation 2 in Panel B for students in the bottom of both the math and English test score distributions. The variation includes lagged student test scores instead of student fixed effects. 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.8: Impact of AC From Difference-in-Differences, Dropping Treated Individuals in Year of Treatment, Using Student Fixed Effects

	Math	English	Held Back	Attendance
	(1)	(2)	(3)	(4)
Panel A: Full Sample				
Have AC	-0.0025	0.0135	-0.0051	0.0034**
	(0.0247)	(0.0283)	(0.0037)	(0.0016)
N	1,432,180	1,429,147	1,438,504	3,577
R^2	0.86	0.84	0.26	0.80
Panel B: Energy Star Sample				
Fraction AC	0.0022	-0.0039	-0.0024	0.0036
	(0.0365)	(0.0417)	(0.0057)	(0.0023)
N	1,093,402	1,090,579	1,098,296	3,236
R^2	0.86	0.85	0.28	0.83

Notes: This table reports the estimated coefficients from the difference-in-differences model in Equation 1 in Panel A and Equation 2 in Panel B, after dropping treated observations in the year of treatment. 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 student fixed effects. 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.9: Impact of AC From Difference-in-Differences, Dropping Treated Individuals in Year of Treatment, Using Lagged Test Scores

	Math (1)	English (2)	Held Back (3)	Attendance (4)
Panel A: Full Sample				
Have AC	-0.0037	-0.0034	0.0006	0.0034**
	(0.0145)	(0.0137)	(0.0011)	(0.0016)
N	1,025,553	1,027,063	1,029,295	3,577
R^2	0.72	0.69	0.01	0.80
Panel B: Energy Star Sample				
Fraction AC	0.0016	-0.0080	0.0001	0.0036
	(0.0247)	(0.0222)	(0.0014)	(0.0023)
N	765,793	766,993	768,528	3,236
R^2	0.72	0.70	0.01	0.83

Notes: This table reports the estimated coefficients from a variation of the difference-in-differences model in Equation 1 in Panel A and Equation 2 in Panel B, after dropping treated observations in the year of treatment. This variation uses lagged student test scores as controls in each equation instead of student fixed effects. 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.

Table A.10: Impact of AC From Difference-in-Differences by Wave of Treatment, Using Student Fixed Effects

	Wave 1				Waves 2 & 3				Wave 4		
	Math	English	Held Back	Attendance	Math	English	Held Back	Attendance	Math	English	Held Back
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel A: Full Sample											
Have AC	-0.0285	-0.0687***	-0.0141**	0.0065**	-0.0106	0.0171	-0.0020	0.0016	0.0179	-0.0027	-0.0219***
	(0.0240)	(0.0231)	(0.0058)	(0.0027)	(0.0283)	(0.0300)	(0.0029)	(0.0015)	(0.0279)	(0.0322)	(0.0061)
N	1,142,110	1,140,036	1,147,358	2,656	1,297,773	1,294,907	1,303,322	3,096	1,136,630	1,134,402	1,141,701
R^2	0.86	0.84	0.27	0.77	0.86	0.84	0.27	0.81	0.86	0.84	0.27
Panel B: Energy Star Sample											
Fraction AC	-0.0319	-0.0982**	-0.0158	0.0084**	-0.0104	-0.0028	-0.0012	0.0012	0.0045	0.0324	-0.0332***
	(0.0370)	(0.0381)	(0.0113)	(0.0041)	(0.0407)	(0.0418)	(0.0041)	(0.0021)	(0.0453)	(0.0568)	(0.0090)
N	824,670	822,762	828,568	2,348	976,821	974,173	980,979	2,788	822,979	820,937	826,709
R^2	0.86	0.85	0.28	0.82	0.86	0.85	0.28	0.81	0.86	0.85	0.28

Notes: This table reports the estimated coefficients from the difference-in-differences model in Equation 1 in Panel A and Equation 2 in Panel B separately by each wave of AC installation. In Panel A, *Hav* 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 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 201 2016-17. Robust standard errors clustered at the school level are in parentheses.

Table A.11: Impact of AC From Difference-in-Differences by Wave of Treatment, Using Lagged Test Scores

	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	-0.0012	-0.0215	0.0063*	0.0084**	0.0042	0.0009	-0.0016	0.0012	0.0106	0.0267	-0.0046*	0.0110*
	(0.0325)	(0.0322)	(0.0034)	(0.0041)	(0.0231)	(0.0202)	(0.0011)	(0.0021)	(0.0376)	(0.0356)	(0.0024)	(0.0044
N	601,398	602,411	603,863	2,348	708,967	710,134	711,539	2,788	599,615	600,711	601,955	2,346
R^2	0.73	0.70	0.01	0.82	0.73	0.70	0.01	0.81	0.73	0.70	0.01	0.85

Notes: This table reports the estimated coefficients from a variation of the difference-in-differences model in Equation 1 in Panel A and Equation 2 in Panel B separately by each wave of AC installation, which lagged student test scores as controls instead of student fixed effects. 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, *Fractio* 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 s 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.12: Impact of AC From Difference-in-Differences for Schools with Lowest Prior AC Coverage, Using Student Fixed Effects

	Math (1)	English (2)	Held Back (3)	Attendance (4)
Have AC	-0.0051	-0.0159	-0.0044	0.0021
	(0.0286)	(0.0302)	(0.0041)	(0.0013)
N	936,975	934,591	941,161	3,416
R^2	0.86	0.85	0.28	0.82

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 student fixed effects. *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.13: Impact of AC From Difference-in-Differences for Schools with Lowest Prior AC Coverage, Using Lagged Test Scores

	Math	English	Held Back	Attendance
	(1)	(2)	(3)	(4)
Have AC	0.0123	0.0037	0.0008	0.0021
	(0.0189)	(0.0173)	(0.0012)	(0.0013)
N	679,264	680,423	681,911	3,416
R^2	0.73	0.70	0.01	0.82

Notes: This table reports the estimated coefficients from a variation of 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. This variation uses lagged student test scores as controls instead of student fixed effects. 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.14: 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. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.