Online Appendix for "School's Out: How Summer Youth Employment Programs Impact Academic Outcomes"

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I. Boston SYEP Intervention and Experimental Design

The Boston SYEP is administered by the Boston Mayor's Office of Workforce

Development (OWD) and implemented by four non-profit community organizations, known as intermediaries. All Boston city residents aged 14 to 24 years are eligible for the program and youth apply directly to the program through one of the four intermediaries. The intermediaries are responsible for reviewing applications, supervising job placements, and delivering the program's career-readiness curriculum. Youth typically apply to the intermediary in their neighborhood. Administrative records indicate that less than 5 percent of youth apply to more than one agency and zero youth receive more than one offer of employment.

Two of the intermediaries make use of random assignment to assign youth to jobs because of the high number of applications they receive for the limited number of SYEP jobs available. The analysis in this paper is restricted to youth who applied for a job for summer 2015 through Action for Boston Community Development (ABCD), which uses simple random assignment for all job placements. The other intermediary that uses random assignment, the Department of Youth Employment and Engagement (DYEE), does so only on a partial basis where 60 percent of the jobs for a given employer are assigned randomly and the other 40 percent are selected. DYEE also chose not to implement the survey during the summer of 2015.

The enrollment period typically spans February through June, and applicants are notified of their lottery status and job assignment in late June. ABCD uses a computerized system with a random-assignment algorithm to select applicants based on their applicant ID numbers and the

number of available slots as determined by the amount of funding ABCD receives each year. This system effectively assigns the offer to participate in the program at random, creating a control group of youth who apply to the SYEP but are not chosen. Of the 4,235 youth who applied to ABCD in 2015, a total of 1,186 were offered a job via random assignment (28 percent), leaving 3,049 individuals in the control group. Of those selected by the lottery, 83.6 percent accepted a job offer, with only a handful of youth dropping out of the program during the summer. As shown in Table A1, randomization successfully balanced all observable characteristics across treatment and control groups, except for the share that is Asian which is significantly different at the 10 percent level. However, when testing 15 characteristics in a population of roughly 4,200 individuals, one would expect that at least one characteristic would be significantly different by chance. An F-test of joint significance further demonstrates that the original lottery assignment was balanced across the treatment and control groups when all preexisting characteristics are controlled for simultaneously.

Are the applicants served by ABCD representative of all youth age 14-24 years in the city of Boston? This question is important for demonstrating external validity for the city of Boston and for city leaders seeking to bring the summer jobs program to scale. Data from the 2011-15 5-Year American Community Survey indicate that ABCD applicants have similar gender and racial characteristics in comparison to the population of low-income Boston youth. Table A6 shows that although ABCD applicants are more likely to be younger, within that younger age group (age 14-17 years) the breakdown by gender and race is very similar. In general, it is reasonable to expect that youth applying to summer jobs programs would be younger given the greater difficulty that less experienced youth have in finding a job on their own.

II. Data Sources

A. Administrative Data on Academic Outcomes

The source of administrative data for measuring school outcomes is collected the Massachusetts Department of Elementary and Secondary Education (DESE). This rich data source includes information on each student in Massachusetts from 2010 through 2019. This includes data on attendance, course grades, MCAS test scores, dropout, and high school graduation. The DESE school record data include all public school records, including charter schools, for an individual in the state of Massachusetts, even if they move across school districts.

Data were matched using name and date of birth where name was that listed as of the end of the school year. There is little reason to believe that a summer jobs program would affect how names are recorded in the data, meaning that the matching error should be uncorrelated with treatment status. This is particularly true for youth applying through ABCD in Boston. There is a rigorous application process which requires verification of household income and receipt of public assistance for the purposes of being able to match youth to the appropriate funding streams that the organization must braid together each year across both government and charitable sources. As a result, the application process involves the signature of a parent to verify that the information is correct and to give consent for obtaining information from administrative schooling, employment, and criminal justice records.

To match youth who applied to participate through ABCD to DESE data files, a fuzzy match was performed using first name, last name, and date of birth¹. Youth are matched to DESE data using Student Information Management System (SIMS) files. The SIMS files include a

¹ The Stata user-written command reclink was used to perform the fuzzy match. Following the fuzzy match, all identified fuzzy matches were hand-checked to ensure accuracy. Of the 3,011 youth that were matched in both the 2014-15 and 2015-16 academic years, 2,373 were perfect matches and 638 were fuzzy matches. For more information on the reclink command, see http://fmwww.bc.edu/repec/bocode/r/reclink.html. Our results also hold using the perfectly matched sample.

unique State Assigned Student Identifier (SASID) that can be used to merge in data on course grades and test scores from other DESE files.

Table A2 describes the details of the matching process at each stage. Among the 4,235 applicants to the Boston SYEP during the summer of 2015, 79.6 percent (N=3,372) were in grades 8-11 during the school year prior to participation, similar to other studies.² Of these, almost all (96.9 percent) were matched to the 2014-15 DESE file—a much higher pre-program match rate than that of previous summer jobs studies, likely due to having state-level records that capture youth even if they transfer out of the Boston Public Schools system. Separate F-tests for each set of covariates used in the main tables confirm that the baseline covariates are also jointly insignificant (see Table A5). We also show similar balance tests for the two subsamples used in the analysis that are used when youth are missing attendance (Table A3) or course grades (Table A4). There were no significant pre-existing differences in the baseline school outcomes between youth in the treatment versus control groups, except the share Asian, as would be expected under random assignment.

1 Attendance and Related Outcomes Data

Data on attendance, dropout, and graduation comes from the Student Information

Management System (SIMS) data files from the Massachusetts DESE. Each entry in this data

file is a unique student/school/year observation. A unique identifier, SASID, is given for each

student. A student will appear in this file multiple times if that student attends multiple schools in

the state of Massachusetts during the school year. For those youth that attend multiple schools

during a school year, days in membership, days attended, and unexcused absences are calculated

as sums of those variables across all schools attended. One observation is then kept per student,

² Note that the majority of students in 12th grade prior to the program do not have data for the following school year unless they fail to graduate, which is rare conditional on staying in school through 12th grade.

corresponding to the school where the student spent the greatest number of days in membership. The length of the school year in Massachusetts varies slightly across school districts between 180 and 190 days. Those youth for whom days in membership is a given year is above 190 are excluded from estimating attendance outcomes as most of these are classified as 999 for missing data. In the 2015-16 school year, less than 5 percent of youth fall into this category.

Dropout and graduation outcomes are measured using SIMS data files also. A student is classified as a dropout if the variable enrollment status takes on values between 30 and 36 in the SIMS file for a given year. These values comprise all enrollment dropout statuses, where these statuses may include a reported reason why the student chose to drop out if known. A student is classified as a graduate if enrollment status takes on values of 04 or 10. Value 04 corresponds to graduate with a competency determination. Value 10 corresponds to receipt of a certificate of attainment. Only 3 youth in the sample received a certificate of attainment, while the remaining graduated with a competency determination.

2. Course Performance Outcomes Data

Data on course performance comes from the Student Course Schedule (SCS) data files from the Massachusetts DESE. Each entry in this data file is a unique student/class/year observation. A unique identifier, SASID, is given for each student. The number of entries per student in this data file corresponds to the number of courses a student took in a given academic year. For each course, a student may receive a letter grade, a numeric grade, both letter and numeric grades, or neither. Where both letter and numeric grades are given, we use the letter grade. We convert reported grades to a common scale according to the following schedule used by DESE:

Numeric Grade	Letter Grade	Course Grade
97 – 100	A+	4.0
93 – 96	A	3.7
90 – 92	A-	3.3
87 – 89	B+	3.0
83 – 86	В	2.7
80 – 82	B-	2.3
77 – 79	C+	2.0
73 – 76	С	1.7
70 – 72	C-	1.3
67 – 69	D+	1.0
63 – 66	D	0.7
60 – 62	D-	0.3
Below 60	F	0

GPA is calculated based on weighted course grades. Classes designated as Basic or Remedial by the State are included in averages as is. An additional 0.3, 0.8, and 1.3 points are added to the course grades of classes designated as general, advanced, and post-secondary credit respectively. The weighted GPA is found by taking the simple average of the weighted course grades. When measuring course failures, we define a course failure as a letter grade of F. If a student took a course as pass/fail, failure of that course is counted as a course failure, although those courses are not included in the calculation of GPA.

3. MCAS Outcomes Data

Data on the Massachusetts Comprehensive Assessment System (MCAS) comes from the

MCAS data files constructed by DESE. Each entry in these files corresponds to a unique student/year observation for all MCAS exams completed in a given year. Students are expected to take MCAS exams in math and English in grades 3-8 and 10. Proficiency or better for the ELA and Math MCAS is defined as having a score that was classified as "proficient" or "advanced" by DESE.

B. Survey Data on Pre-/Post-Program Behavioral Outcomes

The survey was originally developed and implemented by the Youth Violence Prevention Collaborative, an initiative that began funding summer employment opportunities in Boston neighborhoods that had been identified by the Boston Police Department as having a high number of fatal and non-fatal shootings. Starting in the summer of 2012, the goal was to measure personal and social behaviors that correlate with youth violence and exposure to violence to determine whether summer employment could reduce the exposure of economically disadvantaged teens to risky, violent, and delinquent behaviors. This original survey was typically administered at the end of the summer to program participants and covered basic demographic information as well as questions on risky and delinquent behavior, community engagement, and general satisfaction with SYEP jobs and programming.

With the help of the Office of Workforce Development (OWD), we expanded the survey's content and scope during the summer of 2015. In terms of content, we added questions related to job readiness, post-secondary aspirations, and financial capability. In terms of scope, OWD engaged ABCD to conduct both a pre- and post-survey to measure changes over time for participants. The pre-survey was administered to participants during orientation in early July and the post-survey was administered in mid-August when participants pick up their last paycheck. Surveys were administered to participants on-site using a paper-based collection method.

Although nearly the same number of individuals answered the pre- and post-surveys, these were not necessarily the same individuals as only 66.9 percent of individuals could be matched. However, testing for differential attrition between the pre- survey sample and the matched sample for both ABCD yields no statistically significant differences.

In addition, OWD also worked with ABCD to administer the post-survey to the control group to compare the experiences of participants to the counterfactual experiences of those who had applied but not been selected by the SYEP. The post-survey was administered to the control group on-line via email with the chance to win a free iPad mini for completing the survey. Yet despite several reminders and extensions, the response rates differed significantly across the treatment versus the control group. Indeed, although the number of respondents among the control group was similar (N=664), this represented a response rate of only 21.8 percent.

Moreover, although the control group was randomly selected, those who chose to respond to the post-survey were not. Unlike other household surveys, we know that the characteristics of the control group should be indistinguishable from those of the treatment group because the random assignment was shown to be balanced. This means that we can explore the sign of the bias by exploring how the observable characteristics differ between the two groups. Relative to the treatment group, survey respondents from the control group exhibited characteristics that are on average associated with better economic, academic, and criminal justice outcomes. They were more likely to be older, female, identify as white or Asian, and indicate that they live in a two-parent household.

We argue that this bias goes *against* finding an impact for the Boston SYEP, given that the survey respondents in the control group exhibit demographic characteristics that would suggest a high bar for comparison. In the literature, each of the observable characteristics that

differ for the control group relative to the treatment group has been shown to be associated with better long-term outcomes. In terms of academic outcomes, females are now more likely than males to attend college (Lopez and Gonzalez-Barrera, 2014). There is also a large literature explaining test score gaps that finds lower scores among African-American children and those living in single parent households (Jencks and Phillips 1998). In terms of employment, higher employment rates are observed among females, whites, and older youth (Child Trends. 2017). In terms of criminal justice outcomes, age, male gender, and living in a single-parent home are significant predictors of re-offending among youth (Autor and Wasserman. 2013, Cottle, Lee, and Heilburn 2001).

Moreover, youth in the control group who responded to the survey are likely to be more intrinsically motivated than those who did not. In general, surveying youth is difficult but particularly so when relying on email for deployment since youth are less likely than adults to use email for personal communication (e.g., texting friends is more common), especially during the summer when school is out. The control group was surveyed about their summer experiences via an email that came from the Boston Office of Workforce Development about a program for which they were not selected. As such, taking the time to open the email, read it, and complete the survey suggests a relatively high degree of motivation. One of the survey questions confirms this hypothesis: youth were asked why they wanted to work this summer. Among the respondents, youth in the control group were more likely than those in the treatment group to report wanting a summer job to learn more about college and less likely to report wanting to make money, have something to do, or stay out of trouble.

It is important to acknowledge the other limitations of self-reported survey data such as those raised in Meyer, Mok, and Sullivan (2015). In that paper, the authors measure the degree to

which nationally representative surveys suffer not just from unit non-response but also from item non-response and measurement error by comparing survey results to administrative data. In terms of item non-response, this can be a problem, particularly when asking sensitive questions about behavior among developing youth. For example, one of the other intermediaries that works with court-involved youth (Youth Options Unlimited) chose to include a series of questions based on the Youth Behavioral Risk Survey that asked about risky behavior such as drug and alcohol use and physical violence. However, the non-response rate was too high (roughly 20 percent) so that these responses were not informative. In contrast, the item non-response rates for the survey questions used in the mediator analysis were less than 5 percent for both the ABCD treatment and control groups with no significant differences across the two groups.

Finally, in terms of measurement error, there is little room to assess the magnitude of this bias without access to administrative data that covers the same items as the survey. The only test for measurement error that we can perform is to compare the employment rate for the control group to what is found in the state quarterly wage and employment administrative data. Only 26.4 percent of those responding to the survey in the control group reported that they had worked during the summer. This rate is consistent with the quarterly wage record data provided by the Massachusetts Division of Unemployment Assistance, which shows that a similar proportion of youth in the control group (28.2 percent) reported working during the third quarter (July-September) of 2015. In addition, because we measure impact for the treatment group relative to control group, if we assume that the measurement error is random, then this would reduce efficiency but not cause bias. we do not have any reason to believe that measurement error would differ across the treatment and control groups.

III. Analysis Methods

To assess the impact of the Boston SYEP on academic outcomes, we compare attendance, course performance, MCAS test taking and scores, dropout, and high school graduation during the period following the intervention for youth offered an SYEP placement (the treatment group) to those for youth not offered a placement (control group). Because SYEP participation is allocated via lottery, we obtain causal estimates using a simple comparison of means on the outcome of interest. This "Intent to Treat" (ITT) estimate measures the impact of offering the program on the outcome. In many cases, this is the policy relevant estimate because program administrators want to account for program take-up to assess the degree to which SYEP could improve academic outcomes among all the applicants, not just the participants.

Nonetheless, because not all youth end up participating, the ITT will understate the effects of the program for those youth who choose to participate. To address this, we also conduct estimates of treatment-on-the-treated (TOT).

While ordinary least squares provides the best linear unbiased estimate of the treatment effect under the Gauss-Markov assumptions, we also explore the robustness of the results to alternative assumptions. Specifically, we relax the linear functional form assumption by using non-linear specifications. For example, to analyze treatment-control differences in the number of days attended – a count variable – we use a Poisson quasi-maximum likelihood estimator (QMLE). The consistency of this estimator only requires the correct specification of the conditional mean, not the entire distribution (Wooldridge, 1997). We also use Huber-White robust standard errors to allow for over-dispersion, relaxing the Poisson distributional constraint that the mean equals the variance. To analyze differences in the likelihood of an outcome such as dropout, a 0/1 dependent variable, we use a probit estimator.

IV. Cost Benefit Calculation

A key question from a policy perspective is whether the benefits to society from the program outweigh the program's costs. Although it is somewhat premature to perform a full cost benefit analysis until other key outcomes related to schooling and employment have been measured, we provide some back-of-the-envelope calculations comparing the short-term benefits from the increase in graduation rates to the program's costs.

The cost of administering the program for the City of Boston was about \$2,000 per participant, which includes an average of just over \$1,400 in wages. From a societal perspective, the wage cost is simply a transfer from the government to the youth and so is not generally counted as a net change in overall resources. This leaves an administrative program cost of \$600, although if one wanted to separate the costs and benefits that accrue to the government, participants, and society, then wages would appear as a cost to the government and a benefit to participants. Note that this is the budgetary cost to the City for funding the program. It may understate the costs from a broader perspective, as it does not include the opportunity cost of city staff, time donated by program providers, or the deadweight loss involved in raising the tax dollars.

Our analysis finds that participating in the summer jobs program significantly reduces the likelihood of dropping out of high school and correspondingly raises the likelihood of graduating. Specifically, being randomly selected into the Boston SYEP reduces the likelihood of dropout by 2.5 percentage points relative to the control group. High school graduates have better outcomes than dropouts along a number of dimensions including being more likely to be employed and earn a higher taxable income (Child Trends 2017) as well as being less likely to engage in criminal behavior or require social services (Lochner and Moretti 2004).

By some estimates, each new graduate confers a net benefit to taxpayers of about \$127,000 over the graduate's lifetime. According to the City of Boston, the program costs roughly \$2,000 per participant, resulting in a total cost of \$2.4 million for the 1,200 youth that participated through ABCD during the summer of 2015. Given that the program increases the likelihood of high school graduation by 6 percentage points, this would yield an additional 58 graduates, who on net would collectively confer a benefit of \$6 million over their lifetimes. On an annual basis they would be expected to collectively contribute \$130,000 per year, implying that the City would recoup its investment roughly 18 years post-graduation.

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Table A1. Lottery Summary Statistics and Randomization Check for SYEP Applicants Prior to Administrative Data Match

	Selected	(treatments)	Not Select	Not Selected (controls)		Treatment-Control	
	Mean	Std. Error	Mean	Std. Error	Difference	p -value	
Age	15.917	(0.058)	15.845	(0.033)	0.073	(0.258)	
Percent 14-17 years	0.794	(0.008)	0.802	(0.007)	-0.008	(0.292)	
Percent female	0.531	(0.014)	0.539	(0.009)	-0.008	(0.460)	
Percent in school	0.876	(0.010)	0.884	(0.006)	-0.008	(0.497)	
Percent African American/Black	0.513	(0.015)	0.540	(0.009)	-0.027	(0.197)	
Percent Asian	0.065	(0.007)	0.050	(0.004)	0.015	(0.088)	
Percent White	0.096	(0.009)	0.084	(0.005)	0.012	(0.211)	
Percent other/two or more races	0.325	(0.014)	0.326	(0.009)	0.000	(0.983)	
Percent Chinese	0.002	(0.001)	0.001	(0.001)	0.001	(0.557)	
Percent English	0.951	(0.006)	0.955	(0.004)	-0.004	(0.620)	
Percent Spanish	0.033	(0.005)	0.027	(0.003)	0.006	(0.287)	
Percent other language	0.014	(0.003)	0.018	(0.002)	-0.003	(0.465)	
Percent limited English ability	0.071	(0.007)	0.071	(0.005)	0.000	(0.969)	
Percent homeless	0.067	(0.007)	0.069	(0.005)	-0.002	(0.822)	
Percentage receiving public assistance	0.187	(0.011)	0.172	(0.007)	0.015	(0.240)	
Percent disabled	0.040	(0.006)	0.033	(0.003)	0.007	(0.276)	
Percent in matched school sample pre and post	0.900	(0.010)	0.902	(0.006)	-0.002	(0.871)	
Number of youth	1,	186	3,	049	4,2	35	
F-test of joint significance					F(15, 421	· ·	
					Prob > F	= 0.4596	

Note: The table shows that the treatment variable is uncorrelated with the individual's background variables. Each line of the table provides the mean of the the background variable listed in the first column for the treatment versus the control group as well as the difference between the two groups. The last column provides the p-value from a regression of the background variable on the treatment dummy. The only statistically significant difference is the share of Asian youth being slightly higher (6.5 percent) in the treatment group versus the control group (5.0 percent). Having at least one statistically significant difference at the p<0.10 level would be expected by random chance when testing 16 different characteristics. The F-test of joint significance confirms that random assignment is also balanced across all baseline characteristics.

Source: Author's calculations based on application data provided by the City of Boston Office of Workforce Development.

Table A2. Match and Attrition Rates for SYEP Youth in Adminsitrative Data by Treatment Status

	Treatment	Control	Total
Total number of youth applicants	1,186	3,049	4,235
In grades 8-11 at time of application	951	2,421	3,372
As a percentage of youth applicants	80%	79%	80%
Youth matched in the 2014-15 (pre-SYEP) school year	933	2,336	3,269
And able to be tracked during post-period			
Non-missing administrative record	882	2,226	3,108
Not able to be tracked: transferred to private school or out-of-state or deceased	28	69	97
Able to be tracked:			
Still enrolled at the end of the follow-up period	123	341	464
Dropped out and did not graduate	86	272	358
Graduated at some point	632	1,511	2,143
Received a certificate of completion, transferred to adult education program, or aged out	13	33	46
Non-missing adminsitrative record and able to be tracked during post-period	854	2157	3,011
As a percentage of youth matched in the 2014-15 school year	92%	92%	92%
As a percentage of youth in grades 8-11 at time of application	90%	89%	89%
Number with non-missing baseline attendance	847	2,132	2,979
As a percentage of those with non-missing adminsitrative records and able to be tracked	99%	99%	99%
Number with non-missing baseline grades one year post-program	806	2,043	2,849
As a percentage of those with non-missing administrative records and able to be tracked	95%	95%	95%

Table A3. Mean Preprogram Charactersitics for Treament and Control Groups Matched to Administrative Data - Excluding Students with Missing Baseline Attendance

	Selected ((treatments)	Not Selected (controls)		Treatment	-Control
	Mean	Std. Error	Mean	Std. Error	Difference	p -value
Demographic characteristics						
Age	15.331	(0.048)	15.393	(0.029)	-0.062	(0.262)
Percent female	0.548	(0.017)	0.556	(0.011)	-0.008	(0.310)
Percent African American/Black	0.529	(0.017)	0.538	(0.011)	-0.009	(0.194)
Percent Asian	0.076	(0.009)	0.053	(0.005)	0.023	(0.025) **
Percent White	0.091	(0.010)	0.079	(0.006)	0.012	(0.291)
Percent other/two or more races	0.332	(0.016)	0.331	(0.010)	0.001	(0.955)
Percent Chinese	0.002	(0.002)	0.001	(0.001)	0.001	(0.428)
Percent English	0.953	(0.007)	0.958	(0.004)	-0.005	(0.555)
Percent Spanish	0.031	(0.006)	0.023	(0.003)	0.008	(0.254)
Percent other language	0.014	(0.004)	0.018	(0.003)	-0.004	(0.409)
Percent limited English ability	0.067	(0.009)	0.070	(0.006)	-0.003	(0.800)
Percent homeless	0.048	(0.007)	0.056	(0.005)	-0.007	(0.405)
Percent receiving public assistance	0.181	(0.013)	0.168	(0.008)	0.012	(0.430)
Percent disabled	0.027	(0.006)	0.030	(0.004)	-0.003	(0.620)
Academic characteristics						
Percent high need special education	0.065	(0.008)	0.056	(0.005)	0.009	(0.379)
Percent in METCO (bussing) program	0.066	(0.009)	0.066	(0.005)	0.000	(0.964)
Percent switched schools during academic year	0.103	(0.010)	0.108	(0.007)	-0.006	(0.650)
Percent in grade 8	0.366	(0.009)	0.364	(0.010)	0.001	(0.498)
Percent in grade 9	0.305	(0.016)	0.305	(0.010)	0.000	(0.798)
Percent in grade 10	0.189	(0.013)	0.197	(0.009)	-0.009	(0.415)
Percent in grade 11	0.141	(0.006)	0.134	(0.007)	0.008	(0.632)
School characteristics						
Percent attending a charter school	0.151	(0.013)	0.167	(0.009)	-0.016	(0.354)
Percent of school population scoring proficient or better on MCAS	54.015	(0.896)	54.425	(0.597)	-0.411	(0.403)
Baseline (pre-program) outcomes						
Percent dropped out of school						
Attendance rate	0.906	(0.004)	0.909	(0.003)	-0.003	(0.335)
Percent chronically absent	0.279	(0.015)	0.268	0.010	0.011	(0.398)
Days of attendance	162.229	(0.792)	163.497	(0.583)	-1.268	(0.372)
Days of unexceused absences	11.724	(0.507)	11.337	(0.385)	0.386	(0.333)
Number of youth	8	347	2,	132	2,9	79

Note: This table provides mean values of preexisting demographic, academic, and school characteristics as well as pre-program outcomes for the sample to youth who were matched to the administrative data in both the 2014-15 and 2015-16 school years with standard errors in parentheses. To test whether whether the treatment variable is correlated with any of the individual pre-program characteristics we compare the effect of winning the SYEP lottery on pre-program demographic, academic, and school characteristics as well as baseline (pre-program) outcomes. Each row provides the coefficient and p-value from a regression where the dependent variable takes the value of 1 if the individual received an offer to participate in SYEP and the independent variable is the characteristic that is listed. See Table A5 in the appendix for separate F-tests of joint significance for each grouping of covariates used in the analysis.

Table A4. Mean Preprogram Charactersitics for Treament and Control Groups Matched to Administrative Data - Excluding Graduating Seniors One Year Post

	Selected ((treatments)	Not Selected (controls)		Treatment-Control	
	Mean	Std. Error	Mean	Std. Error	Difference	p -value
Demographic characteristics						
Age	15.331	(0.048)	15.393	(0.029)	-0.062	(0.262)
Percent female	0.548	(0.017)	0.556	(0.011)	-0.008	(0.310)
Percent African American/Black	0.529	(0.017)	0.538	(0.011)	-0.009	(0.194)
Percent Asian	0.076	(0.009)	0.053	(0.005)	0.023	(0.025) **
Percent White	0.091	(0.010)	0.079	(0.006)	0.012	(0.291)
Percent other/two or more races	0.332	(0.016)	0.331	(0.010)	0.001	(0.955)
Percent Chinese	0.002	(0.002)	0.001	(0.001)	0.001	(0.428)
Percent English	0.953	(0.007)	0.958	(0.004)	-0.005	(0.555)
Percent Spanish	0.031	(0.006)	0.023	(0.003)	0.008	(0.254)
Percent other language	0.014	(0.004)	0.018	(0.003)	-0.004	(0.409)
Percent limited English ability	0.067	(0.009)	0.070	(0.006)	-0.003	(0.800)
Percent homeless	0.048	(0.007)	0.054	(0.005)	-0.006	(0.609)
Percent receiving public assistance	0.181	(0.013)	0.168	(0.008)	0.012	(0.430)
Percent disabled	0.027	(0.006)	0.030	(0.004)	-0.003	(0.620)
Academic characteristics						
Percent high need special education	0.062	(0.009)	0.054	(0.005)	0.008	(0.429)
Percent in METCO (bussing) program	0.066	(0.009)	0.064	(0.006)	0.002	(0.856)
Percent switched schools during academic year	0.103	(0.010)	0.108	(0.007)	-0.006	(0.650)
Percent in grade 8	0.344	(0.017)	0.351	(0.011)	-0.008	(0.482)
Percent in grade 9	0.308	(0.016)	0.307	(0.010)	0.001	(0.626)
Percent in grade 10	0.211	(0.007)	0.202	(0.009)	0.009	(0.379)
Percent in grade 11	0.138	(0.004)	0.140	(0.002)	-0.002	(0.738)
School characteristics						
Percent attending a charter school	0.151	(0.013)	0.167	(0.009)	-0.016	(0.310)
Percent of school population scoring proficient or better on MCAS	54.015	(0.896)	54.425	(0.597)	-0.411	(0.703)
Baseline (pre-program) attendance outcomes						
Percent dropped out of school						
Attendance rate	0.910	(0.003)	0.912	(0.003)	-0.002	(0.429)
Percent chronically absent	0.279	(0.016)	0.268	(0.010)	0.011	(0.416)
Days of attendance	162.477	(0.763)	163.148	(0.599)	-0.671	(0.379)
Days of unexceused absences	10.365	(0.520)	10.005	(0.401)	0.359	(0.385)
Baseline (pre-program) course grade outcomes						
Grade Point Average (GPA)	1.924	(0.040)	1.936	(0.025)	-0.013	(0.394)
Percent failing any course	0.287	(0.017)	0.291	(0.011)	-0.004	(0.411)
Percent failing a math course	0.166	(0.013)	0.161	(0.009)	0.005	(0.624)
Percent failing an ELA course	0.210	(0.014)	0.191	(0.009)	0.019	(0.349)
Number of youth	8	306	2,	043	2,84	49

Note: This table provides mean values of preexisting demographic, academic, and school characteristics as well as pre-program outcomes for the sample to youth who were matched to the administrative data in both the 2014-15 and 2015-16 school years with standard errors in parentheses. To test whether whether the treatment variable is correlated with any of the individual pre-program characteristics we compare the effect of winning the SYEP lottery on pre-program demographic, academic, and school characteristics as well as baseline (pre-program) outcomes. Each row provides the coefficient and p-value from a regression where the dependent variable takes the value of 1 if the individual received an offer to participate in SYEP and the independent variable is the characteristic that is listed. See Table A5 in the appendix for separateF-tests of joint significance for each grouping of covariates used in the analysis.

Table A5. F-Tests of Joint Significance for Each Set of Covariates by Sample

	Fu	Full Match Sample			Attendance Match Sample			Grades Match Sample		
		1			Students w		Excluding Students with Missing			
				•	eline Attend	_	_	ine Course G	_	
		N=3,011			N=2,979			N=2,849		
	Number of			Number of			Number of			
Sets of Covariates	Variables	F-stat	Prob>F	Variables	F-stat	Prob>F	Variables	F-stat	Prob>F	
Demographic characteristics	12	1.09	0.3637	12	1.08	0.372	12	1.1	0.3552	
Plus academic characteristics	18	0.97	0.4920	18	0.99	0.468	18	1.01	0.4443	
Plus school charactersistics	20	0.91	0.5743	20	0.92	0.561	20	0.96	0.5091	
Plus individuals baseline outcome										
Dropout	21	0.88	0.6184							
Attendance rate	21	0.91	0.5781	21	0.9	0.5915				
Chronic absenteeism	21	0.84	0.6714	21	0.79	0.7352				
Days of attendance	21	0.87	0.6317	21	0.82	0.6974				
Days of unexceused absences	21	0.90	0.5915	21	0.84	0.6714				
Grade Point Average (GPA)	21	0.86	0.6450				21	0.94	0.5379	
Percent failing any course	21	0.85	0.6583				21	0.88	0.6184	
Percent failing a math course	21	0.89	0.6050				21	0.89	0.605	
Percent failing an ELA course	21	0.88	0.6184				21	0.90	0.5915	

Note: All demographic, academic, and school characteristics are measured pre-program. Demographic characteristics include age, dummy variables for gender (female), race (Black, Asian, and white), primary language spoken (Chinese, English, Spanish), limited English, public assistance, homelessness, and disabled status. Academic characteristics include dummy variables for high need special education status, participation in the METCO program, switching schools, and grade prior to participation (8, 9, 10). School characteristics include a dummy for attending a charter school and the schoolwide MCAS proficiency rate. The Attendance Match Sample excludes students missing baseline attendance and the Grades Match Sample excludes students with missing baseline grades such as dropouts and those transferring to private schools out of state before the start of the school year.

Table A6. ABCD Applicant Characteristics by Lottery Outcome versus Population of Boston Low-Income Youth

	E Characteristics by Editery Co	1	
	Selected (Treatments)	Not Selected (Controls)	Boston Low-Income Youth
Total selected by random assignment	1,186	3,049	
PERCENT IN EACH CATEGORY:			
Age			
14-17 years	79.4%	80.2%	71.7%
18-24 years	20.6%	19.8%	28.3%
Among those Age 14-17 years:			
Gender			
Female	53.1%	53.9%	51.5%
Male	46.9%	46.1%	48.5%
Race			
African American	51.3%	54.0%	50.1%
Asian*	6.5%	5.0%	6.6%
White	9.6%	8.4%	9.5%
Other / Mixed-Race	32.5%	32.6%	33.8%

Note: Low-income youth are identified as those living in households with incomes below poverty level over the past 12 month

Source: ABCD applicants characteristics are from application data provided by the City of Boston Office of Workforce Development Demographic characteristics of Boston low-income youth are from the U.S. Census Bureau, 2011-2015 American Community Survey 5-Year Estimates.

Table A7. ITT Estimates of SYEP Impact on School Attendance Excluding Students Missing Baseline Attendance

	•		One Year Pos	t		
	(Coefficient on W	inning the Lottery	(Treatment Dumm	y)	
	(1)	(2)	(3)	(4)	(5)	
Panel A.						
Attendance rate	0.030 ***	0.027 ***	0.030 ***	0.031 ***	0.030 ***	
	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	
Increased attendance rate	0.042 **	0.045 **	0.046 **	0.045 **		
	(0.021)	(0.021)	(0.021)	(0.021)		
Decreased attendance rate	-0.061 **	-0.063 ***	-0.063 ***	-0.063 ***		
	(0.021)	(0.021)	(0.021)	(0.021)		
Chronic attendance	-0.074 ***	-0.074 ***	-0.074 ***	-0.074 ***	-0.073 ***	
	(0.019)	(0.019)	(0.019)	(0.019)	(0.016)	
Average days attended	5.769 ***	5.501 ***	5.643 ***	5.787 ***	5.115 ***	
-	(1.848)	(1.778)	(1.741)	(1.731)	(1.615)	
Unexcused absences	-2.108 **	-2.027 **	-2.147 **	-2.223 **	-2.263 **	
	(0.851)	(0.843)	(0.825)	(0.820)	(0.734)	
Panel B.						
Number of youth	2,979	2,979	2,979	2,979	2,979	
Log attendance rate	0.039 ***	0.038 ***	0.041 ***	0.042 ***	0.036 ***	
	(0.011)	(0.011)	(0.010)	(0.010)	(0.009)	
Number of youth	2,979	2,979	2,979	2,979	2,979	
Demographic characteristics	No	Yes	Yes	Yes	Yes	
Academic characteristics	No	No	Yes	Yes	Yes	
School characteristics	No	No	No	Yes	Yes	
Baseline outcomes	No	No	No	No	Yes	

Note: The sample includes youth who were matched in both 2014-15 and 2015-16 and able to be tracked throughout the post-period (see Table A2). Each coefficient is from a separate regression where the dependent variable is the outcome listed. All regressions include a set of controls for pre-program demographic, academic, and school characteristics as well as the baseline (pre-program) outcomes listed in Table 1. Probit is used to estimate results for binary outcomes. For these non-linear specifications, the coefficients reported in the table are the average marginal effects. Robust standard errors in parentheses.

Table A8. ITT Estimates of SYEP Impact on Course Performance Excluding Students Missing Baseline Course Grades

			One Year Po	ost				
		Coefficient on Winning the Lottery (Treatment Dummy)						
	(1)	(2)	(3)	(4)	(5)			
Overall GPA	0.131 **	0.102 **	0.114 **	0.117 **	0.117 **			
	(0.050)	(0.047)	(0.044)	(0.044)	(0.038)			
Failed any course	0.001	0.000	0.003	0.002	0.002			
	(0.030)	(0.022)	(0.022)	(0.022)	(0.021)			
Failed a math course	-0.008	-0.007	-0.004	-0.004	-0.004			
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)			
Failed an ELA course	-0.002	-0.004	-0.003	-0.004	-0.003			
	(0.019)	(0.019)	(0.018)	(0.018)	(0.018)			
Demographic characteristics	No	Yes	Yes	Yes	Yes			
Academic characteristics	No	No	Yes	Yes	Yes			
School characteristics	No	No	No	Yes	Yes			
Baseline outcomes	No	No	No	No	Yes			
Number of youth	2,849	2,849	2,849	2,849	2,849			

Note: The sample includes youth who were matched in both 2014-15 and 2015-16 and able to be tracked throughout the post-period (see Table A2). Each coefficient is from a separate regression where the dependent variable is the outcome listed. All regressions include a set of controls for pre-program demographic, academic, and school characteristics as well as the baseline (pre-program) outcomes listed in Table 1. Probit is used to estimate results for binary outcomes. For these non-linear specifications, the coefficients reported in the table are the average marginal effects. Robust standard errors in parentheses.

Table A9. ITT Estimates of SYEP Impact on Standardized Test-Taking and Performance

	Coe	efficient on Winning the Lott	tery (Treatment)
	Mathematics	Englsh	Science and Technology/Engineering
Took MCAS on time	0.023	0.024	0.032 **
	(0.016)	(0.015)	(0.013)
Normalized scaled score	0.018	0.068	0.068
	(0.048)	(0.047)	(0.047)
Percentage proficient or better	0.010	0.004	0.023 *
- 1	(0.015)	(0.013)	(0.014)
Number of youth	2,023	2,023	2,023
Demographic characteristics	Yes	Yes	Yes
Academic characteristics	Yes	Yes	Yes
School characteristics	Yes	Yes	Yes

Note: The sample includes youth who were matched in both 2014-15 and 2015-16 and able to be tracked throughout the post-period (see Table A2). Each coefficient is from a separate regression where the dependent variable is the outcome listed. All regressions include a set of controls for preprogram demographic, academic, and school characteristics as well as the baseline (pre-program) outcomes listed in Table 1. Probit is used to estimate results for binary outcomes. For these non-linear specifications, the coefficients reported in the table are the average marginal effects. Robust standard errors in parentheses.

Table A10. Mediation of the Impact of SYEP on Graduating from High School On Time during the Post-Program Observation Period

(1)	(2)	(3)	(4)			
Dependen	t Variable: Graduated on	time during the follow-up	period			
No Mediators	Attendance	Overall GPA	All Mediators			
0.044 **	0.022	0.026	0.014			
(0.018)	(0.017)	(0.017)	(0.017)			
	0.240 ***		0.157 ***			
	(0.012)		(0.014)			
		0.214 ***	0.156 ***			
		(0.010)	(0.011)			
3,011	3,011	3,011	3,011			
	No Mediators 0.044 ** (0.018)	Dependent Variable: Graduated on No Mediators 0.044 ** 0.022 (0.018) 0.240 *** (0.012)	Dependent Variable: Graduated on time during the follow-up			

Note: The sample includes youth who were matched in both 2014-15 and 2015-16 and able to be tracked throughout the post-period (see Table A2). Each coefficient is from a separate regression where the dependent variable is the outcome listed. All regressions include a set of controls for preprogram demographic, academic, and school characteristics as well as the baseline (pre-program) outcomes listed in Table 1. All independent variables of interest have been standardized to have a mean of zero and a standard deviation of one. Probit is used to estimate results and the coefficients reported in the table are the average marginal effects with robust standard errors in parentheses.

Table A11. Alternative ITT Estimates of SYEP Impacts by Dosage Intensity

	Attendance Rate	Chronic Absenteeism	Days Attended	Days Unexcused	Overall GPA
	(1)	(2)	(3)	(4)	(5)
Panel A. Estimating Separate Coefficients for One versus Two Summers o	f Treatment				
OLS Estimate: Dependent variable = Outcome two years post					
Coefficient on winning the SYEP lottery in 2015	0.016	-0.019	1.994	-1.575	-0.013
·	(0.011)	(0.022)	(2.071)	(1.038)	(0.045)
Coefficient on winning the SYEP lottery in 2015 and 2016 (2 summers)	0.032 **	-0.030	7.267 **	-1.382	0.135 *
• • • • • • • • • • • • • • • • • • • •	(0.016)	(0.037)	(3.138)	(1.435)	(0.075)
Panel B. Instrumenting for a Second Summer of Treatment		, ,		, ,	
IV Estimate: Dependent variable = Outcome two years post					
Coefficient on predicted number of SYEP summers	0.020 **	-0.003	3.147 **	-1.533 **	0.158 **
•	(0.008)	(0.015)	(1.423)	(0.753)	(0.075)
Number of youth who won the 2015 lottery and had not yet graduated	2,636	2,636	2,636	2,636	2,636

Note: The sample includes youth who were matched in both 2014-15 and 2015-16 and able to be tracked throughout the post-period, excluding those who had graduated before the second year of follow-up (see Table A2). Each coefficient is from a separate regression where the dependent variable is the outcome listed. All regressions include a set of controls for pre-program demographic, academic, and school characteristics as well as the baseline (pre-program) outcomes listed in Table 1. Probit is used to estimate results for binary outcomes. For these non-linear specification, the coefficients reported in the table are the average marginal effects. Robust standard errors in parentheses.

Table A12. Comparison of Summer 2015 Post-Survey Responses: ABCD Treatment versus Control Groups

Table A12. Comparison of Summer 20	All groups	nses: ABCD Treatment versus Control Groups "In-school" youth: Age 14-18 years						
	combined	African A		Hisp	inic			
CATEGORY		Males	Females	Males	Females			
Social and community engagemen								
I have a lot to contribute to the groups I belong to	0.156 ***	0.180 **	0.132 **	0.173 **	0.128 *			
	(0.029)	(0.068)	(0.057)	(0.088)	(0.073)			
I feel connected to people in my neighborhood	0.212 ***	0.260 ***	0.148 ***	0.251 ***	0.224 ***			
	(0.025)	(0.059)	(0.050)	(0.084)	(0.065)			
I feel safe walking around my neighborhood	0.193 ***	0.200 ***	0.195 ***	0.260 *** (0.078)	0.174 ** (0.070)			
I have a positive role model in my life	(0.028) 0.005	(0.066) 0.012	(0.053) -0.03	-0.02	0.000			
Thave a positive role model in my me	(0.011)	(0.027)	(0.028)	(0.043)	(0.028)			
I know how to manage my emotions and my temper	0.065 **	0.162 **	0.089	0.037	0.034			
	(0.033)	(0.071)	(0.062)	(0.091)	(0.081)			
I know how to ask for help when I need it	0.116 ***	0.029	0.090	0.082	0.080			
	(0.030)	(0.070)	(0.058)	(0.090)	(0.075)			
I know how to constructively resolve a conflict with a peer	0.136 ***	0.133 **	0.057	0.151 *	0.174 (0.070) **			
I need to improve my conflict resolution skills	(0.029) -0.130 ***	(0.065) -0.151 **	(0.056) -0.138 **	(0.086) -0.098	-0.149 **			
Theed to improve my conflict resolution skins	(0.024)	(0.057)	(0.047)	(0.071)	(0.057)			
Job readiness skill	(0.021)	(0.057)	(0.017)	(0.071)	(0.037)			
Have all key information to apply for a job	0.094 ***	0.064	0.080 **	0.080	0.059			
	(0.021)	(0.053)	(0.042)	(0.057)	(0.055)			
Have prepared a resume	0.245 ***	0.317 ***	0.187 ***	0.313 ***	0.238 ***			
** 1	(0.027)	(0.052)	(0.055)	(0.075)	(0.071)			
Have prepared a cover letter	0.217 ***	0.257 ***	0.230 ***	0.285 ***	0.204 **			
Have asked an adult to serve as a reference.	(0.028) -0.001	(0.061) -0.016	(0.055) -0.055	(0.085) 0.105	(0.071) -0.056			
riave asked an addit to serve as a reference.	(0.027)	(0.065)	(0.052)	(0.074)	(0.065)			
Have reviewed at least one job application form	0.039	-0.001	0.027	0.086	0.025			
	(0.024)	(0.053)	(0.044)	(0.071)	(0.057)			
Have completed at least one online job application.	-0.033	-0.003	-0.082	0.023	-0.090			
	(0.028)	(0.063)	(0.052)	(0.078)	(0.066)			
Have searched for jobs online.	0.025	0.152 **	-0.110 **	0.103	-0.018			
Have asked an adult for help in finding job opportunities	(0.031) 0.071 ***	(0.066) 0.041	(0.057) 0.026	(0.090) 0.135 **	(0.078) 0.068			
Trave asked an addit for help in finding job opportunities	(0.024)	(0.053)	(0.042)	(0.060)	(0.055)			
Have developed answers to the usual interview questions	0.069 ***	0.111 *	0.056	0.088	0.031			
·	(0.026)	(0.062)	(0.051)	(0.071)	(0.062)			
Have practiced my interviewing skills with an adult	0.064 **	0.118 *	0.074	0.069	0.012			
	(0.031)	(0.071)	(0.059)	(0.085)	(0.075)			
Have appropriate professional clothes to wear to interview.	0.043 **	0.088 **	0.008	0.098 *	0.024			
Many and a star for home to set to made and do	(0.020)	(0.044) 0.085 **	(0.034) 0.055 *	(0.055) 0.113 **	(0.042)			
Have made a plan for how to get to work every day	(0.019)	(0.041)	(0.034)	(0.046)	0.028 (0.034)			
Can pass a criminal background check	-0.053 ***	-0.064	(0.034)	0.000	-0.076 *			
can pass a criminar sackground check	(0.016)	(0.044)		(0.037)	(0.043)			
Can pass a drug test	-0.042 ***	-0.029	-0.023		-0.052 *			
	(0.015)	(0.036)	(0.025)		(0.035)			
I need to improve my job readiness skills	-0.053 *	-0.120 *	-0.020	-0.182 **	-0.009			
W. 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	(0.030)	(0.066)	(0.055)	(0.077)	(0.073)			
Work and academic aspiration Plan to work in the fall	-0.074 **	0.080	-0.076	-0.038	-0.204 ***			
I fall to work ill the fall	(0.030)	(0.070)	(0.057)	(0.086)	(0.063)			
Plan to enroll in education or training program after high school	0.003	-0.002	0.017	-0.007	0.011			
a. a	(0.017)	(0.040)	(0.034)	(0.048)	(0.039)			
Plan to attend a four year college or university	0.110 ***	0.099	0.171 ***	-0.103	0.169 **			
	(0.081)	(0.065)	(0.052)	(0.084)	(0.066)			
Plan to attend a two year college	0.062 ***	0.049	0.094 ***	0.117 *	0.018			
Lucad to immuoro my academia akilla	(0.019)	(0.041)	(0.033) 0.211 ***	(0.070) 0.185 **	(0.044)			
I need to improve my academic skills	0.129 *** (0.029)	0.114 * (0.070)		(0.087)	0.024 (0.072)			
	(0.027)	(0.070)	(0.054)	(0.007)	(0.072)			

Note: Each coefficient is the marginal effect from a separate probit regression of the outcome on a dummy variable for treatment controlling for age, gender, race, two parent family, and English as the primary language. Robust standard errors are in parentheses. *Indicates difference is statistically significant at the 10 percent level, ** at the 5 percent level, and*** at the 1 percent level.

Table A13. Relationship between Short-Term Behavioral Changes and Longer-Term Academic Outcomes

	(1)			(2)	(3)		(4)			(5)			
	Atten	Attendance rate		Attendance rate>=90%		Unexcused absences		Dropped out ever		r (Graduated on time		
	Coefficient	SE		Coefficient	SE		Coefficient	SE	Coefficient	SE	Coeffic	ient SE	
Panel A. Academic aspirations													
Planning to attend a four-year college	0.009	(0.012)		0.041	(0.950)		-1.980	(2.367)	0.007	(0.027)	-0.01	6 (0.051)	
Saving for tuition	0.047	(0.025)	*	0.011	(0.102)		-10.454	(4.742) **			0.18	0.100)	*
Panel B. Job readiness skills													
Having key information to apply for a job	-0.002	(0.014)		0.061	(0.038)		-2.144	(1.908)	0.029	(0.023)	-0.02	5 (0.046)	
Preparing a resume	0.018	(0.010)	*	0.031	(0.032)		-3.515	(1.613) **	0.000	(0.022)	0.04	(0.040)	
Preparing a cover letter	0.018	(0.012)		0.050	(0.035)		-3.464	(1.820) *	0.022	(0.022)	0.02	(0.043)	
Developing answers to interview questions	-0.008	(0.014)		0.057	(0.036)		-1.943	(1.791)	0.026	(0.022)	0.00	(0.043)	
Practicing interviewing with an adult	0.009	(0.011)		0.047	(0.035)		-1.806	(1.668)	0.002	(0.023)	0.02	(0.043)	
Being on time	0.020	(0.009)	**	0.070	(0.031)	**	-2.720	(1.383) **	-0.052	(0.023)	** 0.10	(0.037)	**
Keeping a schedule	0.025	(0.009)	**	0.087	(0.031)	**	-2.287	(1.382) *	-0.029	(0.022)	0.06	2 (0.037)	*
Panel C. Community engagement and social skills													
Contributing to the groups they belong to	0.018	(0.011)		0.004	(0.041)		-2.871	(2.097)	-0.055	(0.032)	* 0.13	7 (0.052)	**
Connecting to people in their neighborhood	0.014	(0.013)		0.059	(0.044)		-3.287	(2.512)	-0.007	(0.030)	0.11	θ (0.058)	**
Managing emotions	0.020	(0.012)		-0.008	(0.051)		-2.390	(2.107)	-0.080	(0.046)	* 0.15	(0.059)	**
Asking for help	0.015	(0.011)		0.027	(0.049)		-4.342	(2.471) *	-0.014	(0.032)	0.13	1 (0.057)	**
Gaining a mentor	0.016	(0.010)		0.015	(0.029)		-3.801	(1.369) **	-0.026	(0.019)	0.09	(0.035)	**
Resolving conflict with a peer	0.003	(0.010)		-0.018	(0.043)		0.104	(1.769)	-0.004	(0.030)	0.04	(0.022)	**
Demographic characteristics		Yes			Yes			Yes		Yes		Yes	
Academic characteristics		Yes			Yes			Yes		Yes		Yes	
Baseline outcomes		Yes			Yes			Yes		Yes		Yes	
Number of youth		2,852			2,852		2	2,852		2,970		1,953	

Note: This table estimates the relationship between improvements in short-term behaviors and skills that occur over the summer and subsequent improvements in school outcomes after participating in the program. All regressions include a set of controls for pre-program demographic, academic, and school characteristics as well as the baseline (pre-program) outcomes listed in Table 1. Probit is used to estimate results for binary outcomes. A Poisson specification is used to estimate the impact on days attended and days truant. For these non-linear specification, the coefficients reported in the table are the average marginal effects. Robust standard errors are in parentheses.

Table A14. Effects Sizes in Context of Baseline or Expected Outcomes

	Baseline		Program	Impact	Eff	ect Size	Interpretation		
	Pooled Mean	Pooled SD	Estimate	SE	% of Baseline	Cohen's d	Magnitude per Kraft (2018)	% of Control group below Treatment mean	
One Year Post									
Attendance rate	0.901	0.133	0.024	0.006	2.7%	0.1807	Medium	57%	
Likelihood of chronic attendance	0.276	0.452	-0.059	0.016	-21.2%	0.1437	Medium	56%	
Days attended	160.720	28.899	3.351	1.239	2.1%	0.1160	Medium	54%	
Days truant	11.732	17.449	-2.073	0.821	-17.7%	0.1761	Medium	56%	
GPA	1.900	1.116	0.129	0.036	6.8%	0.1156	Medium	54%	
	Post-Period		Program Impact		Effect Size		Interpretation []		
	Control Group Mean	Control Grup SD	Estimate	SE	% of Control Group Mean	Cohen's d using Control Group SD	Magnitude per Kraft (2018)	% of Control group below Treatment mean	
Cumulative over the Four-Year Observation Period	Ivicuii	SD	Listimate	S.E.	Group Mean	Control Group SD	111111 (2010)	Treatment mean	
Dropout at any point	0.126	0.327	-0.025	0.012	-19.9%	-0.0767	Medium	52%	
On time high school graduation	0.634	0.482	0.044	0.018	7.0%	0.0917	Medium	54%	
	Post-Period		Program Impact		Effect Size		Interpretation		
	Boston Public Schools Mean	Boston Public Schools SD	Estimate	SE	% of BPS Group Mean	Cohen's d using BPS SD	Magnitude per Kraft (2018)	% of Control group below Treatment mean	
Cumulative over the Four-Year Observation Period							\ -7		
Dropout - cohort rate	0.141	0.427	-0.025	0.012	-17.8%	-0.0587	Medium	51%	
On time high school graduation	0.733	0.582	0.044	0.018	6.0%	0.0759	Medium	53%	