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Building College and Career Pathways for High School Students: Youth CareerConnect

Technical Report for the Impact Study

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DISCLAIMER

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ABSTRACT

In 2014, the U.S. Department of Labor (DOL) awarded $107 million in four-year grants to 24 applicants to the Youth CareerConnect (YCC) program, a high school–based program aimed at improving the college and career readiness of young adults. The YCC program was designed to provide students with a rigorous program that included a career focus in a high-growth H-1B industry, employer partnerships and engagement, integrated academic and career curricula, work-based learning and exposure to the world of work, individualized career and academic counseling, small learning communities, and professional development. At the same time that it awarded YCC grants, the Employment and Training Administration of DOL contracted with Mathematica and its partner, Social Policy Research Associates, to conduct a rigorous evaluation of the YCC program. Rigorously evaluating the effects of the YCC program on student outcomes required that multiple technical pieces be put in place, from selecting districts to participate in the evaluation to collecting and processing high-quality data and measuring impacts to conducting rigorous analysis to estimate impacts. This report provides details of these processes.

ACKNOWLEDGMENTS

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Contents

Tables

Figures

INTRODUCTION

In April 2014, the U.S. Department of Labor (DOL) and its Employment and Training Administration (ETA) used the fees companies pay to certify job openings to hire foreign workers under the H-1B visa program to award $107 million in grant funds to implement the Youth CareerConnect (YCC) program (Table 1). The YCC grants, which ranged from about $2.25 million to $7 million over a four-year period, were awarded to a diverse set of organizations. The YCC program was considered a promising approach to address both high unemployment rates among youth and employer needs for a highly skilled domestic workforce. It redesigned the high school experience to strengthen youth's college and career readiness for middle- to high-skilled jobs in industries that often rely on the H-1B visa program to meet the need for workers.

Table 1. Summary of YCC grants

Grantee	Location	Organization type	Funding
Academia de Directores Médicos de Puerto Rico, Inc.	San Juan, PR	Nonprofit	$2,842,834
Anson County Schools	Wadesboro, NC	LEA	$2,247,373
Bradley County School District	Cleveland, TN	LEA	$4,499,121
Buffalo Board of Education	Buffalo, NY	LEA	$3,898,700
Colorado City Independent School District	Colorado City, TX	LEA	$3,482,704
East San Gabriel Valley Regional Occupational Program	West Covina, CA	LEA	$4,499,251
Galveston Independent School District	Galveston, TX	LEA	$3,975,000
Ivy Tech Community College of Indiana	Kokomo, IN	IHE	$3,273,878
Jobs for the Future, Inc.	Boston, MA	Nonprofit	$4,867,815
Kentucky Educational Development Corporation	Ashland, KY	Nonprofit	$5,520,019
Laurens County School District 56	Clinton, SC	LEA	$6,890,232
Los Angeles Unified School District	Los Angeles, CA	LEA	$7,000,000
Manufacturing Renaissance	Chicago, IL	Nonprofit	$2,670,909
Metropolitan School District of Pike Township	Indianapolis, IN	LEA	$7,000,000
New York City Department of Education	New York, NY	LEA	$6,999,601
Pima County	Tucson, AZ	Workforce entity	$5,351,690
Prince George's, Inc.	Largo, MD	Nonprofit	$7,000,000
Putnam County Board of Education	Eatonton, GA	LEA	$2,418,343
Rosemount Independent School District 196	Rosemount, MN	LEA	$2,990,026
School District number 1 in the City and County of Denver	Denver, CO	LEA	$6,999,980
St. Paul Independent School District 625	St. Paul, MN	LEA	$3,680,658
Toledo Public Schools	Toledo, OH	LEA	$3,824,281
Upper Explorerland Regional Planning Commission	Postville, IA	Workforce entity	$2,784,360
Westside Community Schools	Omaha, NE	LEA	$2,647,212

Source: Grantee application information from the U.S. Department of Labor.

IHE = institution of higher education, LEA = local education agency.

At the same time as the grants were awarded, ETA contracted with Mathematica and its partner, Social Policy Research Associates, to conduct a rigorous evaluation of the YCC program. The evaluation included an implementation study and an impact study involving both a quasi-experimental design (QED) and a randomized controlled trial (RCT). The main findings from the implementation study are presented in three reports (Dillon 2019, Geckeler et al. 2019, and Maxwell et al. 2017), and the main findings from the impact study are presented in Maxwell et al. (2019). The goal of the impact study was to address the general research question, *What is the impact of the YCC program on critical milestones that can be attained in high school and momentum points associated with education and employment success?* The research focus on milestones and momentum points that occur in high school was driven by timing. Data collected for the evaluation ended in spring 2018, when most YCC participants were still in high school.

Evaluation findings about the YCC program
Available at
https://www.dol.gov/agencies/oasp/evaluation/completedstudies

Summary of all results

- *Brief.* Summarizes the findings of the evaluation's impact and implementation studies (Maxwell and Dillion 2019).

Implementation study results

- *Early years.* Explores implementation of the YCC program through the 2015-16 school year, after two years of YCC funding (Maxwell et al. 2017).
- *Implementation.* Explores the evolution of YCC program implementation through the 2017-18 school year, and the approaches grantees planned for sustaining the YCC program after grant funding ended (Geckeler et al. 2019).
- *Employer and workforce agency partnerships.* Examines YCC programs' partnerships with employers and local workforce development system agencies (Dillon 2019).

Impact study results

- *Impact findings.* Examines the impact of participation in the YCC program on student success during high school (Maxwell et al. 2019).
- *Technical documentation.* Provides a technical discussion about the data, samples, and analysis that underlie the estimated impacts presented in the impact findings report (this report).

This technical report provides details on the data, samples, methods, and analyses for the impact study. Rigorously evaluating the effects of the YCC program on student outcomes required us to put in place multiple technical pieces, from selecting districts to participate in the evaluation to collecting and processing high-quality data and measuring impacts to conducting rigorous analysis to estimate impacts. We provide details of these processes in this technical report:

- In Chapter I, we provide an overview of the YCC program and key features of the impact study design that we discuss in more detail in the remaining chapters.
- In Chapter II, we give an overview of the districts, data, and samples available for the study.
- In Chapter III, we describe construction of the outcomes and samples used, the process for identifying treatment and comparison/control groups and their baseline equivalence, and the analytic approach to estimating and interpreting impacts.
- In Chapter IV, we discuss checks for the robustness of the analysis results by providing results from the sensitivity analyses conducted.
- In Chapter V, we provide data tables underlying many of the figures and tables in the main impact report.

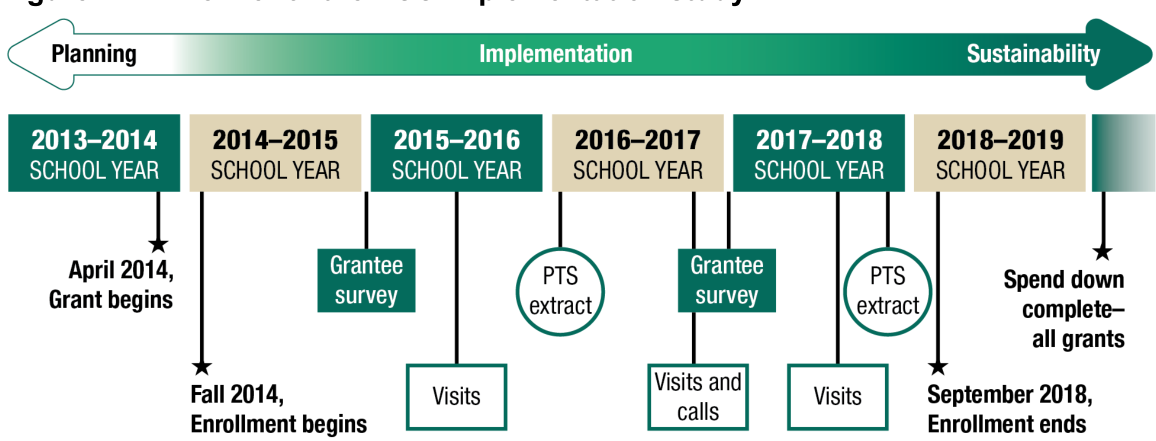
I. YOUTH CAREERCONNECT AND ITS EVALUATION

In this chapter, we provide a context for understanding the YCC program and the design of and methods used for the impact study, both of which are presented in more detail in subsequent chapters. We first present an overview of the implementation of the YCC program (Section A) and then discuss key features of the impact study (Section B).

A. The YCC implementation study documented services and activities provided by grantees in three program components

YCC grantees had a five-month planning period starting in April 2014, with program implementation starting in the fall of the 2014–2015 school year and extending for four years. Many YCC grantees received extensions to spend down their grant funds: 6 of the 24 grantees ended their grants as scheduled in September 2018, 2 ended in March 2019, 9 concluded in June or July 2019, and 7 ended in September 2019. The YCC implementation study followed grantees throughout this period and built an understanding of program operations, successes, and challenges as the program was implemented in schools. It drew information from four unique sources: (1) two rounds of surveys to grantees that were completed in summer 2015 and 2017 and provided information on service delivery models, staffing, staff development, partnerships, and implementation of the YCC core program elements; (2) three rounds of site visits to schools and districts in the winters of 2015, 2017, and 2018, supplemented with one round of telephone call interviews; (3) quarterly narrative reports that grantees submitted to DOL on accomplishments and challenges encountered during the past quarter and activities planned for the next quarter; and (4) a Participant Tracking System (PTS) that captured the characteristics of, services provided to, and short-term outcomes of all YCC participants. Figure I.1 shows the timing of data collection.

Figure I.1. Timeline for the YCC implementation study



Note: A school year runs from June to May.
PTS = Participant Tracking System.

All grantees participated in the implementation study through the grantee surveys, quarterly reporting, and PTS; but only 10 participated in the site visits and telephone calls (Table I.1).

Table I.1. YCC grantees in the evaluation

		Students enrolled in the YCC program		Implementation study[a]	Impact study	
Grantee	Funding	Number	Percent	Visits and calls	QED	RCT
Academia de Directores Médicos de Puerto Rico, Inc.	$2,842,834	699	2.4	No	No	No
Anson County Schools	$2,247,373	350	1.2	No	No	No
Board of Education, Buffalo	$4,499,121	519	1.7	Yes	Yes	No
Bradley County School District	$3,898,700	834	2.8	No	No	No
Colorado City Independent School District	$3,482,704	443	1.5	No	No	No
East San Gabriel Valley Regional Occupational Program	$4,499,251	1,541	5.2	No	No	No
Galveston Independent School District	$3,975,000	910	3.1	No	Yes	No
Ivy Tech Community College of Indiana	$3,273,878	716	2.4	No	No	No
Jobs for the Future[b]	$4,867,815	549	1.8	Yes	Yes	No
Kentucky Educational Development Corporation	$5,520,019	1,525	5.1	Yes	Yes	Yes
Laurens County SD 56	$6,890,232	754	2.5	Yes	Yes	No
Los Angeles Unified School District[c]	$7,000,000	3,229	10.9	Yes	Yes	Yes
Manufacturing Renaissance	$2,670,909	262	0.9	Yes	Yes	Yes
Metropolitan School District of Pike Township	$7,000,000	2,563	8.6	Yes	Yes	Yes
New York City Department of Education	$6,999,601	3,276	11.0	Yes	Yes	No
Pima County	$5,351,690	856	2.9	Yes	Yes	No
Prince George's, Inc.	$7,000,000	996	3.4	No	Yes	No
Putnam County Board of Education	$2,418,343	338	1.1	No	No	No
Rosemount Independent School District 196	$2,990,026	485	1.6	No	No	No
St. Paul Independent School District 625	$6,999,980	799	2.7	No	Yes	No
School District No. 1 in the City and County of Denver	$3,680,658	5,657	19.0	No	No	No
Toledo Public Schools	$3,824,281	683	2.3	Yes	Yes	No
Upper Explorerland Regional Planning Commission	$2,784,360	1,290	4.3	No	No	No
Westside Community Schools	$2,647,212	450	1.5	No	Yes	No
Sample size	**n.a.**	**29,724**	**n.a.**	**10**	**14**	**4**

Source: Participant Tracking System (PTS), through September 30, 2018, for number and percentage of students.

[a] All 24 grantees were included in two rounds of grantee surveys, PTS, and analysis of quarterly performance reports.

[b] Jobs for the Future had three different districts included in the QED.

[c] As we discuss in Chapter II, Los Angeles Unified School District did not participate in all aspects of the RCT.

QED = quasi-experimental design; RCT = randomized controlled trial.

n.a. = not applicable.

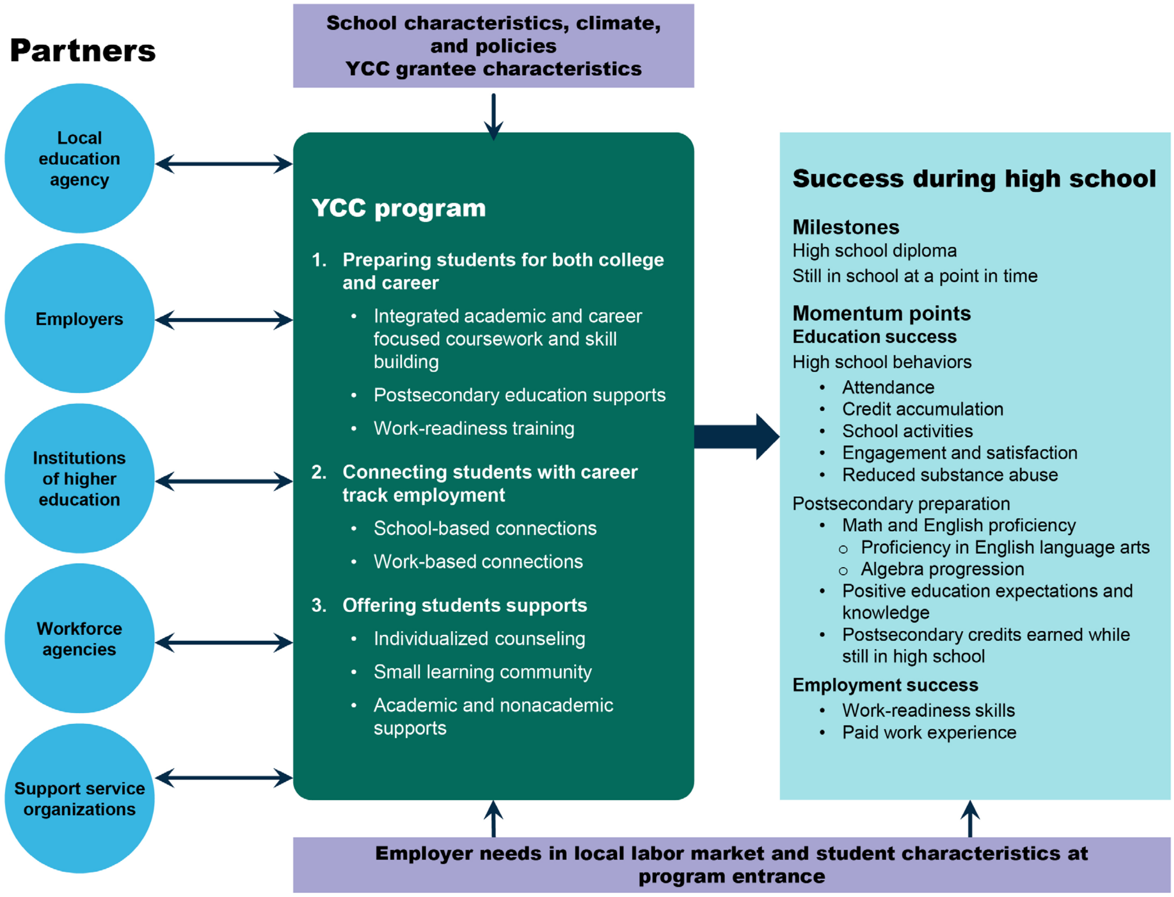
Between April 1, 2014 and September 30, 2018 grantees enrolled 29,724 students. Grantees showed wide variation in the number of students they enrolled primarily due to the size of the funding amount, which was directly related to enrollment target (see Table I.1). At the extremes, School District No. 1 in the City and County of Denver enrolled 5,657 students, or 19 percent of all YCC students, while Manufacturing Renaissance enrolled 262 students, or less than 1 percent. Four grantees (School District No. 1 in the City and County of Denver, New York City Department of Education, Los Angeles Unified School District [LAUSD], and the Metropolitan School District of Pike Township), enrolled nearly half (49.5 percent) of all YCC students.

Results of the implementation study suggested that schools in which grantees implemented the YCC program provided students with a diverse set of services and activities that can be organized into three program components:

1. **Preparing students for both college and career** included services and activities such as an integrated academic and career-focused curriculum, postsecondary education supports, and work-readiness training.
2. **Connecting students with career-track employment** included school-based connections (for example, mentoring, having guest speakers from work, and preparing for the workplace) as well as work-based connections (for example, field trips to workplaces, job shadowing, internships, and apprenticeships).
3. **Offering supports** included offering students individualized academic and career counseling, small learning communities, and academic and nonacademic supports.

Figure I.2 on the next page illustrates how these program components (green box) might affect short-term education and employment success. Program components were supported by and often provided in conjunction with five different types of partners (circles). By the 2017–2018 school year, when grant funding was originally scheduled to end, sufficient time had not elapsed for the YCC program to demonstrate an impact on long-term employment and earnings. It could, however, have had an impact on critical milestones and momentum points attainable in high school (light green box) that help students progress toward ultimate education and employment success (as discussed in Section B). Finally, as Figure I.2 illustrates, the context in which the YCC program was implemented can be expected to affect its structure and outcomes (purple boxes).

Figure I.2. The YCC program as schools implemented it



B. The YCC impact study includes a rigorous QED and RCT components

The impact study addressed the general research question, *What is the impact of the YCC program on critical milestones that can be attained in high school and momentum points associated with education and employment success?*, by answering three subquestions.

1. What is the impact of the YCC program on school attendance, credit accumulation, proficiency in English language arts, and algebra progression?
2. Does the impact of the YCC program vary by (1) key student characteristics (prior academic achievement and low-income status); (2) program experiences (receiving an internship, having a mentor, and completing an individual development plan, or IDP); or (3) cohort of students?
3. What appears to be the impact of the YCC program on high school graduation, staying in school, school engagement and satisfaction, positive behavior at school, postsecondary credits earned during high school, educational expectations and knowledge, work-readiness skills, paid work experiences, and reduced substance abuse?

To answer these questions, the impact study design contains two complementary components.[1] One component is a large-scale QED study conducted in 16 districts; the other is an RCT conducted in 4 school districts (see Chapter II for details). Table I.1 shows the grantees involved in each component. The impact study was designed to exploit the relative strengths of both components to obtain an overall picture of the effects of the YCC program. Each component brings strengths to the design. The QED has the following advantages:

- **Large sample sizes.** The QED was conducted in 16 districts with 6,207 students in the treatment group that received services funded by the YCC program and 109,541 students in the comparison group that did not receive YCC services. Although the districts and students were not selected to be representative of all YCC students, the treatment group accounts for 4.8 percent of all YCC students. The treatment group had a smaller proportion of females, whites and English language learner students as compared to all YCC students, whereas proportion of students who took an industry-specific course, had school-based WBL experience, or received mentoring or counseling was greater among the treatment group than all YCC students.
- **Multiple cohorts of students with up to a four-year follow-up.** The QED estimated impacts for six cohorts of students who received YCC program services for up to four years. We describe the way cohorts were constructed later in the chapter.
- **Subgroup analysis.** The QED's large sample allowed for subgroup analyses that build an understanding of how impacts vary by student characteristics, program experiences, and cohort (which could capture differences in both students entering the YCC program over time and program maturation).
- **Causality.** Although QED methods are not as rigorous in assessing causality as an RCT, research has shown that, in the education context, credible impact findings can be achieved using detailed matching variables from school records data (Shadish et al. 2008).

By comparison, the RCT brings these advantages:

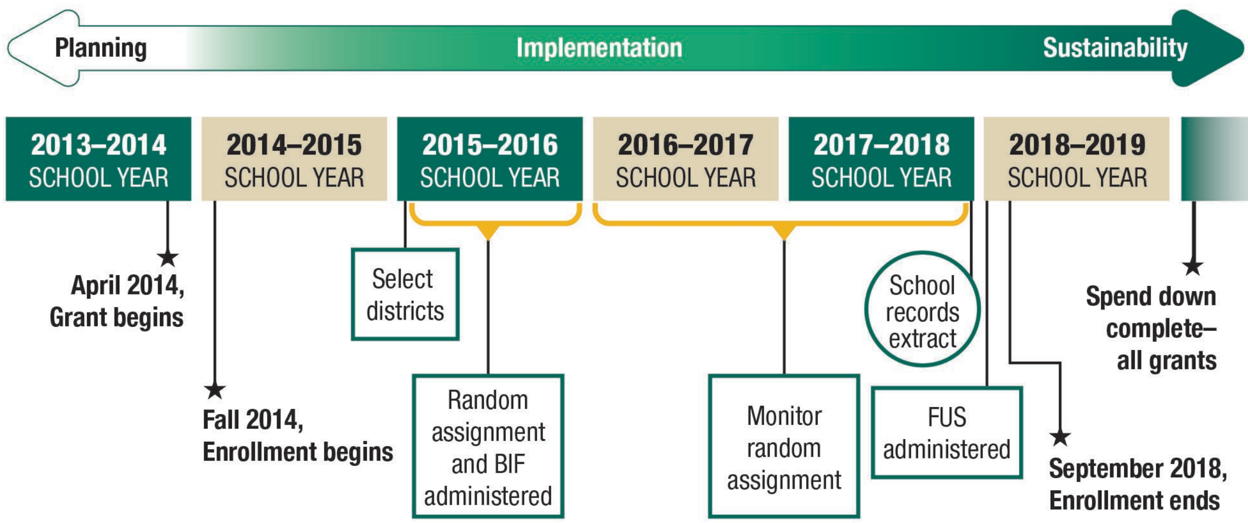
- **Lottery based selection of treatment and control groups.** The RCT was conducted in four districts. Students were assigned to the YCC program using a lottery system designed for the evaluation in three districts and a preexisting lottery system in one district. The random assignment of students into treatment and control groups helped ensure that students were similar in both observable and unobservable characteristics before they entered the YCC program or another high school program.

[1] Mathematica received necessary approvals for the YCC evaluation. The Office of Management and Budget (OMB) approved the data collection activities to be in accordance with the Paperwork Reduction Act on April 16, 2015 (OMB control # 1291-0003). The New England Institutional Review Board (IRB#15-043) approved data collection on February 19, 2015, and the National Institute of Child Health and Human Development issued a Certificate of Confidentiality (CC-HD-15-20) on March 16, 2015. Mathematica also obtained all necessary approvals and executed a memorandum of understanding with each district in the impact study.

- **Rich data through a follow-up survey.** A follow-up survey (FUS) was administered to students in three of the four RCT districts to allow for the collection of a richer set of outcome data than were available through student records used to measure outcomes for the QED.

Arguably, the biggest constraint for both the QED and RCT is time. As Figure I.3 shows, the end of the 2017 to 2018 school year is the latest point at which outcomes could be captured within the timeline of the YCC grants and the current evaluation. Although this time period allows for up to four years of outcomes for early YCC participants in the QED, it allows for only two years of outcomes for those in the RCT. In all cases, outcomes must be assessed when students are still in high school, even though the YCC program was designed to prepare for employment in high-demand industries, which would generally entail employment after high school.

Figure I.3. Timeline for the YCC impact study



Note: A school year runs from June to May. Random assignment and BIF administration varied across districts, depending on when they enrolled students in the program, with one district holding lotteries in 2016 and 2017 to fill vacant seats. See Chapter II for details. Most, but not all, outcomes were captured in the 2017–2018 school year. For example, the proficiency in English language arts outcome was captured from 2015–2016 to 2017–2018. See Chapter III for details.

BIF = baseline information form; FUS = follow-up survey.

The timing constraint requires that outcomes measured in high school be related to those that are ultimately associated with education and employment success. Assessing the impact of the YCC program on these milestones and momentum points enables researchers and policymakers to gauge progress toward ultimate credential attainment and employment (Center for Postsecondary and Economic Success [CLASP] 2013). We consider milestones to be measurable academic achievements or intermediate outcomes, such as staying in school and graduating from high school, and momentum points to be measurable educational attainments, such as attendance or credit accumulation, that are empirically correlated with the completion of a milestone.[2]

[2] The study does not have access to social security numbers for the QED sample. Thus, it will not be possible to obtain longer-term employment data for this sample from administrative records (such the New Directory of New Hires), although college enrollment information could be obtained from the National Student Clearinghouse.

II. DISTRICTS, DATA, AND SAMPLES AVAILABLE FOR THE IMPACT STUDY

Selecting grantees to participate in the impact study began shortly after YCC grants were awarded in April 2014 to ensure that we had sufficient time to conduct random assignment for students applying to the YCC program during the 2015–2016 school year for the start of enrollment in fall 2016. Concurrently, we identified districts suitable for the QED and designed data collection instruments and samples for the analysis. We discuss these processes in this chapter by providing details of how districts were selected for inclusion in each impact study component (Section A), what data were collected and samples were included in each component (Section B), and what coding and data-processing procedures were applied to ensure high-quality data (Section C).

A. Districts selected for the QED and RCT were those that best met the study's inclusion criteria

The 24 YCC grantees implemented program services in a wide variety of settings, as Table II.1 shows. As of September 30, 2018, program providers had these features:

- Grantees were located in 18 states and Puerto Rico and included a mix of school and occupational center districts spread across cities, suburban areas, towns, and rural areas.
- Grantees offered the program in 130 high schools in 75 school districts; in 3 occupational centers that provide the career and technical education employment needs for their community; and in 3 community colleges (not including colleges in which YCC students could enroll in courses that provided college credit during high school).
- The program was typically implemented in a single school district (by 17 of 24 grantees) but in some cases it was implemented in multiple districts that could number more than a dozen (by 7 grantees).

Table II.1. YCC grantees and their schools enrolling YCC participants

Local YCC program name	School name	High school district	Locale
Grantee: Academia de Directores Médicos de Puerto Rico, Inc.			
Puerto Rico Youth Health Careers Program	Escuela Superior Lila María Mayoral	Puerto Rico Department of Education	Suburban
	Escuela Superior Dr. Rafael López Landrón	Puerto Rico Department of Education	Suburban
	Escuela Superior Natividad Rodríguez	Puerto Rico Department of Education	Suburban
Grantee: Anson County Schools			
Anson YCC Program	Anson HS	Anson County Schools	Town
Grantee: Board of Education, Buffalo, New York			
Medical Careers Pathway Program	MST–Math, Science, Technology School	Buffalo Public SD	City
Grantee: Bradley County SD			
Pathways Bradley	Bradley Central HS	Bradley County SD	City
	Walker Valley HS	Bradley County SD	City
Grantee: Colorado City ISD			
Colorado Career Academy	Colorado Career Academy	Colorado City ISD	Town
	Wallace HS	Colorado City ISD	Town
Grantee: East San Gabriel Valley Regional Occupational Program			
East San Gabriel Valley ROP	Baldwin Park HS	Baldwin Park USD	Suburban
	Covina HS	Covina-Valley USD	Suburban
	Gladstone HS	Azusa USD	Suburban
	Sierra Vista HS	Azusa USD	Suburban
	Bob Margett Career Pathway School (Community Day School)	Azusa USD	Suburban
Grantee: Galveston Independent SD			
Galveston Career Connect	Ball HS	Galveston ISD	Town
	AIM College and Career Prep	Galveston ISD	Town
	Odyssey Academy	Galveston ISD	Town
Grantee: Ivy Tech Community			
Integrated Technology Education Program	Hamilton Heights HS	Hamilton Heights SD	Suburban
	Carroll HS	Northwest Allen CS	Rural
	Tipton HS	Tipton SD	Town
	Eastern HS	East Washington SD	Town
	Maconaquah HS	Maconaquah SD	Rural
	Manchester HS	Manchester SD	Rural
	North Miami HS	North Miami SD	Rural
	Northfield Jr./Sr. HS	MSD Wabash County	Rural
	Southwood Jr./Sr. HS	MSD Wabash County	Rural
	Northwestern HS	Northwestern SD	Rural
	Peru HS	Peru CS	Town
	Tri-Central HS	Tri-Central SD	Rural
	Wabash HS	Wabash City SD	Town
	Western HS	Western SD	Rural
	Logansport Community HS Century Career Center [a]	n.a.	Town

Local YCC program name	School name	High school district	Locale
	Elwood Community School Corporation John H. Hinds Career Center [a]	n.a.	Town
	Heartland Career Center [a]	n.a.	Rural
Grantee: Jobs for the Future, Inc.			
Massachusetts Advanced Pathways Program	Brockton HS	Brockton SD	Suburban
	Marlborough HS	Marlborough SD	Suburban
	West Springfield HS	West Springfield SD	Suburban
Grantee: Kentucky Educational Development Corporation			
Project ACHIEVE	Casey County HS	Casey County SD	Rural
	Garrard County HS	Garrard County SD	Rural
	Johnson Central HS	Johnson County SD	Rural
	Knox Central HS	Knox County SD	Town
	Lynn Camp HS	Knox County SD	Town
	Lawrence County HS	Lawrence County SD	Town
	Lee County HS	Lee County SD	Rural
	Middlesboro HS	Middlesboro ISD	Town
	Pulaski County HS	Pulaski County SD	Town
	Southwestern HS	Pulaski County SD	Town
Grantee: Laurens County SD 56			
Carolina Alliance for Technology	Clinton HS	Laurens District 56	Rural
	Laurens HS	Laurens District 55	Rural
	Ridge View HS	Richland District 02	Suburban
	Westwood HS	Richland District 02	Rural
Grantee Los Angeles USD			
Los Angeles USD YCC Program	Teacher Preparatory Academy/Technology Preparatory Academy	Los Angeles USD	City
	Hawkins HS Responsible Indigenous Social Entrepreneurship	Los Angeles USD	City
	Sylmar HS Sylmar Biotech Health Academy	Los Angeles USD	City
	Bernstein HS STEM Academy of Hollywood	Los Angeles USD	City
	Contreras Learning Center, The School of Business and Tourism	Los Angeles USD	City
	Manual Arts HS, School of Medicine, Arts and Technology	Los Angeles USD	City
Grantee: Manufacturing Renaissance			
Manufacturing Careers & College Connect	Austin Polytechnical Academy	Chicago PS	City
Grantee: Metropolitan SD of Pike Township			
Pike HS YCC Program	Pike HS	Metropolitan SD of Pike Township	City
Grantee: New York City Department of Education			
CUNY P-TECH	In-Tech Academy	New York City Department of Education	City
	Queens Vocational and Technical HS	New York City Department of Education	City
	Academy for Software Engineering	New York City Department of Education	City
	Urban Assembly Gateway School for Technology	New York City Department of Education	City

Local YCC program name	School name	High school district	Locale
	Transit Tech Career and Technical HS	New York City Department of Education	City
	Brooklyn Technical HS	New York City Department of Education	City
	Ralph McKee Career and Technical Education HS	New York City Department of Education	City
	HS of Computers and Technology	New York City Department of Education	City
	HS for Construction Trades, Engineering and Architecture	New York City Department of Education	City
	Columbia Secondary School	New York City Department of Education	City
	Chelsea CTE HS	New York City Department of Education	City
	Energy Tech HS	New York City Department of Education	City
	City Polytechnic HS of Engineering, Architecture, and Technology	New York City Department of Education	City
	Inwood Early College for Health and Information Technologies	New York City Department of Education	City
	MECA (Manhattan Early College School for Advertising)	New York City Department of Education	City
	Cisco Network Academy at the School of Co-operative Technical Education	New York City Department of Education	City
	HSE (high school equivalency) program at Jamaica Hospital	New York City Department of Education	City
Grantee: Pima County			
CREO (STEM Math)	Pueblo Magnet HS	Tucson USD	City
	Tucson High Magnet School	Tucson USD	City
	Buena HS	Sierra Vista USD	City
	CPIC-CAS (Center for Academic Success) Charter School	Center for Academic Success, Inc.	City
	Desert View HS	Sunnyside USD	City
	Sunnyside HS	Sunnyside USD	City
	Nogales HS	Nogales USD	Town
	Rio Rico HS	Santa Cruz Valley USD	Town
	Yuma HS	Yuma Union HS District	City
	Pima Community College [b]	n.a.	Mixed
	Arizona Western College [b]	n.a.	Mixed
	Cochise College [b]	n.a.	City
Grantee: Prince George's, Inc.			
Prince George's YCC Program	Potomac HS	Prince George's County PS	Suburban
	Parkdale HS	Prince George's County PS	Suburban
	Bladensburg HS	Prince George's County PS	Suburban
	Fairmont Heights HS	Prince George's County PS	Suburban
Grantee: Putnam County Board of Education			
Youth Empowered for Success	Putnam County HS	Putnam County SD	Rural

Local YCC program name	School name	High school district	Locale
Grantee: Rosemount ISD 196			
E3 STEM (Exploration, Education, Employment in Science, Technology, Engineering and Math)	Apple Valley HS	Rosemount ISD 196	Suburban
	Eagan HS	Rosemount ISD 196	Suburban
	Eastview HS	Rosemount ISD 196	Suburban
Grantee: St. Paul ISD 625			
St. Paul PS YCC Program	Como Park Senior HS	St. Paul ISD 625	City
	Humboldt HS	St. Paul ISD 625	City
Grantee: SD Number 1 in the City and County of Denver			
Denver Plan for Postsecondary and Workforce Readiness	Martin Luther King Early College	SD Number 1 in the City and County of Denver	City
	John F. Kennedy HS	SD Number 1 in the City and County of Denver	City
	CEC Middle College	SD Number 1 in the City and County of Denver	City
	High Tech High Early College	SD Number 1 in the City and County of Denver	City
	Abraham Lincoln HS	SD Number 1 in the City and County of Denver	City
	George Washington HS	SD Number 1 in the City and County of Denver	City
	West HS	SD Number 1 in the City and County of Denver	City
	East HS	SD Number 1 in the City and County of Denver	City
	Manual HS	SD Number 1 in the City and County of Denver	City
Grantee: Toledo Public Schools			
Pathways to Prosperity	Bowsher HS	Toledo PS	City
	Scott HS	Toledo PS	City
	Start HS	Toledo PS	City
	Toledo Technology Academy	Toledo PS	City
	Woodward HS	Toledo PS	City
Grantee: Upper Explorerland Regional Planning Commission			
IA-PIPE: Northeast Iowa Pathways to Employment	Waukon HS (Allamakee)	Allamakee CS	Town
	Central Community School (Elkader)	Central CSD	Rural
	Clayton Ridge HS (Guttenberg)	Clayton Ridge CSD	Rural
	Decorah HS	Decorah CSD	Town
	Starmont HS	Starmont CSD	Rural
	Kee HS (Eastern Allamakee)	Eastern Allamakee CSD	Rural
	Edgewood-Colesburg Jr./Sr. HS	Edgewood-Colesburg CSD	Rural
	Crestwood HS (Howard-Winneshiek)	Howard-Winneshiek CSD	Town
	Maquoketa Valley HS (Delhi)	Maquoketa Valley CSD	Town
	MFL MarMac HS	MFL MarMac CSD	Rural
	New Hampton HS	New Hampton CSD	Town
	North Fayette Valley HS	North Fayette Valley CSD	Rural
	Oelwein HS	Oelwein CSD	Town
	John R. Mott HS (Postville)	Postville CSD	Rural
	Riceville HS	Riceville CSD	Rural
	South Winneshiek HS	South Winneshiek CSD	Rural

Local YCC program name	School name	High school district	Locale
	Turkey Valley Jr./Sr. HS	Turkey Valley CSD	Rural
	West Central (Maynard)	West Central CSD (Maynard)	Rural
	West Delaware HS (Manchester)	West Delaware County CSD	Town
	Cascade Jr./Sr. HS	Western Dubuque CSD	Rural
	Western Dubuque HS at Epworth	Western Dubuque CSD	Rural
	Hempstead HS	Dubuque CSD	City
	Dubuque Senior HS	Dubuque CSD	City
Grantee: Westside Community Schools			
Westside YCC	Westside HS	Westside Community Schools	City

Source: Schools were identified by using the Participant Tracking System as of September 30, 2018.

Notes: This table provides an overview of the grantees, schools, and school districts implementing the YCC program. We identified each school's district and the district's locale using the Common Core of Data for the 2016–2017 and 2017–2018 school years (https://nces.ed.gov/ccd). Because some high school names changed during the course of YCC funding, with some changing multiple times, we standardized names across the appendices using those listed in this table.

CS = community school; CSD = community school district; CTE = career and technical education; HS = high school; ISD = independent school district; PS = public school; SD = school district; STEM = science, technology, engineering, and mathematics; USD = unified school district, n.a. = Not applicable since listed school is not a high school.

[a] Occupational or career center.

[b] Community college.

The wide variation in the entities offering the YCC program presented challenges in selecting those to participate in the impact study. After reviewing YCC grantees' applications in summer 2014 and calling them to clarify information about their proposed implementation of the program, we developed criteria and began the selection process for each component. Our goal was to include districts that would allow for a rigorous assessment of whether the YCC program improved students' education and employment success as defined by the milestones and momentum points described in Chapter I. To achieve this goal, we established seven criteria for inclusion in the impact study, with two additional criteria for the RCT to determine which districts were best positioned for that component. The criteria ensured that districts met these characteristics:

- **Had a sharp contrast between the YCC and the alternative program(s) in which non-YCC students are likely to enroll.** If the districts offered program components similar to those in the YCC program, we would be unlikely to identify the effect of YCC-funded services, because control and treatment group students could receive similar services.
- **Enrolled students in the YCC program starting in the 9th or 10th grade.** This restriction ensured consistent outcome measures for all students assigned to the treatment and comparison/control groups. If, for example, districts started the YCC program in 11th or 12th grade and articulated it to a community college program, we would expect different outcomes from those that started the YCC program in the first two years of high school.
- **Had enrollment that made identification of a comparison/control group possible.** We assessed whether the district or a high school had a sufficient number of students that could be used to form a comparison/control group composed of students who did not participate in the YCC program. Some districts offered the YCC program to all students.
- **Enrolled at least 50 YCC students a year.** We wanted sufficient sample to warrant the expense of obtaining school records data from a district.
- **Could provide needed school records data.** We assessed whether the district could provide information needed to capture outcomes (for example, credit accumulation, high school graduation, and test scores), critical covariates (for example, prior academic achievement, English language learner status), identifiers to match information from school records to the service information in the PTS, and data that could be used to form a comparison group for the QED.
- **Had key features of the YCC program model in place by fall 2016.** To ensure a fair test during the course of the study, key components of the YCC program needed to be sufficiently implemented by the start of the study.
- **Could participate in both the QED and RCT.** We wanted to compare results from each component as a robustness check on the validity of our results. Because criteria for the RCT were more constraining (see the last two criteria), we gave priority to selecting districts for the QED that met the criteria for participating in the RCT.

- **Had excess demand for the YCC program (RCT only).** We wanted sufficient sample in both the treatment and control groups for treatment-to-control ratios. As a result, districts needed significantly more students who were interested in and eligible for the YCC program than they could ultimately serve given grant resources.
- **Could conduct random assignment (RCT only).** We developed procedures to conduct a study-specific lottery or worked with a district's preexisting lottery, but having some lottery format was critical to the design of the RCT.

Because districts were purposefully selected using these criteria, the impact estimates might not reflect the impact of YCC across all grantees. For example, because a sharp contrast between YCC and alternative programs was a requirement for inclusion in the impact analyses, the impact analyses estimate the effect of YCC participation relative to a counterfactual in which relatively few YCC-type program services were available. Further, the impact results generalize only to the types of students interested in YCC and not necessarily to students more generally.

To collect the information needed to apply these criteria, Mathematica compiled information from four sources: (1) all 24 grant applications, (2) initial telephone calls to all 24 grantees in fall 2014, (3) visits to 13 of the more promising grantees to assess the feasibility of an RCT, and (4) telephone calls to 20 districts to discuss the availability of school records data. Based on information obtained, we identified 18 districts for inclusion in the QED and 11 districts for inclusion in the RCT. We ultimately eliminated 2 districts from the QED after assessing the thoroughness of the school records data submitted and 7 districts from the RCT because control groups could not be formed during or shortly after random assignment due to the lack of program oversubscription.

Of note, not all schools within the districts selected were suitable for inclusion in the impact study. For example, some did not offer the YCC program and were not comparable to schools that did offer YCC to all students.[3] Table II.2 shows the districts and schools included in the QED and RCT and details their characteristics. As this table shows, districts included in the impact study had these features:

- They included 239 high schools in the QED and 31 schools in the RCT (23 of which were both in the QED and the RCT). Of these, 34 were schools that offered the YCC program to some or all students, and the remaining 213 were non-YCC schools attended by comparison or control group members.
- Of the 239 schools in the QED (both treatment and comparison), 226 were located in cities, 5 were located in suburban areas, 4 were located in towns, and 2 were located in rural areas. Of the 31 schools in the RCT, 21 were in cities with one each in a town and a rural area.

[3] One school in the Los Angeles Unified School district offered and then discontinued the YCC program. As a result, we removed this school from the impact study.

Table II.2. Districts and high schools included in the impact study

School districts	High schools	Program offered		Location
		YCC	Alternative	
QED				
Brockton SD	Brockton HS	X	X	Suburban
Buffalo SD	MST–Math, Science, Technology School	X		City
	17 comparison schools		X	City
Chicago PS	Austin Polytechnical Academy	X		City
	21 comparison schools		X	City
Galveston ISD	AIM College and Career Prep	X	X	Town
	Ball HS	X	X	Town
Laurens County SD 55	Laurens HS	X	X	Rural
Los Angeles USD	Bernstein HS STEM Academy of Hollywood	X		City
	Contreras Learning Center, The School of Business and Tourism	X		City
	Hawkins HS Responsible Indigenous Social Entrepreneurship	X		City
	Manual Arts HS, School of Medicine, Arts and Technology	X		City
	Sylmar HS Sylmar Biotech Health Academy	X		City
	Teacher Preparatory Academy/Technology Preparatory Academy	X		City
	149 comparison schools		X	City
Marlborough SD	Marlborough HS	X	X	Suburban
Metropolitan SD of Pike Township	Pike HS	X	X	City
New York City SD	City Polytechnic HS of Engineering, Architecture, and Technology	X		City
	Energy Tech HS	X		City
	Inwood Early College for Health and Information Technologies	X		City
	MECA (Manhattan Early College School for Advertising)	X		City
	18 comparison schools		X	City
Pulaski County SD	Pulaski County HS	X	X	Town
	Southwestern HS	X	X	Rural
Santa Cruz Valley USD 35	Rio Rico HS	X	X	Town
St. Paul ISD 625	Humboldt Secondary School	X	X	City
	Como Park Senior HS	X	X	City

School districts	High schools	Program offered		Location
		YCC	Alternative	
Prince George's County PS	Bladensburg HS	X	X	Suburban
	Fairmont Heights HS	X	X	Suburban
	Parkdale HS	X	X	Suburban
	Potomac HS	X	X	Suburban
Toledo PS	Bowsher HS	X	X	City
	Scott HS	X	X	City
	Start HS	X	X	City
	Toledo Technology Academy	X	X	City
	Woodward HS	X	X	City
West Springfield SD	West Springfield HS	X	X	Suburban
Westside CS	Westside HS	X	X	City
RCT				
Chicago PS	Austin Polytechnical Academy	X	X	City
	9 comparison schools		X	City
Los Angeles USD	Sylmar HS Sylmar Biotech Health Academy	X		City
	Teacher Preparatory Academy/Technology Preparatory Academy	X		City
	17 control schools		X	City
Metropolitan SD of Pike Township	Pike HS	X	X	City
Pulaski County SD	Pulaski County HS	X	X	Town
	Southwestern HS	X	X	Rural

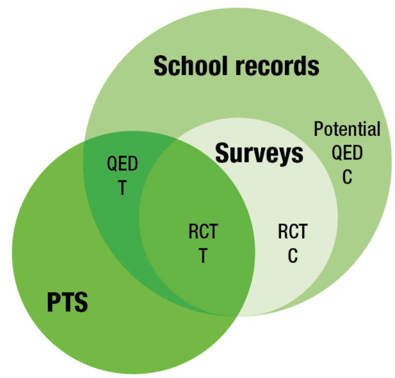
Note: For privacy reasons the name of the schools included in the control/comparison group are not listed. Information on location was taken from the Common Core of Data (CCD) (https://nces.ed.gov/ccd/ccddata.asp). Blank cells indicate that program was not offered for that high school.

CS = community school; HS = high school; ISD = independent school district; LA = Los Angeles; PS = public school; QED = quasi-experimental design; RCT = randomized controlled trial; SD = school district; USD = unified school district.

B. School records, PTS, and survey data define the impact study samples and outcomes

The impact study draws data from three distinct but complementary sources: (1) school records compiled from each districts' administrative data system for both the QED and RCT components, (2) the PTS, and (3) surveys for the RCT administered before study participants entered the study (the baseline information form, or BIF) and about two years after students started their program (FUS).[4] Figure II.1 illustrates how students included in the different data sources overlap in ways that provided a diverse set of information on students, and Table II.3 provides an overview of data collection specifics (each source is discussed in more detail after the table). As the figure and table show:

Figure II.1. Impact study data sources



C = comparison or control group; PTS = Participant Tracking System; QED = quasi-experimental design; RCT = randomized controlled trial; T = treatment group.

- The **school records** included the 457,138 students who were enrolled in the 16 districts in the QED during the period in which the YCC program was implemented (the light green circle in Figure II.1). Because they included students enrolled in the YCC program and students who were not, these records were used to form a treatment group of YCC students (identified from the PTS) and a matched comparison group of students for the QED. School records provided information about student characteristics and academic achievement.
- The **PTS** included the 29,724 students enrolled in the YCC program between April 1, 2014 and September 30, 2018 (dark green circle in Figure II.1). It provided detailed information about YCC student characteristics and services and activities received for all districts in which the YCC program was offered.
- The **surveys** included 540 students (and their parents) who were randomly assigned into treatment and control groups in three of the four districts included in the RCT (the beige circle in Figure II.1). The BIF collected information from 527 students and 539 parents and provided information on a broad set of individual and household characteristics and education, employment, and school behaviors and attitudes; about two years later, the FUS collected information from students only on similar topics, but it pertained to the two years since the BIF was administered.

[4] Copies of all instruments referenced in this report can be found on the OMB site under OMB Control Nos. 1291-0002 (Participant Tracking System), 1291-0003 (baseline data collection and implementation study materials), and 1290-0016 (FUS materials).

Table II.3. Impact study data sources overview

	School records	Participant Tracking System	Baseline information form	Follow-up survey
Population in data	All students in the district	All YCC students	RCT treatment and control groups	RCT treatment and control groups
Information collected	Student characteristics, assessment scores, academic credits	YCC students' characteristics, as well as their YCC services received and activities participated in	Education, employment, life stability, school activities, behavior, and motivation	Updates to BIF information on participation in work-based learning and career-preparation activities, support service receipt, and education plans.
Unit providing information	16 districts	24 grantees	Students and their parents in 3 districts	Students in 3 districts
Dates of data collection	Fall 2014 to spring 2018	April 2014 to September 2018	November 2015 to August 2017	August 2018 to December 2018
Data collection methods	Electronic transfer from districts through a secured file exchange	Grantee staff entered into standardized database	Hardcopy completion during YCC program application	Web and computer-assisted telephone interviewing
Participation rate	100%	100%	98%	81%
Use of data in impact study	Selecting the QED comparison group, defining QED and RCT outcomes and covariates, and defining QED subgroups	Defining RCT and QED treatment groups and QED subgroups	Providing baseline covariates for the RCT	Providing RCT outcomes

Note: Participation rate indicates the percentage of sample actually included in the analysis from those eligible for inclusion (same as response rate in Table II.8).

QED = quasi-experimental design; RCT = randomized controlled trial.

1. School records

The school records data from the 16 districts included in the QED were obtained for six cohorts of students that were constructed based on the year and grade students entered the YCC program in a particular district. We built cohorts of students who could start a program in 9th and 10th grade in fall 2014, 2015, and 2016. Each cohort contains students who participated in the YCC program (identified using the PTS data) and other students in the district who did not (who formed the pool for selecting QED comparison groups, as discussed in Chapter III). Districts did not always contain all cohorts (see below). A similar approach was followed for the RCT, where school records were collected for 9th and 10th graders in 2016 who were part of the lottery. We obtained data on all students through winter/spring 2018, which allowed us to follow students for two to four school years after they enrolled in their high school program.

Table II.4 shows the number of school years for which we captured outcome information on each cohort in the QED. School records data included information for two years prior to a student entering a cohort, which often includes information from middle school as well as from all high school years through spring 2018. In the table, “9” and “10” designate the grade in which the YCC program began in the district, and “A”, “B”, and “C” designate the year in which the cohort was formed:

- **Cohort A** started a high school program in fall 2014 and was followed for four years, from freshman (9th-grade cohort) or sophomore (10th-grade cohort) through senior years, including fifth-year seniors.
- **Cohort B** started a high school program in fall 2015 and was followed for three years, from freshman or sophomore through junior (9th-grade cohort) or senior (10th-grade cohort) years.
- **Cohort C** started a high school program in fall 2016 and was followed for two years, from freshman or sophomore year through sophomore (9th-grade cohort) or junior (10th-grade cohort) years. Students in the RCT are part of this cohort.

Table II.4. Cohort development for obtaining school records

Cohort	2014	2015	2016–	2018	Number of school years followed	Year in high school at follow-up
Programs starting in 9th grade						
9A	X			O	4	Senior
9B		X		O	3	Junior
9C			X	O	2	Sophomore
Programs starting in 10th grade						
10A	X			O	4	Fifth-year senior
10B		X		O	3	Senior
10C			X	O	2	Junior

Note: “X” designates the fall of the year in which a cohort of students in 9th or 10th grade enters the YCC program or an alternative program. “O” indicates the year outcomes will be captured. Blank cells indicate that a cohort was not developed and outcome data were not captured.

The 16 QED districts enrolled vastly different numbers of students (Table II.5). As a result, the numbers of YCC students and students available for constructing a comparison group differed across districts. In addition, because different districts started the YCC program in different grades and some districts started the program in more than one grade, the cohorts included in each district’s data varied. The selection of comparison groups for the QED was conducted separately by cohort and district (see Chapter III).

Table II.5. Students in each district's school records data

District	Total number of students with records	QED: Total number of students (treatment and comparison)	QED: Treatment group	QED: Cohorts for which data were obtained	RCT: Total number of students (treatment and control)	RCT: Treatment group
Brockton Public Schools	1,672	1,556	131	9B, 9C	n.a.	n.a.
Buffalo Public Schools	7,498	7,498	271	9A, 9B, 9C, 10A	n.a.	n.a.
Chicago Public Schools	50,568	47,998	65	9A, 10B, 10C	66	53
Galveston Independent School District	1,396	1,252	319	9A, 9B, 9C, 10A, 10B, 10C	n.a.	n.a.
Laurens County School District 55	1,100	1,067	138	9A, 9B, 9C, 10B	n.a.	n.a.
Los Angeles Unified School District	110,766	110,487	1,691	9A, 9B, 9C, 10A, 10B, 10C	399	152
Marlborough Public Schools	874	621	209	9A, 9B, 9C, 10C	n.a.	n.a.
New York City Department of Education	242,037	241,971	1,220	9A, 9B, 9C, 10A, 10B, 10C	n.a.	n.a.
Metropolitan School District of Pike Township	2,822	2,356	936	9A, 9B, 9C, 10A, 10B, 10C	323	205
Prince George's County Public Schools	27,758	27,604	530	9A, 9B, 9C, 10A, 10B, 10C	n.a.	n.a.
Pulaski Public Schools	2,287	2,212	147	9A, 9B, 9C, 10A, 10B, 10C	99	55
Santa Cruz Valley Unified School District	721	719	79	9A,9B,9C	n.a.	n.a.
St. Paul Independent School District 625	1,363	1,350	333	9A,9B,9C,10A,10B,10C	n.a.	n.a.
Toledo Public Schools	3,517	3,290	421	9A, 9B, 9C, 10B, 10C	n.a.	n.a.
West Springfield School District	1,044	1,041	129	9A, 9B, 9C, 10A, 10B, 10C	n.a.	n.a.
Westside Community Schools	1,715	1,627	246	9A, 9B, 9C, 10A, 10B, 10C	n.a.	n.a.
Sample size	**457,138**	**452,649**	**6,865**	**n.a.**	**887**	**465**

Note: Numbers show total number of students from the school records data and not necessarily the numbers for the analytic sample.

QED = quasi-experimental design; RCT = randomized controlled trial.

n.a. = not applicable (districts were not included in the RCT or sample size not relevant).

Data elements in school records were used in four ways: (1) to conduct multiple imputations for filling in values for data elements when the values in the data records were missing, (2) to identify students enrolled in the YCC program and form the treatment group for the QED, (3) to create a comparison group for the QED and baseline variables for the analysis, and (4) to construct outcome measures (see sidebar). Although these data provide a rich, robust information source, their definitions and completeness varied by district. In some instances, data were missing at the student level, while other elements (such as expulsion data) may have been inconsistently tracked across districts. Similarly, test taking and course structure were not consistent across all districts or even across grades within districts, which required further clarification and standardization. In Section C, we describe the approach taken to addressing some of these challenges; and in Chapter III, we describe the approach for constructing and standardizing outcome measures across districts.

School record data elements

Student characteristics

- Date of birth (C, M)
- District ID (M)
- Ethnicity (C, MI)
- Free and reduced price lunch eligible (C, MI, SA)
- Gender (C, M, MI)
- Grade (C)
- Limited English language proficiency (C, MI)
- Name (M)
- Personal identifier (M)
- Race (C, MI)
- School ID (C)
- School year (C, M)
- Special education participation (C, MI)

Academic achievement

- Algebra I and II course enrollment (O)
- Annual credit accumulation (O)
- High school diploma attainment (O)
- Standardized scores on math and English exams (O, SA, MI in 7th and 8th grade only)
- School days present (O)

Note: Letters in parentheses denote the purpose(s) of the evaluation that each data element was used.

C = covariate construction and matching for comparison group; M = matching to participant tracking system; MI = multiple imputation; O = outcome construction; SA = subgroup analysis.

2. Participant Tracking System

DOL required all YCC grantees to use the PTS to report on program performance throughout the grant period. YCC grantees were responsible for collecting and entering data from YCC students' enrollment through the first quarter after their program exit. Relevant to the impact study, DOL required grantees to provide detailed information on participants' characteristics and YCC services and activities received (see sidebar next page). PTS data were used for the impact study for three purposes: (1) to identify treatment group students who participated in the YCC program, (2) to monitor crossovers for the RCT, and (3) to describe YCC-funded services received by YCC students to provide a context for interpreting the impact study findings.

Because DOL used the PTS to measure grantee performance and monitor the information entered, grantees had an incentive to report accurate and complete information. Further, the system had built-in checks to prevent duplicate entry of participants and common types of data entry errors, and Mathematica provided training on using the system and technical assistance throughout the grant period. Still, staff reported during site visits that they had relatively large caseloads and sometimes struggled to find the time and resources required to report all services and activities in detail, which suggests that some data entry errors occurred.

PTS data elements

Student characteristics

- Date of birth (M)
- District ID (M)
- Free and reduced price lunch eligible (SA)
- Gender (M)
- Grade and school at time of enrollment (SA)
- Name (M)
- Personal identifier (M)
- School year (M)

Service receipt

- Received an internship (SA)
- Had a mentor (SA)
- Completed an individual development plan (SA)

Note: Letters in parentheses denote the stage(s) of the evaluation that each data element was used.
M = matching to school records; SA =subgroup analysis.

3. Surveys

Survey information was obtained at two distinct times for students in three of the four districts in the RCT: Chicago Public Schools, Metropolitan School District of Pike Township, and Pulaski County School District. In the first time period, the BIF was administered to students and parents; in the second, the FUS was administered to the same students.[5] BIF data collection was attempted in the fourth district, LAUSD, but district rules prevented Mathematica staff from administering BIFs at the time of program application. As such, LAUSD was dropped from surveying. All surveys were administered in both English and Spanish.

Topical coverage for students was similar in both periods, although the timeframe for which information was collected differed: information in the BIF covers the baseline period before the intervention, while information in the FUS covers the two-year period after random assignment (Table II.6). Relevant to the impact study, students were asked about education, employment, life stability, activities, school behavior, and motivation.

[5] The BIF data collection was attempted across the 11 districts considered for inclusion in the RCT, but we use information only from the 3 districts ultimately included in it.

Table II.6. Data elements from surveys used in the evaluation

Baseline information form	Follow-up survey used as outcomes
Student survey	
Knowledge and expectations	
• Highest degree expected to complete (MI) • Expect to receive vocational certificate (MI)	• Highest degree expected to complete (O) • Expect to receive vocational certificate (O) • Knowledge of educational requirements for college and career (O)
Education	
• Importance of grades (MI) • Participation in school-organized extracurricular activities (MI) • Satisfaction with school (MI) • School behavior (C, MI) • Hours spent on homework (MI) • Motivation (MI) • Alcohol and drug use (C,MI) • Whether the student is a parent (MI)	• Importance of grades (O) • Participation in school-organized extracurricular activities (O) • Satisfaction with school (O) • School behavior (O) • Hours spent on homework (O) • Motivation (O) • Alcohol and drug use (O) • Whether the student is a parent (O) • High school enrollment and course-taking (O)
Employment	
• Work experience in paid and unpaid jobs (including details on hours worked per week and whether job was arranged through school) (C, MI)	• Work experience in paid and unpaid jobs (including details on hours worked per week and whether job was arranged through school) (O) • Work-readiness and badges, degrees, certificates, and licenses earned (O)
Parent survey	
Demographic and household characteristics • Household structure (MI) • Income sources (MI) • Parent/guardian education level (MI) • Employment status (MI) • Primary language spoken at home (MI)	Not covered in FUS.
Education and expectations • Number schools child has attended starting with 1st grade (MI) • Degree expectations for child (C, MI) • Talked to child about education after high school (C, MI) • Parent involvement in child's decision to join YCC (MI)	Not covered in FUS.

Note: Letters in parentheses donate the stage(s) of the evaluation that each data element was used. Multiple imputations were done on all data from the BIF.

C = covariate construction and matching for comparison group; FUS = follow-up survey MI = multiple imputation; O = outcome construction.

BIFs. In RCT sites, program staff distributed and collected BIFs during the period in which students applied to the YCC program prior to the lottery. Because the application period differed across districts, the timing of BIF administration varied. BIFs were self-administered on paper to both parents (the "primary adult" who completed the form) and students. Mathematica trained all appropriate YCC program staff at each district to properly recruit students, obtain consent from parents and students, and instruct participants on completing the BIFs. Staff asked parents to provide consent for their students to participate in the study by completing a paper consent form, as well as the paper parent BIF. A $5 gift card was offered to parents in return for a signed consent form, regardless of whether they agreed to participate in the study. Student BIFs were administered on paper after parent consent was collected. To protect student privacy, the BIFs were returned to program staff in a sealed envelope, which was opened only by a member of the Mathematica study team. We received 527 BIFs from the 540 students who went through the random assignment process and 539 BIFs from parents (Table II.7). The rate of completion represented 100 percent of parents and 98 percent of students. The response rate by treatment status varied by district, but was overall similar across treatment and control groups, at 98 and 97 percent respectively.

Table II.7. Survey completion and response rates

District	Starting sample	Completed surveys: Parent	Completed surveys: Student	Response rates: Parent	Response rates: Student treatment	Response rates: Student control	Response rates: Student overall
Baseline information form							
Chicago Public Schools	69	69	67	100%	96%	100%	97%
Metropolitan School District of Pike Township	359	359	355	100%	99%	98%	99%
Pulaski County School District	112	111	105	99%	95%	92%	94%
Total	**540**	**539**	**527**	**100%**	**98%**	**97%**	**98%**
Follow-up survey							
Chicago Public Schools	69	n.a.	42	n.a.	67%	36%*	61%
Metropolitan School District of Pike Township	359	n.a.	299	n.a.	83%	84%	83%
Pulaski County School District	112	n.a.	95	n.a.	86%	83%	85%
Sample size	**540**	**n.a.**	**436**	**n.a.**	**81%**	**81%**	**81%**

* Indicates differences between treatment and control response rates are statistically significant at the 5 percent level.

n.a. = not applicable.

FUS. Between August 2018 and December 2018, about two years after the BIF, the 540 treatment and control group members for whom we received parental consent were contacted to complete a FUS. These individuals were notified about the survey request via surface mail, email, text message, or telephone. We employed a multimode approach using three phases of data collection:

- **Phase 1.** Students were directed to the web survey or to call Mathematica to complete the survey using computer-assisted telephone interviewing (CATI) with an interviewer trained in the FUS and study background. Additionally, the study team coordinated with the YCC program in each school to schedule group administration of the web survey.

- **Phase 2.** Mathematica contacted students through outbound CATI calls.
- **Phase 3.** We attempted to make contact with students through in-person locating conducted by a study locator trained in the FUS and study background.

Study participants who completed the survey online or by calling in within the first four weeks of the survey fielding period received $40, and those who completed the survey thereafter received $25, regardless of how they completed the survey. The average response rate was 81 percent but varied by district (see Table II.9). The response rate by treatment status varied by district, with Chicago Public Schools having a significantly lower response rate for the control group. Because that district only contributed about 14 percent of the sample for the RCT, overall response rates across treatment and control groups were similar at 81 percent.

C. Processes ensured high-quality data

Careful coding and data-processing procedures helped to provide the highest quality data files from the PTS, school records, and surveys. Mathematica conducted intensive data diagnostics to determine data quality across all data sources and targeted diagnostics to address missing data, standardization of outcomes, and outliers. We used these specific techniques for each source:

- **PTS.** Preliminary checks provided a thorough review of all data elements and their origin. For example, we confirmed that the correct school identification variable was pulled and verified through probabilistic matching on student names and demographic information that each record in the PTS was for a unique student. No imputations were done for missing data.
- **School records.** We created district-specific files with consistent variable names across districts, ran diagnostics on each file to identify problematic longitudinal trends (for example, low correlations between math scores across school years), and examined summary statistics (for example, the number of records and mean, minimum, and maximum values) to check for outliers. As further checks, each district's records were assessed in relation to other districts with year and grade-level student counts benchmarked against publically available Common Core of Data files. If data quality concerns were found, Mathematica conducted follow-up queries with the district. After quality checks were completed, some records were missing data. We used chained equations to impute missing values of covariates in school records (see Chapter III for details) but not for outcomes.
- **Survey data files** were examined for the distribution of responses, the internal consistency of answers to questions (relationship of answers to some questions to those for others in the FUS), and consistency with baseline data (relationship of answers to questions to those in the BIF). Project staff back-coded responses to open-ended questions (the process of determining whether the answer actually fits into one of the existing response categories) and combined open-ended responses to create new response categories when possible. Industry and occupation descriptions for jobs were assigned a North American Industry Classification System (NAICS) code and a 2010 Standard Occupational Classification code. We used chained equations to impute missing values of covariates in the BIF (see Chapter III for details). For the FUS data, we ran checks to fill gaps in data received and determined which surveys were complete for analysis.

III. ANALYTIC FRAMEWORK AND IMPACT ESTIMATIONS

As we discussed in the previous chapters, the impact study examined the impact of the YCC program on milestones and momentum points that are achievable in high school and associated with longer-term education and employment success. These short-term outcomes were measured using information in the school records provided by 16 districts and the FUS administered to students in three of those districts about two years after they entered the YCC program. To focus the analysis, we prespecified *primary* and *secondary* analyses in the study design documents. We feel these terms better capture the shorter-term outcomes in this study than the more traditional confirmatory and exploratory analyses (which typically distinguish between proximal and distal outcomes). Differentiating between the primary and secondary analyses helped us to minimize the multiple testing problem in which the chance of spurious impact results increases substantially when conducting hypothesis testing across many outcomes and subgroups. We based study conclusions on the smaller number of primary analysis outcomes with the secondary analysis providing support for and depth to it.[6]

Together, the analyses answer the study's three research questions (see sidebar).

1. **Research question 1.** The primary analysis addressed the first research question. It used the full QED sample of 16 districts and examined school attendance, credit accumulation, English language arts (ELA) test scores (for proficiency in English language arts), and algebra progression. An RCT impact analysis added depth and supported the primary analysis by replicating it. Specifically, it used treatment and control group students in the three RCT districts with samples large enough to support these analyses (LAUSD, Metropolitan School District of Pike Township, and Pulaski Public Schools) for replication.
2. **Research question 2.** A subgroup analysis used school records for the full QED sample to examine whether the results of the primary analysis varied by student characteristics, program experiences, or cohort—the year in which the student could have started the YCC program.

Research questions

1. What is the impact of the YCC program on school attendance, credit accumulation, proficiency in English language arts, and algebra progression?
2. Does the impact of the YCC program vary by (1) key student characteristics (prior academic achievement and low-income status); (2) program experiences (receiving an internship, having a mentor, and completing IDP); or (3) cohort?
3. What appears to be the impact of the YCC program on high school graduation, staying in school, school engagement and satisfaction, positive behavior at school, postsecondary credits earned during high school, educational expectations and knowledge, work-readiness skills, paid work experiences, and substance abuse?

[6] Because we prespecified a limited number of primary analysis outcomes, we did not adjust *p*-values from the statistical tests for multiple testing (Schochet 2009). This approach balanced the study objective of minimizing the chances of finding spurious impact findings with the study having sufficient power to detect impacts that truly exist (that is, balancing Type I and II errors).

3. **Research question 3.** Two secondary analyses addressed the third research question. School records for the three cohorts of the QED sample that could have an on-time graduation from high school were used to estimate the impact of the YCC program on high school graduation. In addition, the three districts in the RCT impact analysis examined a broader set of outcomes using information from the three districts that participated in the FUS (Chicago Public Schools, Metropolitan School District of Pike Township, and Pulaski Public Schools).

The primary and secondary analysis not only aligned with the research questions but also with each milestone and momentum point, as Table III.1 shows. This table links each milestone and momentum point with the analysis in which it is included, the data source used for its measure, and the sample from which data are taken.

Table III.1. Milestones and momentum points: Type of analysis, sample, and data source

	Type of analysis			Sample			
Outcome	**Primary**	**RCT impact**	**Sub-group**	**QED**	**QED subsample**	**RCT**	**RCT-3 districts**
Milestones							
High school graduation[a]					SR		
Staying in school		FUS					FUS
Momentum points							
High school behaviors							
School attendance[b]	SR	SR	SR	SR		SR	
Credit accumulation[b]	SR	SR	SR	SR		SR	
School activities		FUS					FUS
Engagement and satisfaction		FUS					FUS
Substance abuse		FUS					FUS
Postsecondary preparation							
Math and English proficiency							
Proficiency in English language arts[b]	SR	SR	SR	SR		SR	
Algebra progression[b]	SR	SR	SR	SR		SR	
Positive education expectations and knowledge		FUS					FUS
Postsecondary credits earned in high school		FUS					FUS
Employment readiness							
Work-readiness skills		FUS					FUS
Paid work experience		FUS					FUS

[a] Because the high school graduation analysis only contains one outcome, we do not have a separate column in the analysis section of the table for that outcome.

[b] Designate primary analysis outcomes.

Blank cells indicate that this analysis and sample were not used for this outcome.

FUS = follow-up survey; QED = quasi-experimental design; RCT = randomized controlled trial; SR = school records.

In this chapter, we focus on details of each analysis, including the construction of samples and outcome variables and the approach for estimating the impacts. In each of the first four sections, we discuss one of the analyses: primary analysis (Section A), RCT impact analysis (Section B), high school graduation analysis (Section C), and subgroup analysis (Section D). In these sections, we discuss how we identified the treatment and control/comparison groups, the approach we used to make them comparable, and the baseline equivalence tests that we used to assess whether the groups are indeed comparable. After discussing and describing the treatment and comparison group analytic samples, we describe how we constructed the outcomes. In the final section (Section E), we discuss our methods for estimating impacts for each analysis.

A. Primary analysis

To produce unbiased impact estimates for the primary analysis, we constructed QED treatment and comparison groups in each of the 16 districts. In each district, we identified students in the treatment group using the PTS and formed comparison groups using baseline data from school records when students were in 7th and 8th grade to account for observable differences between the types of students who did and did not participate in YCC. The goal was to minimize preexisting differences between these groups so that the study could estimate plausible causal effects of the YCC program on primary student outcomes. We used inverse probability weighting (IPW) methods to ensure balanced research groups.

Our QED design built on best practices found in the literature to minimize potential biases in non-experimental impact evaluations due to unobservable differences between the treatment and comparison groups. These practices include: (1) using a rich set of matching variables correlated with the primary outcomes; (2) using common data sources for creating matching variables and measuring outcomes; and (3) identifying samples from the same geographic areas (Glazerman et al. 2003; Heckman et al. 1998, 1997). In addition, for interventions designed to improve students' mathematics and English, evidence suggests that the availability of highly predictive pre-test data for matching can help adjust for selection biases in commonly used pre-test/post-test comparison group designs (Shadish et al. 2008).

1. Defining the treatment and comparison group analytic samples

a. Identifying the treatment group

We used the information entered by each district's program staff into the PTS to identify students who had enrolled in the YCC program (for any length of time), which we used to define the treatment group sample.[7] We excluded five types of treatment students from the analytic sample: (1) those who appeared to enter the YCC program before 9th grade, under the assumption that these data were incorrect; (2) those in districts in which their cohort had fewer than 5 YCC students (both Chicago Public Schools and Toledo Public Schools for the 2013 cohort); (3) those assigned to the RCT control group who actually received YCC program services ("crossovers") (discussed in Section B), because excluding students who did not comply with their random assignment better aligns the QED and RCT impact estimates;(4) those without any 7th or 8th grade standardized scores in math or reading, to ensure students had data on baseline achievement (which were key matching variables); and (5) those with missing outcome data (the analysis for a particular outcome excluded those with missing data on that outcome, though those students would have been counted for other outcomes). Table III.2 summarizes the potential analytic sample in each QED district, exclusions, and the final analytic sample for the treatment group.

[7] PTS information indicated that nearly all those in the treatment group received at least some YCC services.

Table III.2. QED analytic sample summary: Treatment group

District	Student records received	RCT crossover students	Students missing 7th or 8th grade tests	Students missing 9th or 10th grade records	Students who enter YCC before	Propensity score sample	Final analytic sample
Brockton Public Schools	139	0	0	8	0	131	131
Buffalo Public Schools	324	0	6	49	0	269	269
Chicago Public Schools	68	0	2	3	0	63	63
Galveston Independent School District	337	0	9	16	0	312	312
Laurens County School District 55	147	0	0	7	2	138	138
Los Angeles Unified School District	1,862	12	125	138	4	1,583	1,583
Marlborough Public Schools	221	0	1	12	0	208	208
New York City Department of Education	1,325	0	17	100	3	1,205	1,205
Metropolitan School District of Pike Township	1,043	52	21	52	0	918	918
Prince George's County Public Schools	563	0	1	29	4	529	529
Pulaski Public Schools	150	0	1	3	0	146	146
Santa Cruz Valley Unified School District	84	0	0	4	1	79	79
St. Paul Independent School District 625	366	0	5	31	0	330	330
Toledo Public Schools	459	0	19	34	1	405	405
West Springfield School District	132	0	8	3	0	121	121
Westside Community Schools	252	0	3	5	1	243	243
Total	**7,472**	**64**	**218**	**494**	**16**	**6,680**	**6,680**

Source: School records, Participant Tracking System.

Note: Student records received refers to the total number of unique students entering high school over the study period in student records provided by districts; students missing all 7th and 8th grade tests and students missing 9th or 10th grade records were excluded from the analysis; in some cases students were included in the propensity score model but excluded from the analytic sample to improve balance (see below).

RCT= randomized controlled trial.

b. Identifying the comparison group

Those students included in the district's school records and not defined as enrolled in the YCC program were considered eligible for the comparison group if they had entered 9th grade between the 2013–2014 school year and the 2016–2017 school years (as discussed in Chapter II, Section B.1), and if the treatment group included students entering 9th grade in the same school year. We selected comparison group students who were in the same schools as treatment students whenever possible but used students in similar schools when the YCC program comprised the whole school. We excluded four groups of comparison students from the analytic sample: (1) those without any 7th or 8th grade standardized scores in math or reading, to ensure students had data on baseline achievement (which were key matching variables); (2) those without school records in both the 9th and 10th grades, to ensure they were enrolled in the district when cohorts were formed; (3) those assigned to the RCT treatment group who did not actually receive YCC program services ("no shows") (discussed in Section B), because excluding students who did not comply with their random assignment better aligns the QED and RCT impact estimates; and (4) those missing outcome data. Table III.3 summarizes the potential analytic sample in each QED district, exclusions, and the final analytic sample for the comparison group.

Table III.3. QED analytic sample summary: Comparison group

District	Student records received	Students missing 7th or 8th grade tests	Students missing 9th or 10th grade records	RCT no show	Propensity score sample	Potential analytic sample
Brockton Public Schools	1,840	78	399	0	1,363	1,303
Buffalo Public Schools	8,570	626	1,174	0	6,770	6,507
Chicago Public Schools	55,682	1,737	7,251	13	46,681	4,339
Galveston Independent School District	1,178	55	226	0	897	864
Laurens County School District 55	1,104	28	164	0	912	912
Los Angeles Unified School District	128,688	9,329	17,068	74	102,217	80,574
Marlborough Public Schools	488	38	68	0	382	379
New York City Department of Education	269,908	8,615	27,467	0	233,826	7,602
Metropolitan School District of Pike Township	1,809	172	300	26	1,311	1,311
Prince George's County Public Schools	32,586	1,704	4,699	0	26,183	3,876
Pulaski Public Schools	2,295	69	204	0	2,022	2,004
Santa Cruz Valley Unified School District	702	13	57	0	632	613
St. Paul Independent School District 625	1,211	83	181	0	947	861
Toledo Public Schools	4,439	389	1,396	0	2,654	1,532
West Springfield School District	1,030	88	101	0	841	785
Westside Community Schools	1,527	52	136	0	1,339	1,339
Total	**513,057**	**23,076**	**60,891**	**113**	**428,977**	**114,801**

Source: School records, Participant Tracking System.

Note: Student records received refers to the total number of unique students in student records provided by districts; students missing all 7th and 8th grade tests and students missing 9th or 10th grade records were excluded from the analysis; in some cases students were included in the propensity score model but excluded from the analytic sample to improve balance (see below).

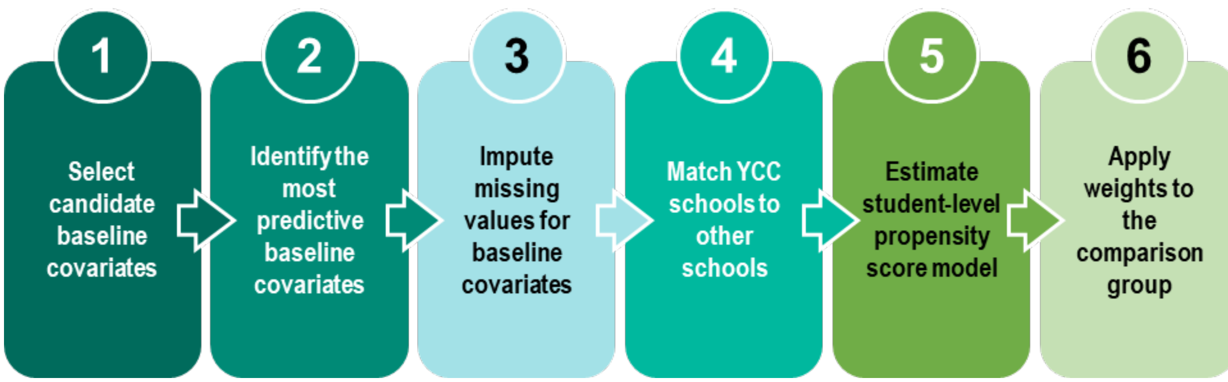
RCT= randomized controlled trial.

c. Constructing the comparison group: Propensity scores and inverse-probability weights

We chose to use IPW methods to develop the comparison group (Horvitz and Thompson 1952), rather than explicitly matching treatment students to one or more comparison students. Under the IPW approach, impacts were estimated using nearly the entire sample to estimate the propensity scores—the probability that a student with a given set of characteristics participated in the YCC program—to ensure that treatment and comparison groups were similar on observed, preexisting characteristics (Rosenbaum and Rubin 1983). We estimated propensity scores using baseline student information measured prior to when students could have entered the YCC program (7th and/or 8th grade). We applied weights—constructed as the inverse of the estimated propensity scores—to the comparison group so that they matched the YCC participants on observable characteristics. The key advantage of the IPW approach is that it maximizes the number of comparison and treatment group students included in the analysis; in contrast, the matching approach would require dropping students from the analysis who cannot be matched. Dropping students from the analysis would reduce statistical power to detect program effects and would mean that impact estimates only capture the effect of the YCC program among the remaining, matched students.

Figure III.1 shows the steps we used to construct the propensity scores and IPWs. Each step is discussed in detail in the text that follows.

Figure III.1. Propensity scores and inverse probability weight construction



Step 1. Selected the candidate baseline covariates from the school records. We selected as candidates for baseline covariates the baseline measures associated with school engagement (for example, Stout and Christensen 2009), behavior (for example, Rumberger 2011), and academic achievement (for example, Ginsburg et al. 2014) that the literature suggests are likely to be correlated with the primary outcomes for the evaluation (Table III.4).

Table III.4. Candidate baseline covariates included in the student-level propensity score model

Variable type	Variable
Demographic	• Age going into 8th grade • An indicator that equals 1 if female and 0 if other gender • For each race/ethnicity, an indicator that is equal to 1 if the student is white, black, Asian, American Indian, multiracial, or Hispanic and 0 if otherwise
Low-income status	• For both 7th and 8th grade, indicators that equal 1 if eligible for the free and reduced price lunch status program, or, where that was not available, lived in a census tract where more than 20 percent of residents were poor, and 0 if not
Academic measures	• For both 7th and 8th grade, school attendance • For both 7th and 8th grade, math and reading assessment standardized scores • For both 7th and 8th grade, indicators that equal 1 if ever suspended from school and 0 if not • An indicator that equals 1 if repeated 7th or 8th grade and 0 if not • An indicator that equals 1 if received special education services in 8th grade and 0 if not • An indicator that equals 1 if English language learner in 8th grade and 0 if not

Step 2. Identified the most predictive baseline covariates for outcomes for the primary analysis. To select the covariates that were most predictive of primary outcomes, we used the least absolute shrinkage and selection operator (LASSO) procedure (Tibshirani 1996), which was estimated using the least angle regression algorithm and tenfold cross-validation for the tuning parameter (Efron et al. 2004). LASSO selects covariates that best predict the outcome by setting (shrinking) parameter estimates to zero for covariates with little predictive power. It retains only those covariates contributing to accurate out-of-sample forecasts. Our cross-validation approach (splitting the sample into random groups for sequential estimation and forecasting) adjusted for anomalous correlations between the covariates and outcomes (Efron et al. 2004). To ensure that the selected covariates did not depend on the randomly generated cross-validation samples, we ran the LASSO model 100 times and used the covariate set selected most often. Our LASSO model pooled treatment group members across QED districts and cohorts, weighted each district equally, included only main effects (not interaction or quadratic terms), and used only observations with nonmissing covariates and outcomes. Samples ranged from 2,786 to 4,207 students across the four outcomes of school attendance, credit accumulation, ELA test scores, and algebra progression. Because we ran separate models for the four outcomes, we identified a distinct set of covariates for each outcome. We then selected covariates for the subsequent propensity score models and impact models that were predictive of any of the four outcomes. This method resulted in each of the candidate variables in Table III.4 being selected, so all of these candidate baseline covariates were included in the propensity score model.

Step 3. Imputed missing values for the baseline covariates. To maximize the number of individuals included in the analysis, we used multiple imputation by chained equations (Azur et al. 2011) to iteratively impute missing values of the covariates used in the propensity score and impact models. Notably, 62 percent of students had missing data for at least one covariate. The chained equation approach allows imputed data to exhibit the same correlations and variances as the actual data.

We used predictive mean matching to impute missing covariates. Specifically, for each covariate, we used the imputation model to estimate a predicted covariate value for each sample member. Matching was then based on similarity of predicted values: for each student missing a covariate, we identified the five students with non-missing covariate values closest to the student's predicted values. The actual covariate for one of those five students was then randomly selected, and that became the imputed value for the student missing the covariate. We used ordinary least squares for continuous covariates, multinomial logit models for categorical variables (such as race/ethnicity), and ordered logit models for ordinal variables.

Importantly, to preserve the relationship between the baseline and outcome data, we included all four primary outcomes—school attendance, credit accumulation, ELA test score, and algebra progression—in the imputation models. We did not use imputed outcome variables in the impact analysis; rather, we excluded students with missing data for the outcome under investigation.

The imputation procedure was done separately for different samples:

- First, within each district we attempted to impute variables separately for the treatment and comparison students and by cohort.
- In some cases, these samples had insufficient variation in covariates, and so the chained equations algorithm would not converge, or a covariate was missing for a large share of the sample.
- If a covariate was missing for more than 30 percent of the sample, or if the chained equations algorithm would not converge, we either pooled the treatment and comparison groups (including a treatment indicator in the model), pooled across cohorts (including cohort indicators in the model), or pooled across cohorts and the treatment and comparison groups.
- Finally, for districts missing variables for more than 30 percent of students, we estimated an imputation model that pooled districts and included district indicators in this model. The methods of accounting for treatment groups and cohorts and the variables imputed across districts are listed in Table III.5.

Table III.5 Imputation method by district and covariates imputed across districts

District	Method of accounting for treatment groups: Separate models by treatment group	Method of accounting for treatment groups: Regressions included treatment indicator	Method of accounting for cohorts: Separate models by cohort	Method of accounting for cohorts: Regressions included cohort indicator	Covariates imputed by pooling across districts
Brockton School District	X			X	None
Buffalo Public Schools		X		X	7th grade attendance low-income status
Chicago Public Schools		X	X		None
Galveston Independent School District		X		X	7th and 8th grade attendance rates
Laurens County School District 55		X		X	7th and 8th grade low-income status, 8th grade English learner status
Los Angeles Unified School District		X		X	7th and 8th grade low-income status
Marlborough Public Schools	X		X		None
Metropolitan School District of Pike Township	X			X	None
New York City Department of Education	X		X		None
Prince George's County Public Schools	X		X		None
Pulaski Public Schools	X		X		None
Santa Cruz Valley Unified School District		X	X		7th and 8th grade low-income status
St. Paul Independent School District 625		X	X		None
Toledo Public Schools		X	X		None
West Springfield School District		X		X	None
Westside Community Schools	X		X		None

Source: School records.

Note: A blank cell indicates that this method was not used in this district.

We created five imputed data sets for each district. In the impact analysis, we estimated impacts using each of the five imputed data sets, and accounted for variation in the impact estimates across and within these data sets using Rubin's rule (Rubin 2004). Table III.6 provides sample sizes for the number of students with and without imputed covariates.

Table III.6. Sample sizes for the number of students with and without imputed covariates

Covariate	Non-imputed sample	Imputed sample
Age at entry into 8th grade	115,747	0
Female	115,744	3
Race/ethnicity	115,622	125
Low-income status, 7th grade	110,160	5,857
Low-income status, 8th grade	113,393	2,354
School attendance, 7th grade	109,658	16,089
School attendance, 8th grade	114,134	1,613
Ever suspended, 7th grade	115,216	531
Ever suspended, 8th grade	85,080	30,667
Math assessment scores, 7th grade	79,346	36,401
Math assessment scores, 8th grade	91,989	23,758
Reading assessment scores, 7th grade	114,840	907
Reading assessment scores, 8th grade	114,214	1,533
English language learner, 8th grade	115,748	0
Received special education services, 8th grade	115,745	3

Source: School records.

Note: About 95 percent of students had either a 7th grade or an 8th grade math assessment score, and about 98 percent of students had either a 7th grade or an 8th grade reading assessment score.

Step 4. Matched YCC schools offering YCC program to other schools. Most (12 of 16) QED districts offered the YCC program using only a within-school model (that is, the school offered both the YCC and other programs). In these districts, we drew comparison students from all of the schools that the YCC students attended. For example, Pulaski Public Schools had two YCC schools; in this district, we pooled together the treatment students from both schools and all non-YCC students in both schools were included in the pooled comparison group.

The four other districts (Buffalo Public Schools, Chicago Public Schools, LAUSD, and New York City Department of Education) used a whole-school model in which all students in the school received YCC services. In these districts, we drew comparison group students from schools in the same district that did not offer the YCC program, taking the following steps to ensure that the schools were comparable to those offering the YCC program:

1. We calculated the Mahalanobis distance between each YCC and each non-YCC district high school using covariates from a range of data sources that measured student achievement, school characteristics, student demographics, and graduation rates before the YCC program began (Table III.7). The Mahalanobis distance is a standardized distance measure (so that it is not affected by how measures are scaled) between schools based on a set of characteristics.

Table III.7. Covariates included in the school-level matching model

Variable type	Variable	Source
Student achievement	• Grade 7 and 8 standardized test scores for students who entered each high school in the year before YCC was implemented, averaged to the high school level	District school records
School characteristics	• Indicators for whether the school is in a city, suburb, or rural area • School type (for example, vocational, special education, or regular school)	Common Core of Data
Student demographics	• Percentage of students in the pre-YCC year who were: • Female • Black, Asian, Hispanic, white, American Indian, multiracial • Eligible for the free and reduced price lunch program	Common Core of Data
Graduation rates	• Share of students entering the school who graduate in four years with a regular high school diploma	EdFacts

Source: Common Core of Data measures were obtained from https://nces.ed.gov/ccd/pubschuniv.asp; EdFacts data were obtained from https://www2.ed.gov/about/inits/ed/edfacts/data-files/index.html.

2. We used caliper matching with replacement to match high schools that did and did not offer the YCC program, dropping non-YCC schools that were outside the caliper (that is, that were not sufficiently similar). Caliper matching matches each YCC school to the set of schools whose distance metric from Step 1 falls within a given range (called the caliper) of it. We allowed each comparison high school to match to more than one YCC school (that is, we matched with replacement). For each district, we selected the smallest caliper that resulted in at least a five to one ratio of comparison students to treatment students if possible, or we selected all comparison schools where this was not possible, to ensure sufficient numbers of comparison students for the subsequent student-level matching in Step 5 below. This removed high schools that differed markedly from schools with the YCC program. Table III.8 shows the number of YCC and non-YCC schools in each district and the school-level matching diagnostics for these districts. For the Buffalo Public Schools we selected all possible comparison schools because it was not possible to select a subset that resulted in a five to one ratio of comparison students to treatment students. Though some of the selected non-YCC schools did not perfectly resemble YCC schools, by giving more weight to students in those schools who most resembled YCC students, we obtained a comparison group of students that resembles YCC students.

Table III.8. Results from school-level matching

District	Number of YCC schools	Number of non-YCC schools	Selected non-YCC schools	Average standardized difference in matching covariates (all non-YCC schools)	Average standardized difference in matching covariates (selected non-YCC schools)
Buffalo Public Schools	1	17	17	0.686	0.686
Chicago Public Schools	1	106	21	0.505	0.336
Los Angeles Unified School District	6	170	100	0.274	0.214
New York City Department of Education	2	427	18	0.639	0.563

Source: School records data, Common Core of Data, EdFacts.

Step 5. Estimated the student-level propensity score model. We estimated propensity scores using a variety of methods and the baseline covariates identified from the LASSO procedure in Step 2. For each method, we estimated propensity scores separately by district and by cohort. In districts where YCC was offered using a within-school model, and for which there were multiple schools offering YCC (Galveston Independent School District, Prince George's County Public Schools, Pulaski Public Schools, Toledo Public Schools, and St. Paul Independent School District 625), we included school fixed effects in the model to ensure that each school was equally represented in the treatment and comparison groups.

We estimated propensity scores using several methods and selected the method that best balanced the characteristics of the treatment and comparison samples for each district and cohort. First, we estimated standard logistic regression models where an indicator for participating in YCC was regressed on the matching variables (using main effects and no interactions). Second, we estimated several logistic regression models that included two-way covariate interactions identified using this three-step procedure:

1. We assessed balance on each covariate from the standard logistic regression model, and if the standardized difference on any covariate exceeded 0.10 we proceeded to the next step.
2. We identified a limited set of two-way interactions for inclusion by selecting each covariate for which the standardized difference exceeded 0.10 in the first estimation and then interacted it with all other covariates. We again estimated a LASSO model, in which the dependent variable was an indicator for having participated in YCC, and which included all main effects and the interaction terms. We re-estimated the propensity score model using all main effects and the interaction terms identified by LASSO as worth keeping, and assessed the balance on each main effect. If the standardized difference exceeded 0.10 for any main effect, we proceeded to the next step.
3. We used results from the second logit model that included main effects and the limited set of interactions to identify a broader set of interactions. We selected each covariate for which the standardized difference was greater than 0.10 in the second estimation and interacted it with all other covariates.

Our final approach used machine learning techniques to estimate the propensity scores. These methods allow for more flexibility on how the matching variables and their interactions enter the model. Specifically, we used generalized boosted models implemented using the Toolkit for Weighting and Analysis of Nonequivalent Groups (TWANG) (McCaffrey et al. 2005). This approach produces a series of trees, where each branch splits as new covariates are identified. This method works by testing covariates at each tree node to find the best predictor of enrollment in YCC. The data are then split on that covariate and, within each split, the method searches again for the covariate that best predicts enrollment in YCC. The share of students in the tip of each branch who are in the YCC group is an estimate of the propensity score.

Step 6. Applied weights to the comparison group. After constructing the propensity scores for each comparison student, we weighted the comparison group to resemble the treatment group, using weights of 1 for the treatment group and $\frac{\hat{p}_i}{1-\hat{p}_i}$ for the full comparison group, where $\hat{p}_i$ was the estimated propensity score for student i. This approach was used for each district and cohort.

After the propensity scores were estimated, we constructed a trimmed sample to remove less than 1 percent of the treatment and comparison students who had very large propensity scores, using the algorithm proposed by Crump et al. (2009) for the optimal overlap for the average effect for students in the treatment group. Students with high propensity scores tended to have few comparison students, and these comparison students were given large weights in the analysis and balancing tests. Chance differences in baseline characteristics among those comparison students can therefore cause imbalance, which might bias our results. We examined match quality using both the trimmed and untrimmed weights using the metrics discussed in the next section, and selected the trimmed or untrimmed sample that led to the best balance on those metrics.

d. Identifying metrics for assessing balance of the QED treatment and comparison groups

We used two sets of diagnostics to gauge whether the IPW approach created balanced treatment and comparison groups for each of our various model specifications, guided by the approach laid out in Stuart (2010):

1. **Standardized differences in covariates.** Differences in covariates, even if not statistically significant, can still lead to biased estimates. We therefore assessed balance for each covariate by examining the standardized difference between the groups, which divides the difference in weighted means of the treatment and comparison groups by the standard deviation. Because our focus is on the average treatment effect for the treated, we used the standard deviation for the treatment group to calculate the standardized difference.
2. **Comparisons of propensity score distributions.** We visually inspected the distribution of propensity scores for the treatment and comparison groups to ensure sufficient overlap for successful comparisons. To quantify this overlap, we divided the distribution of propensity scores for the treatment group into deciles and calculated the ratios of the number of

comparison to treatment students within each decile. In the next section, we focus on the smallest of these ratios across deciles as a summary measure of overlap.

e. Matching results

We calculated the balancing metrics discussed above for each model specification, and compared them to identify the best-performing model, separately by district and cohort. Our first key result is that the optimal logit model specification almost always resulted in better balance than the machine learning (TWANG) approach (see Table III.9 for summary measures). For all districts and cohorts, across deciles of the propensity score the smallest ratio of comparison students to treatment students was greater in the preferred logit model than in the machine learning model. Across all districts and cohorts, the average standardized differences across variables was smaller in the preferred logit model than in the machine learning model. Across all districts and cohorts, the largest standardized difference across variables was greater for the machine learning model than for the preferred logit model. Thus we used the preferred logit specification in each district for the analysis.

Table III.9. Propensity score diagnostics by district and cohort: Preferred logit and machine learning models

	Preferred logit model specification	Preferred logit model: Minimum C to T sample ratios across propensity score deciles	Preferred logit model: Average standardized difference	Preferred logit model: Largest standardized difference	Machine learning model: Minimum C to T sample ratios across propensity score deciles	Machine learning model: Average standardized difference	Machine learning model: Largest standardized difference
Brockton Public Schools							
2015	Base	5.3	0.011	0.038	0.8	0.061	0.143
2016	Base (trimmed)	2.3	0.018	0.046	0.3	0.077	0.236
Buffalo Public Schools							
2013	Base (trimmed)	9.7	0.006	0.014	3.0	0.116	0.253
2014	Base	5.3	0.009	0.023	2.2	0.091	0.322
2015	Base (trimmed)	4.5	0.007	0.020	2.5	0.097	0.281
2016	Base (trimmed)	5.6	0.008	0.027	2.0	0.098	0.203
Chicago Public Schools							
2014	Base	24.0	0.008	0.016	8.5	0.163	0.545
2015	Base	10.0	0.013	0.031	5.1	0.101	0.257
Galveston Independent School District							
2013	Fully interacted (trimmed)	1.6	0.022	0.059	0.0	0.120	0.378
2014	LASSO (trimmed)	1.2	0.020	0.071	0.0	0.065	0.213
2015	Base	0.8	0.034	0.068	0.0	0.075	0.186
2016	Base	1.1	0.021	0.052	0.0	0.056	0.148
Laurens County School District 55							
2014	Fully interacted (trimmed)	1.0	0.052	0.137	0.1	0.109	0.313
2015	LASSO (trimmed)	1.1	0.056	0.095	0.2	0.080	0.158
2016	Base	5.8	0.014	0.036	1.4	0.109	0.441
Los Angeles Unified School District							
2013	Base	46.3	0.001	0.004	29.9	0.100	0.215
2014	Base	28.0	0.000	0.001	12.8	0.032	0.089
2015	Base	19.3	0.001	0.002	10.0	0.032	0.094
2016	Base	23.4	0.001	0.002	12.5	0.037	0.123
Marlborough Public Schools							
2014	Base	0.3	0.054	0.134	0.0	0.106	0.330
2015	Base	0.3	0.042	0.097	0.1	0.052	0.146
2016	LASSO	0.5	0.056	0.124	0.0	0.122	0.216

		Preferred logit model			Machine learning model		
	Preferred logit model specification	Minimum C to T sample ratios across propensity score deciles	Average standardized difference	Largest standardized difference	Minimum C to T sample ratios across propensity score deciles	Average standardized difference	Largest standardized difference
Metropolitan School District of Pike Township							
2013	Base	0.6	0.024	0.050	0.1	0.074	0.181
2014	LASSO	0.3	0.024	0.071	0.1	0.047	0.113
2015	Base	0.2	0.034	0.075	0.0	0.060	0.140
2016	Fully interacted (trimmed)	0.4	0.031	0.084	0.1	0.070	0.182
New York City Department of Education							
2013	Base (trimmed)	4.3	0.011	0.021	2.4	0.112	0.277
2014	Base (trimmed)	2.1	0.004	0.009	1.0	0.054	0.096
2015	Base	1.5	0.009	0.027	0.9	0.038	0.096
2016	Base (trimmed)	1.6	0.010	0.036	0.8	0.049	0.133
Prince George's County Public Schools							
2013	Fully interacted (trimmed)	1.9	0.042	0.078	1.3	0.174	0.371
2014	Fully interacted (trimmed)	1.8	0.017	0.051	0.5	0.121	0.387
2015	LASSO (trimmed)	1.2	0.019	0.046	0.3	0.089	0.239
2016	Base	0.9	0.026	0.077	0.5	0.084	0.199
Pulaski Public Schools							
2013	LASSO (trimmed)	3.2	0.036	0.081	1.3	0.174	0.340
2014	Fully interacted (trimmed)	1.4	0.041	0.088	0.5	0.110	0.221
2015	LASSO (trimmed)	2.6	0.033	0.085	1.0	0.148	0.287
2016	Base (trimmed)	2.5	0.034	0.080	0.6	0.079	0.182
Santa Cruz Valley Unified School District							
2014	LASSO (trimmed)	2.5	0.064	0.143	0.3	0.179	0.456
2015	Base (trimmed)	2.3	0.068	0.203	0.5	0.191	0.441
2016	Fully interacted (trimmed)	0.9	0.045	0.092	0.0	0.115	0.297
St. Paul Independent School District 625							
2013	LASSO (trimmed)	0.8	0.058	0.135	0.0	0.111	0.252
2014	Base (trimmed)	0.6	0.020	0.055	0.0	0.077	0.276
2015	Base (trimmed)	0.4	0.027	0.060	0.0	0.080	0.188
2016	Fully interacted	0.3	0.035	0.086	0.1	0.091	0.191
Toledo Public Schools							
2014	LASSO (trimmed)	1.1	0.027	0.049	0.1	0.155	0.443
2015	Base (trimmed)	0.8	0.034	0.066	0.0	0.169	0.432
2016	Base (trimmed)	1.4	0.041	0.099	0.1	0.170	0.431

	Preferred logit model specification	Preferred logit model			Machine learning model		
		Minimum C to T sample ratios across propensity score deciles	Average standardized difference	Largest standardized difference	Minimum C to T sample ratios across propensity score deciles	Average standardized difference	Largest standardized difference
West Springfield School District							
2013	Base (trimmed)	1.4	0.038	0.101	0.5	0.171	0.495
2014	Base (trimmed)	4.0	0.031	0.080	0.4	0.099	0.245
2015	Base (trimmed)	0.9	0.063	0.129	0.0	0.098	0.207
2016	Base	1.9	0.022	0.066	0.3	0.137	0.539
Westside Community Schools							
2013	Base (trimmed)	6.2	0.024	0.055	2.3	0.143	0.298
2014	Base	2.3	0.026	0.053	0.1	0.083	0.182
2015	Base (trimmed)	1.7	0.011	0.036	0.1	0.061	0.143
2016	Base (trimmed)	1.8	0.010	0.019	0.1	0.054	0.244

Source: School records, Participant Tracking System.

Note: Base refers to the logit model with no interactions. LASSO refers to the logit model where variables with standardized differences greater than 0.10 are interacted with all other variables, and a subset of those are chosen using LASSO. Fully interacted refers to the model that includes all interactions between variables with standardized differences greater than 0.10 in the LASSO model and all other covariates. Trimmed models are those where students with high propensity scores are omitted, following the algorithm proposed by Crump et al. (2009).

C = comparison; T = treatment.

Our second key result is that the quality of the matches appears to meet industry standards in terms of being able to yield plausible causal impact estimates of YCC participation on key outcomes. Across all districts and cohorts, the average standardized differences was always less than 0.25, the level below which studies that control for baseline differences are eligible to meet the highest rating assigned by the What Works Clearinghouse for quasi-experimental designs. Across about 82 percent of districts and cohorts, the largest average standardized difference was less than 0.10. Across about 38 percent of districts and cohorts, the largest average standardized differences was less than 0.05, the level below which studies that do not control for baseline differences are eligible to meet the highest rating assigned by the What Works Clearinghouse for quasi-experimental designs. Furthermore, as shown in Table III.10, when districts and cohorts are pooled together, the weighted difference in covariates never exceeds 0.02 effect size units. We present baseline equivalence tests for each sample used in the primary impact analysis in Chapter V Tables V.14 and V.15.

Table III.10. Baseline equivalence for the QED treatment and matched comparison group samples for the preferred logit models pooled across districts and cohorts (percentage unless otherwise stated)

Baseline characteristic	Treatment group mean	Comparison group mean (unweighted)	Comparison group mean (weighted)	Difference in means (weighted)	Effect size
Age at entry into 8th grade (in years)	14.1	14.1	14.1	0.0	0.01
Female	43.9%	50.1%	43.7%	0.2	0.00
Race/ethnicity[a]					
American Indian	0.4	0.3	0.3	0.1	0.01
Asian	5.6	4.3	5.6	0.1	0.00
Black	33.6	30.6	33.4	0.2	0.00
Hispanic	27.2	30.7	27.4	-0.2	-0.00
White	31.1	32.1	31.1	-0.1	-0.00
Multiracial	2.3	2.0	2.2	0.0	0.00
Low -income status, 7th grade	64.4	66.2	64.0	0.4	0.01
Low-income status, 8th grade	62.1	64.6	61.7	0.4	0.01
School attendance, 7th grade	95.1	95.0	95.2	-0.1	-0.01
School attendance, 8th grade	95.2	94.6	95.3	0.0	-0.01
Ever suspended, 7th grade	10.7	11.3	10.6	0.1	0.00
Ever suspended, 8th grade	10.8	11.0	10.7	0.1	0.00
Math assessment scores, 7th grade (*z*-score)	0.1	-0.1	0.1	0.0	0.00
Math assessment score, 8th grade (*z*-score)	0.2	0.0	0.2	0.0	0.00
Reading assessment scores, 7th grade (*z*-score)	0.1	-0.1	0.1	0.0	0.00
Reading assessment score, 8th grade (*z*-score)	0.1	0.0	0.1	0.0	0.00
English language learner, 8th grade	9.5	9.9	10.1	-0.6	-0.02
Received special education services, 8th grade	11.2	14.1	11.3	-0.2	-0.01
Sample size	6,204	109,543	6,203	n.a.	n.a.

Source: School records, Participant Tracking System.

Note: Weighted comparison group means that each comparison student is weighted by $\frac{\hat{p}_i}{1-\hat{p}_i}$, where $\hat{p}_i$ is the estimated propensity score. Number may not add to 100 percent because participants can belong to more than one category.

[a] We conducted an *F*-test to assess the joint baseline equivalence across all race and ethnicity categories; differences were not significant at the 5 percent level (*p*-value=0.867).

n.a. = Not applicable.

2. Constructing outcomes

School districts do not always define data elements in the same way or collect data at the same time. For example, the timing of test taking and course structure sometimes differed across districts or across years within districts. To minimize inconsistencies in data collected between districts and within districts, we took the following steps.

- We provided each district with a memo outlining the data elements and cohorts for which we were requesting data. The memo was followed by a conversation between district staff and the study staff to review the data request and identify missing data elements or differences between district definitions and those provided. We revised the memo to reflect each district's data availability and asked the district contact person to confirm that our changes were accurate. Upon confirmation, we submitted to the district the updated version of the data request for the data elements and cohorts described in the memo.
- We collected codebooks from each district to understand how it defined each variable in the school records. When definitions of a variable varied across districts, we constructed study measures to be as consistent and inclusive as possible.

The primary impact analyses focused on four outcomes constructed from the school records data: school attendance (continuous measure), credit accumulation (continuous measure), ELA test scores (continuous measure), and algebra progression (an indicator variable). Each measure was constructed to maximize consistency across districts, as discussed below.

- **School attendance.** The number of days attended depends on the number of possible days of attendance. Because the possible number of days of attendance varied across districts, we standardized the outcome by computing school attendance as a percentage of total possible days present in the 2017–2018 school year.
- **Credit accumulation.** Policies and requirements also varied across districts. We standardized this variable by converting it to a *z*-score within district, year, and ninth grade cohort.
- **ELA test score.** Test scores not only varied across districts and years but also across grades (which depends on when a student takes the subject).[8] To ensure that ELA test scores were comparable across students and captured the most relevant high school assessment for students, we took these three steps: (1) standardized all test scores within year and district by converting them into *z*-scores (using the mean and standard deviation from the full population of students taking the test in the district in a given year); (2) used only those assessments that were required by the district or state (not optional assessments); and (3) used test scores from the year after a student's first year in YCC through 2017–2018 to maximize the available

[8] We focused on exams taken in the 10th and 11th grade to ensure students had at least one year of exposure to the YCC program. When the YCC program started in grade 10, only grade 11 exams, when available, were used. While all English exams were captured in the same grade (10th or 11th) for students within a district, pulling exams across years substantially increased the analytic sample for districts with multiple cohorts. For example, if the required ELA test was given in the 11th grade, we would have only included students who were 11th graders in 2017-18 had we not constructed the variable across years.

sample for analyses. Any *z*-scores that were greater than 5 or less than -5 were set to missing, under the assumption that these were data errors; *z*-scores between 3.5 and 5 were truncated to 3.5; and *z*-scores between -3.5 and -5 were truncated to -3.5.

- **Algebra progression.** This measure captured credits in either algebra I or algebra II, earned after the first potential year of YCC services. For 9th grade entrants, the outcome measure is set to 1 for students who earned either algebra I or algebra II credit in grade 10 or above, to 0 if algebra credit was not earned, and to missing if students earned algebra I and algebra II credit prior to 9th grade. Similarly, for 10th grade entrants, the outcome is set to 1 for students who earned either algebra I or algebra II credit in 11th grade or above, to 0 if algebra credit was not earned, and to missing if students earned algebra I and algebra II credit prior to 10th grade. That is, we set the algebra progression outcome to missing for students whose algebra progression could not have been affected by participation in YCC. As a result, students who were took both algebra I and algebra II prior to entering YCC are omitted from the analysis.

Some districts were unable to provide data on each outcome measure. Additionally, the differences in the timing of ELA tests across districts meant that some districts had whole cohorts without ELA scores. Table III.11 lists the districts and cohorts for which outcome data were available and summarizes the percentage of students in each district with missing data for each outcome. For each outcome measure, we estimated the effect of the YCC program among the sample for which outcome data were observed, without imputing outcome data.

Credit accumulation data was not available in two districts and ELA assessments were unavailable in one. Records for algebra progression were mostly complete (missing for 11 percent of students). Records for school attendance were missing for about 26 percent of students, while credit accumulation (missing for 31 percent of students) and ELA *z*-scores (missing for 42 percent of students) had higher rates of missing. All impact analyses are conducted by outcome and the analytic sample is not consistent across outcome domains.

Table III.11. YCC cohorts used to measure primary analysis outcomes and percentage of missing primary outcomes among cohorts for which some data were provided

	School attendance		Credit accumulation		ELA *z*-scores		Algebra progression[a]	
District	Cohorts	Percent missing	Cohorts	Percent missing	Cohorts	Percentage missing	Cohorts	Percent missing
Brockton Public Schools	9B,C	2.2	9B,C	2.2	9B,C	4.1	9B,C	0.0
Buffalo Public Schools	9A,B,C,10A	28.2	9A,B,C,10A	31.3	9A,B,C,10A	42.8	9A,B,C,10A	2.6
Chicago Public Schools	9A,10B,C	11.5	9A,10B,C	25.0	9A,10B,C	17.0	9A,10B,C	6.6
Galveston Independent School District	9A,B,C,10B,C	13.7	9A,10B,C	72.7	9A,B,C,10B, C	44.3	All	14.8
Laurens County School District 55	9A,B,C,10B	8.5	9A,B,C,10B	6.6	None	100.0	9A,B,C,10B	1.8
Los Angeles Unified School District	All	28.4	All	28.3	9A,B,10A,B,	41.0	All	13.7
Marlborough Public Schools	9A,B,C	10.4	9A,B,C	10.4	9A,B,C	3.4	9A,B,C	0.0
Metropolitan School District of Pike Township	9A,B,C,10B,C	24.2	9A,10B	74.1	9A,B,C	54.1	All	14.8
New York City Department of Education	All	23.7	All	21.0	All	69.5	All	0.9
Prince George's County Public Schools	9A,B,C,10B,C	22.5	None	100.0	All	58.7	All	16.9
Pulaski Public Schools	9A,B,C,10B,C	27.3	9A,B,C,10B,C	28.6	9A,B,C,10B,C	34.3	9A,B,C,10B,C	14.2
Santa Cruz Valley Unified School District	9A,B,C	5.0	9A,B,C	7.0	9A,B,C	4.7	9A,B,C	0.0
St. Paul Independent School District 625	All	16.3	All	16.3	9A,B,C	40.9	All	12.9
Toledo Public Schools	9A,B,C,10B,C	7.4	9A,B,C,10B,C	5.6	9A,B,C,10C	37.8	9A,B,C,10B,C	2.2
West Springfield School District	All	18.8	NA	100.0	9A,9B,9C	30.1	All	4.2
Westside Community Schools	9A,B,C,10B,C	24.4	9A,B,C,10B,C	24.4	9A,B,10A,B,C	33.1	All	21.3

Source: School records, Participant Tracking System.

Notes: Missing records for English language arts test score and successful completion of algebra include outcomes that were set to missing because they were measured prior to YCC participation and so could not have been affected by YCC participation.

[a] Includes algebra I or II, depending on which course was used in the construction of this outcome.

NA = not applicable, that is, the district did not provide any data on this outcome.

B. RCT impact analysis

The RCT impact analysis estimated impacts of the YCC program using the districts included in the RCT. It contained two types of analyses. The first included estimating impacts on the four outcomes in the primary analysis and included the three districts with sufficiently large samples (LAUSD, Metropolitan School District of Pike Township, and Pulaski Public Schools). The purpose of this analysis was to compare impacts using aligned samples from the QED and RCT studies. The second included estimating impacts for the broad array of outcomes captured in the FUS, and included the three RCT districts in which the FUS was administered (Chicago Public Schools, Metropolitan School District of Pike Township, and Pulaski Public Schools).

Two types of RCT impact analysis

1. Replicated the primary QED analysis with three RCT districts
2. Estimated impacts on a broader set of outcomes available in the FUS in three RCT districts

1. Defining the treatment and control group analytic samples

The RCT sample included students who applied to a 9th- or 10th-grade YCC program that started in the 2016–2017 school year (cohorts 9C and 10C). The YCC applicants for whom we had parental consent and student assent (see Chapter II) were randomly assigned to the treatment group (students offered entry in the YCC program) or a control group (students not offered entry in the YCC program). In three of the four RCT districts, students were assigned to the treatment and control groups through a lottery. In the fourth district, LAUSD, students were assigned based on an existent centralized, choice-based high school assignment system. In all districts, students assigned to receive an offer of entry to the YCC program were included in the treatment group (regardless of their subsequent enrollment or duration of enrollment), and students not assigned to receive an offer of entry to the YCC program were included in the control group.

a. Making random assignments through a lottery

In Chicago Public Schools, the Metropolitan School District of Pike Township, and Pulaski Public Schools, Mathematica developed a lottery to randomly assign students to the treatment and control groups (Figure III.2).[9] The lottery process started with students expressing interest in and completing an application to the YCC program. Program staff reviewed the application and determined a student's eligibility. After staff identified eligible students, parents consented for their student to participate in the study (and students assented) and completed the BIF (see Chapter II). (We did not collect consent or BIF data in LAUSD.) Only eligible students participated in the lottery. Lottery specifics varied in each district:

- The Chicago Public Schools held three lotteries between April 2016 and August 2017. In each, students selected for the YCC program became part of the treatment group and students

[9] Students without consent to participate in the evaluation were still included in the lottery because the districts used the lottery to determine enrollment in the YCC program. However, these students did not complete surveys and were not included in the RCT impact analysis.

not selected were entered into the next lottery, along with any students who newly applied after deciding to pursue enrollment in YCC. At the end of the third lottery, all students offered entry in the YCC program became the treatment group and students not offered entry in any lottery formed the control group.

- The Metropolitan School District of Pike Township held lotteries separately for 9th and 10th graders and maintained a randomly sorted wait list to fill vacancies created by (for example) students declining the offer to enroll in the YCC program. At the end of the first month of the fall semester, all students offered entry in the YCC program became the treatment group and students remaining on the wait list formed the control group.
- The Pulaski Public Schools held two lotteries at about the same time, one for each of their two YCC pathways: biomedical sciences and engineering. Students were only able to enter one lottery. Those selected for the YCC program became the treatment group and those not selected formed the control group. No wait list was used to fill vacancies.

Figure III.2. Random assignment through a lottery

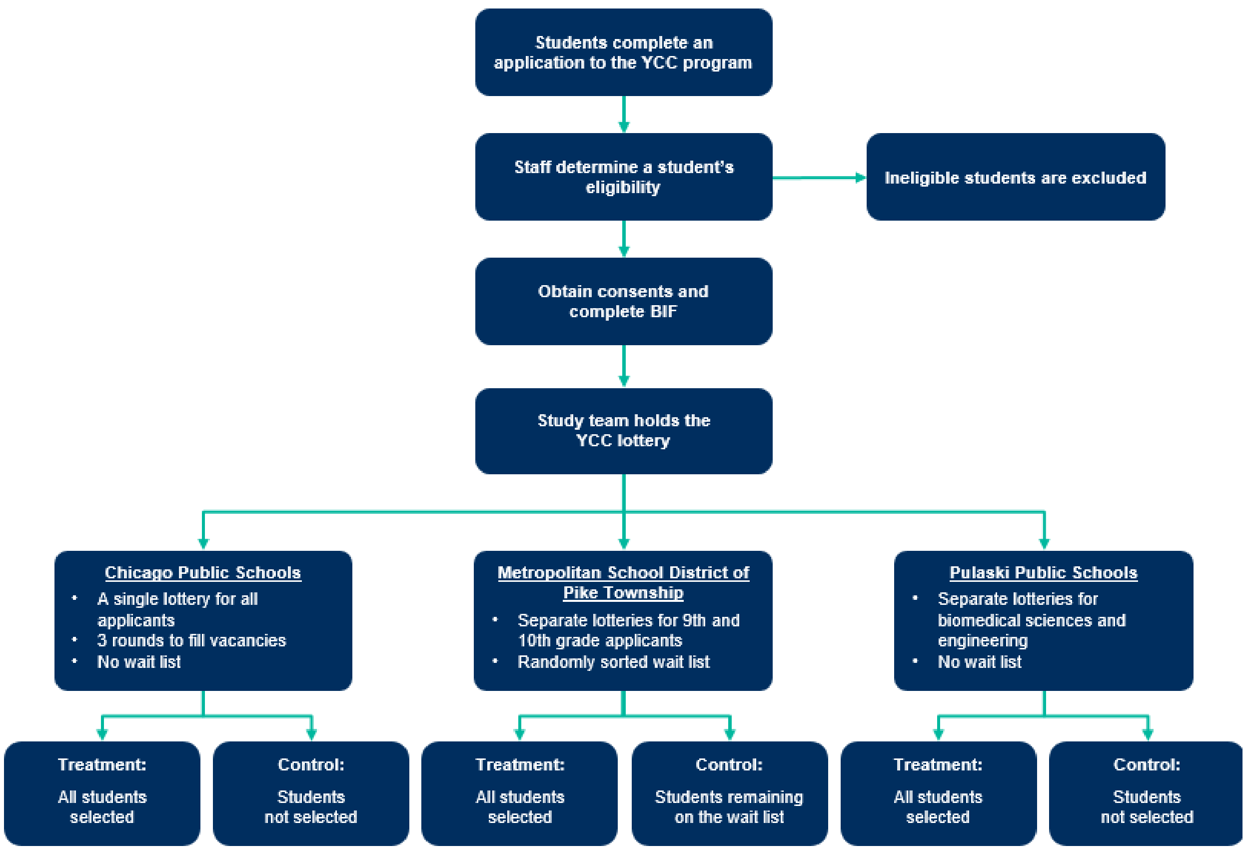


Table III.12 shows the sample sizes of eligible applicants for each lottery; the number of applicants with consent; and the number assigned to the treatment and control groups. Across lottery samples, one student was randomly assigned without having consented and was dropped from all analyses.

Table III.12. Lottery sample sizes and sampling rates

District	Number of eligible applicants	Number with consent	Treatment group: Number	Treatment group: Percentage	Control group: Number	Control group: Percentage
Chicago Public Schools	69	69	55	79.7	14	20.3
First lottery (April 2016)	47	47	25	53.2	22	46.8
Second lottery (October 2016)	31	31	14	45.2	17	54.8
Third lottery (August 2017)	30	30	16	53.3	14	46.7
Metropolitan School District of Pike Township	360	359	226	63.0	133	37.0
9th grade lottery	217	216	125	57.9	91	42.1
10th grade lottery	143	143	101	70.6	42	29.4
Pulaski Public Schools	112	112	64	57.1	48	42.9
Biomedical science	65	65	38	58.5	27	41.5
Engineering	47	47	26	55.3	21	44.7
Total	**541**	**540**	**345**	**63.9**	**196**	**36.3**

Source: Participant Tracking System.

Note: Only students with consent to be in the study were included in the treatment and control groups (one student who was randomly assigned without consent was omitted from all analyses). In Chicago Public Schools, the number of students with consent exceeds the number in the treatment and control groups because some students participated in multiple lotteries.

b. Making random assignments through the district's centralized assignment system

LAUSD, which used a whole-school YCC model, used a centralized, choice-based high school assignment system that randomly assigned students to a school when the number of students that chose that school exceeds the number of seats available. The centralized assignment system had students rank school choices within a zone of choice (a set of schools within the same geographic area that a student is eligible to apply to) and used their ranked choices to sort them into schools. Students were assigned to their first-choice school unless that school had more students ranking it first than it had available seats. When the number of choices exceeded the number of seats, LAUSD randomly assigned students ranking it first to the school. Students not assigned to a first-choice school were moved to the second round of school selection, in which they were assigned to their second-choice school unless that school had more students ranking it second than available space, in which case students were again randomly assigned. That process was repeated until all students were assigned to a high school.

Because this centralized assignment system mirrored the lottery process used in the other three RCT districts, we used it to construct treatment and control groups. Specifically, we used the data file with the school rankings for all students eligible to enroll in a school offering the YCC program to estimate the probability that a student was offered a seat in the YCC school. For that estimation, we simulated the lottery assignment process 10,000 times and calculated the percentage of times each student was assigned to a YCC school and used this as the probability that a student was selected for the YCC program.[10] Students whose probability of assignment was less than 10 percent or greater than 90 percent (155 students) were excluded from all analyses. While all six YCC schools in LAUSD are included in the primary analysis, only two of

[10] This probability also formed the IPW in the RCT impact estimation model (see Section E).

the six schools offering the YCC program had sufficient oversubscription during the student assignment process to generate a treatment and control group. Table III.13 summarizes the sample sizes and sampling rate for LAUSD by students' probability of assignment to YCC in these two schools, as calculated during the simulation process. Of the 520 students eligible for random assignment, 39 percent and 61 percent were assigned to the treatment and control groups, respectively, similar to the distribution across the other three districts.

Table III.13. LAUSD random assignment sampling rate

		Treatment group		Control group	
Probability of assignment to a school offering the YCC program	Number eligible for random assignment	Number	Percentage	Number	Percentage
Study eligible (10–90% probability)	520	204	39.2	316	60.8
10 to 20%	80	18	22.5	62	77.5
20% to 30%	114	28	24.6	86	75.4
30% to 40%	103	41	39.8	62	60.2
40% to 50%	0	0	0.0	0	0.0
50% to 60%	219	113	51.6	106	48.4
60% to 70%	0	0	0.0	0	0.0
70% to 80%	0	0	0.0	0	0.0
80% to 90%	4	4	100.0	0	0.0

Source: School records, Participant Tracking System.

Note: Counts include a limited number of treatment students (14) and comparison students (10) who refused to participate in the study.

c. Monitoring YCC services received by the treatment and control groups

A critical component of a successful RCT is ensuring that students in the treatment group received key YCC services and activities and that students in the control group did not. Maintaining a clear distinction increases the ability to detect an impact from the YCC program. We therefore worked closely with districts to monitor the YCC services and activities offered in order to ensure that students in the treatment group received YCC services and activities and those in the control group did not. We used two primary approaches for this monitoring:

1. The PTS allowed us to monitor whether students in the treatment group received key YCC services and activities. If they did not, we confirmed with YCC staff that the students were enrolled in the YCC program. The PTS did not allow students in the control group to be recorded as receiving services. When districts attempted to enroll them, we informed the district that these students should not be offered YCC services and activities and that DOL would not count them when assessing the grantees' performance against prespecified goals for the grantee.
2. We confirmed with each district that students in the treatment group remained enrolled in the YCC program and that students in the control group did not enroll in it or receive key YCC services. When possible, we used course rosters and district school enrollment information to verify district reports.

Our monitoring allowed us to track which treatment group students did not receive any YCC services—called *no-shows*—and which control group students received YCC services—called *crossovers*. Table III.14 provides counts of the no-show and crossover rates in each district. In total, about 36 percent of students assigned to the YCC program were no shows, and about 13 percent of students assigned to the control group became crossovers. These rates diminish the effect of an offer to participle in YCC, because the difference in service receipt is smaller than the treatment-control group distinction implies, which makes the impact estimate less precise, because random assignment explains a lower proportion of the variation in service receipt.

Table III.14. RCT no-show and crossover rates (number and percentage of students)

	Assigned with consent		Treatment group no-shows		Control group crossovers	
District	Treatment group	Control group	Number	Percentage	Number	Percentage
Chicago Public Schools[a]	55	14	22	40.0	0	0.0
Los Angeles Unified School District[b]	190	306	111	58.4	12	3.9
Metropolitan School District of Pike Township[c]	226	133	59	26.1	55	41.4
Pulaski Public Schools	64	48	0	0.0	0	0.0
Total	**535**	**501**	**192**	**35.9**	**67**	**13.4**

Source: Participant Tracking System.

[a] High student mobility contributed to higher than average rates of no-shows in Chicago Public Schools.

[b] A small number of treatment (14) and comparison (10) students who refused to participate in the study are excluded from these counts. High student mobility between the time in which students were assigned a school and the beginning of the school year contributed to high rates of no-shows in LAUSD.

[c] The Metropolitan School District of Pike Township could not staff both YCC and non-YCC sections of courses after the first year. As a result, about 40 percent of control group students enrolled in a YCC class.

d. Making exclusions from the analytic sample

As with the primary analysis, we excluded students from the RCT impact analytic sample for an outcome if they had missing data for that outcome (but included students with missing baseline characteristic covariates by imputing the missing values). Table III.15 summarizes the original randomized sample, sample exclusions, and the final analytic samples in each RCT district.

Table III.15. RCT impact analysis (number of students)

		Sample exclusions			Analytic samples	
District	Randomized sample with consent	Missing school records	Missing outcome data in school records	Missing FUS outcomes	School records outcome	FUS outcomes
Treatment						
Chicago Public Schools	55	2	20	18	NA	37
Los Angeles Unified School District	190	37	17	0	136	0
Metropolitan School District of Pike Township	226	19	21	39	186	187
Pulaski Public Schools	64	9	3	9	52	55
Total	535	67	61	66	407	279
Control						
Chicago Public Schools	14	1	2	9	11	5
Los Angeles Unified School District	306	56	37	0	213	0
Metropolitan School District of Pike Township	133	13	17	21	103	112
Pulaski Public Schools	48	4	2	8	42	40
Total	501	74	58	38	369	157

Source: School records, Participant Tracking System.

Note: Chicago Public Schools students were omitted from analyses of school records outcomes. LAUSD students were not included in the FUS sample, so 345 treatment students and 195 control students had the opportunity to respond to the FUS.

FUS = follow-up survey; NA = Not Available.

e. Determining baseline equivalence of the RCT treatment and control groups

Although random assignment ensures that, on average, the treatment and control groups are similar on baseline characteristics, we expect that, by chance, groups may not be similar for some variables. To identify these random imbalances, we assessed the baseline equivalence of the treatment and control group using the same three tests as described for the primary analysis (Section a.1.b), and using the sample of students with at least one non-missing outcome variable. Table III.16 summarizes the baseline characteristics and baseline equivalence test results for these students in the RCT impact samples. All baseline characteristics were measured prior to students' assignment to the treatment or control groups. Some differences exist between the treatment and control groups. However, no differences were statistically significant, and the effect size for each difference was below the 0.25 threshold used by the What Works Clearinghouse to determine whether an analysis can sufficiently account for the difference using statistical controls. All analyses using the RCT sample control for each characteristic presented in Table III.16.

Table III.16. RCT sample baseline characteristics and baseline equivalence

Baseline characteristic	Treatment group mean	Control group mean	Difference in means	Effect size
School records[a]				
Age at entry into 8th grade	14.1	14.0	0.0	0.0
Female	51.5%	52.9%	-1.5	0.0
Race/ethnicity[b]				
Black	27.6%	31.3%	-3.7	-0.1
Hispanic	39.8%	38.9%	0.9	0.0
White	52.3%	52.9%	-0.6	0.0
Multiracial	3.9%	4.1%	-0.2	0.0
Low-income status, 8th grade	67.8%	70.5%	-2.7	0.0
School attendance, 8th grade	97.0%	97.0%	0.0	0.0
School attendance, 7th grade	97.1%	96.9%	0.2	0.0
Repeated 7th or 8th grade	8.9%	8.9%	0.1	0.0
Reading assessment scores, 8th grade	0.3	0.3	0.0	0.0
Reading assessment scores, 7th grade	0.3	0.2	0.1	0.1
Math assessment scores, 8th grade	0.4	0.3	0.1	0.0
Student behaviors[c]				
Positive behavior scale	4.2	4.1	0.1	0.1
Ever worked	16.8%	21.2%	-4.4	-0.1
Parent involvement and expectations[d]				
Discussed postsecondary education with the student more than twice	84.5%	86.7%	-2.2	0.0
Expects student to receive a vocational certificate	47.9%	45.1%	2.8	0.0
Sample size	**391**	**366**	**n.a.**	**n.a.**

Source: Parent and student baseline information forms, school records.

Note: The sum of the percentage of students who are of each race may sum to more than 100 due to rounding. Sample sizes vary across baseline characteristics due to missing data, and the reported sample is the largest sample size across baseline characteristics.

[a] Reported in school records data.

[b] We conducted an *F*-test to assess the joint baseline equivalence across all race and ethnicity categories. Differences were not significant at the 5 percent level (*p*-value=0.901)

[c] Student report, from the student baseline information form.

[d] Parent report, from the parent baseline information form.

* Indicates a statistically significant difference at the 5 percent level.

+ Indicates a statistically significant difference at the 5 percent level.

n.a. = not applicable.

2. Constructing outcomes

Outcomes differed in the two analyses that comprise the RCT impact analysis. Outcomes in the first analysis were identical to the primary analysis (see Section A.2). Outcomes in the second analysis were more expansive.

a. Replicating primary analysis with RCT sample

Using students randomly assigned to the treatment or control groups, we replicated the primary analysis to determine whether the primary analysis appropriately accounted for selection bias. We compared these results to primary sample results based on the subsample of districts and cohorts included in the RCT analysis.

b. Estimating impacts using a broader set of outcomes

Outcomes from the FUS capture one milestone and a plethora of momentum points that are not available in school records data. These outcomes are captured using indicator, count, and continuous variables (Table III.17).

Indicator variables. The majority of outcomes drawn from the FUS are binary and take a value of one or zero. These constructs were developed in four ways:

1. Response to a single yes/no question takes the value of one if the student selected yes to the question.
2. Likert-scale questions take a value of one if the student selected the most positive of the response options (for example, likes school a lot and believes grades are very important).
3. Response selection take the value of one if the student selected the option from among several options in the list, even if responses about other specific activities in the list were missing (for example, expects to receive a technical, trade school, or two-year college degree; participated in sports).
4. Response to more than one question take the value of one if the student selected yes to one or more questions (for example, earned a badge at school for a specific skill, talent, or achievement, or took courses at school that lead to an industry-recognized credential).

Count variables. Three variables were constructed by adding a series of indicator variables. The work-readiness index summed eight indicator variables, each of which captures students' self-reported participation in school-based work-readiness activities. Positive school behavior summed five indicator variables capturing students' self-reported behaviors. Grit scores summed eight indicator variables capturing students' self-reported perseverance (Duckworth and Quinn 2009).

Continuous variables. The total number of hours spent per week on homework is the sum of three separate variables: total hours spent on homework during school hours, total hours spent on homework before or after school hours on weekdays, and total hours spent on homework during the weekend. Values greater than 20 were set to missing, under the assumption that the data were inaccurate.

Table III.17. FUS outcome measure construction

Outcome	Measure
Milestone	
Enrolled in HS in 2018–19	Equals 1 if a student indicated enrollment in high school in the 2018–2019 school year; equals 0 if the student did not indicate enrollment; set to 0 for the 10 students who graduated early
Momentum points	
High school behaviors	
School activities	
Participated in a school-sponsored activity	Equals 1 if a student indicated participation in at least one school-sponsored activity in the past 12 months; equals 0 if student did not
Engagement and satisfaction	
Believe grades are very important	Equals 1 if a student indicated good grades are very important to them; equals 0 if student indicated grades are important, somewhat important, or not important at all
Like school a lot	Equals 1 if a student indicated they like a lot the school they currently attend in fall 2018 or most recently attended; equals 0 if student indicated they like it, it is/was okay, or do not like it at all
Number of hours spent on homework per week	Equals the total number of hours a student spent on homework in a typical week when school was in session
Positive school behavior index (0–5)	Sum of five separate indicator variables that captured students' self-reported positive school behaviors in the past three months in which they were in school: never late for school; never cut or skipped classes; never had an unexcused absence from school; never got in trouble for not following school rules; and never was suspended or put on probation
Substance abuse	
Never drank alcohol	Equals 1 if a student indicated never drinking alcohol; equals 0 if student indicated they had
Never used or tried marijuana	Equals 1 if a student indicated never having used or tried marijuana; equals 0 if student indicated they had
Postsecondary preparation	
Positive education expectations and knowledge	
Expect to receive a two- or four-year college degree	Equals 1 if a student indicated expecting to graduate from a technical or trade school, a two-year college, or a 4-year college, or to earn an advanced degree; equals 0 if they did not
Expect to receive a vocational certificate	Equals 1 if a student indicated expecting to receive a vocational certificate; equals 0 if they did not
Took an AP course	Equals 1 if a student indicated taking AP courses at school; equals 0 if they did not
Took a dual-enrollment courses	Equals 1 if a student indicated taking dual-enrollment courses at school; equals 0 if they did not
Understand courses needed to attend a four-year college	Equals 1 if a student indicated they understood the courses needed to attend a four-year college; equals 0 if they do not
Understand education or training needed for desired career	Equals 1 if a student indicated they understood the education or training needed beyond high school for the career they want; equals 0 if they did not
Employment readiness	
Work-readiness skills	
Earned a badge that leads to an industry-recognized credential	Equals 1 if a student indicating having either: (1) earned a badge for a specific skill, talent, or other achievement; or (2) taken courses that lead to an industry-recognized credential; equals 0 if did not
Earned a degree, certificate, or license at school	Equals 1 if a student indicated earning a license or certificate that would help them get a job; equals 0 if did not

Outcome	Measure
Grit score (0–8)a	The sum of eight separate indicator variables that each captures students' self-reported perseverance or determination, with a1 on each variable indicating more perseverance and a value of 0 indicating less
Holds a credential	Equals 1 if a student indicated earning a degree, certificate, or license through high school coursework or activities; equals 0 if did not
Work-readiness index	The sum of eight separate indicator variables that each indicates participation in specific work-readiness activities at school
Paid work experience	
Ever worked for pay	Equals 1 if a student had ever worked for pay, not counting work around the house; equals 0 if did not
Ever had a job arranged through school	Among students who had ever worked for pay, equals 1 if a student had ever had a job arranged through school and equals 0 if did not

[a] Individual questions and overall grit score variable construction are drawn from Angela Duckworth's Short Grit Scale (Duckworth and Quinn 2009).

AP = advance placement; HS = high school.

Some outcomes data are missing because students did not necessarily answer all FUS questions, did not provide a valid response to a question, or said they did not know the answer to the question. Our approach to treating outcomes as missing data depends on the type of variable. For indicator variables based on a single question, we set the outcome variable to missing for students who did not provide a valid response to the individual question. For count variables, we set the outcomes to missing if more than 25 percent of source variables are missing. For outcomes based on multiple variables, our approach to setting the outcome to missing depended on the circumstances. For participating in at least one school-sponsored activity, the outcome variable was set to missing if at least two of the seven source variables were missing and none of them equaled one. For earning a badge for a specific skill, talent, or achievement or taking courses at school that lead to an industry-recognized credential, the outcomes were set to missing if both of these measures were missing. Table III.18 summarizes the percentage of students in each district with missing data for each FUS outcome.

Table III.18. FUS outcomes missing, by district (percentages)

	Chicago Public Schools	Metropolitan School District of Pike Township	Pulaski Public Schools
Milestone			
Enrolled in HS in 2018–2019	39.1	16.7	15.2
Momentum points			
High school behaviors			
School activities			
Participated in a school-sponsored activity	40.6	18.7	17.0
Engagement and satisfaction			
Believe grades are very important	40.6	18.7	17.0
Like school a lot	39.1	17.8	17.0
Number of hours spend on homework per week	43.5	20.1	17.9
Positive school behavior index (0–5)	40.6	18.7	16.1
Substance abuse			
Never drank alcohol	40.6	19.5	16.1
Never used or tried marijuana	40.6	19.2	17.0
Postsecondary preparation			
Positive education expectations and knowledge			
Expect to receive a two--or four-year college degree	43.5	23.1	19.6
Expect to receive a vocational certificate	40.6	19.2	15.2
Took an AP course	46.4	19.5	16.1
Took a dual-enrollment course	46.4	20.3	23.2
Understand courses needed to attend a four-year college	44.9	25.1	18.8
Understand education or training needed for desired career	42.0	24.8	24.1
Employment success			
Work-readiness skills			
Earned a badge that leads to an industry-recognized credential	42.0	20.6	19.6
Earned a degree, certificate, or license at school	42.0	24.8	20.5
Grit score (0–8)	44.9	22.0	18.8
Holds a credential	49.3	24.2	20.5
Work-readiness index (0–8)	40.6	17.8	17.0
Paid work experience			
Ever worked for pay	40.6	19.5	16.1
If ever worked, ever had a job arranged through school	18.8	11.6	5.3

Source: Follow-up survey.

AP = advance placement; HS = high school.

A potential source of bias in the second RCT impact analysis is survey nonresponse bias. This bias can emerge from one of two sources: (1) different characteristics of students who responded to and did not respond to the FUS or had different rates of missing data on outcomes or (2) treatment and control groups had different patterns of nonresponse. Response rates varied across districts. They were highest in Pulaski Public Schools (with 86 percent of treatment students and 83 percent of control students responding) and the Metropolitan School District of Pike

Township (with 83 percent of treatment students and 84 percent of control students responding). Response rates were somewhat lower in Chicago (with 67 percent of treatment students and 36 percent of control students responding).

To assess the extent of survey nonresponse bias, we compared the baseline characteristics of respondents and nonrespondents separately for the treatment and control groups (Table III.19), as measured through the school records, and used *t*-tests and a joint *F*-test to identify differences ($p \leq 0.05$). We found that, among the treatment group, survey respondents were less likely to have repeated 7th or 8th grade, had higher achievement in ELA, had higher values on the positive behavior scale, and were less likely to have a parent who expected them to complete a vocational certificate. Among the control sample, a higher portion of respondents than nonrespondents were white, and respondents had higher achievement in ELA in middle school.

To correct for potential survey nonresponse bias created by differences shown in Table III.18, we constructed sample weights to align the observable baseline characteristics of respondents and the full analytic sample of respondents and nonrespondents. We constructed weights for the treatment and control groups separately using propensity score methods in which we (1) used a chi-squared automatic interaction detection (CHAID) algorithm to identify interactions of covariates that explained the likelihood of responding; (2) estimated a stepwise logit model predicting whether a student would respond to the FUS to identify main effects and interaction terms to include in the model; and (3) calculated a propensity score for responding to the survey for each individual in the full sample. All models were estimated separately for each district, and the final logit model included interactions identified by the CHAID algorithm, main effects identified by the stepwise logit procedure, an indicator for treatment status, an indicator for being low-income status 8th grade, math and reading achievement scores in 8th grade, and indicators for the lottery in which a student was assigned. We then used the propensity scores to construct nonresponse weights, where the weight for each student was inversely proportional to the student's propensity score.

Using the propensity score method, weighted characteristics of respondents should be similar, on average, to the characteristics of the entire analytic sample. To check this, we tested for baseline equivalence between the treatment and control group using the nonresponse weights. As shown in Table III.19, the difference between treatment and control group survey respondents is less than 0.10 in effect size units for more than two-thirds of covariates and is always less than 0.25. Each of these covariates is included as a control variable in impact models examining FUS outcomes.

Table III.19. FUS baseline characteristics and equivalence, respondents and nonrespondents

	Treatment sample				Control sample				Full sample
Baseline characteristic	Survey respondents	Survey nonrespondents	Mean difference	Effect size	Survey respondents	Survey nonrespondents	Mean difference	Effect size	Effect size (weighted)
School records									
Race/ethnicity[a]									
Black	53.9%	65.3%	-11.4+	-0.2	55.1%	60.8%	-5.7	-0.1	-0.1
Hispanic	16.4%	9.0%	7.4	0.3	12.0%	17.1%	-5.0	-0.1	0.1
White	21.9%	21.1%	0.8	0.0	28.7%	13.3%	15.5*	0.5	-0.0
Free and reduced price lunch, 8th grade	68.2%	79.5%	-11.3	-0.3	66.8%	82.1%	-15.2	-0.4	0.1
School attendance, 7th grade	96.2%	94.7%	1.5+	0.2	96.1%	94.9%	1.2	0.3	0.0
Repeated 7th or 8th grade	7.6%	20.3%	-12.7*	-0.3	12.2%	24.6%	-12.4	-0.3	-0.2
Reading assessment scores, 8th grade	0.2	-0.2	0.4*	0.4	0.2	-0.4	0.6*	0.6	0.0
Reading assessment scores, 7th grade	0.1	-0.3	0.4*	0.4	0.2	-0.3	0.5*	0.7	-0.1
Follow-up survey									
Student behaviors									
Positive behavior scale	3.8	3.5	0.4*	0.3	3.7	3.4	0.2	0.2	0.1
Ever worked	20.8%	23.0%	-2.2	-0.1	17.4%	23.0%	-5.5	-0.1	-0.1
Parent involvement and expectations									
Discussed with student postsecondary education at least twice	49.7%	71.8%	-22.1*	-0.5	44.6%	56.8%	-12.1	-0.2	0.1
Expects student to receive a vocational certificate	80.5%	79.3%	1.2	0.0	75.6%	82.4%	-6.7	-0.2	0.1
Sample size	**279**	**66**	**345**	**n.a.**	**157**	**38**	**195**	**n.a.**	**n.a.**

Source: Follow-up survey.

Note: Sample excludes LAUSD, which did not implement the FUS. Baseline characteristics are those included in all impact models using the RCT sample.

* Indicates a statistically significant difference at the 5 percent level.

+ Indicates a statistically significant difference at the 10 percent level.

[a] We conducted an *F*-test to assess the joint baseline equivalence between survey respondents and non-respondents across all race and ethnicity categories. The differences were not significant at the 5 percent level for the treatment group (*p*-value=0.220) or the control group (*p*-value=0.189).

n.a. = Not applicable.

C. High school graduation analysis

Students who entered high school in fall 2014 or earlier were could have an on-time graduation from high school by the time we collected school records after the end of the 2017–2018 school year. We could therefore estimate the impact of the YCC program on high school graduation for the sample of three of the cohorts of students in the QED (cohorts 9A, 10A, and 10B), comprising 32,103 students in the treatment group and 1,790 students in the comparison group. We captured this milestone as an indicator variable that equals one if a student graduated by the end of 2017–2018 school year and equals zero if they did not.

D. Subgroup analysis

The large number of students with school records data allowed us to assess whether the YCC program produced different impacts for students by three different types of subgroups.

- **Student characteristics.** We used baseline characteristics from school records to determine the extent to which YCC services differentially benefitted students who were and were not at risk of not succeeding in high school, defined in two ways. (1) Low academic achievement was captured by math or reading scores considered below proficient by the standards of their district. All districts provided information on 8th grade academic achievement. (2) Low-income status was captured by eligibility for the free and reduced price lunch program in 8th grade or, where that was not available, living in a census tract with 20 percent poverty or higher in 8th grade. Of the 16 districts providing school records data, 13 provided information on low-income status in the 8th grade.
- **YCC program experiences.** We chose three measures to capture program experiences—whether a student participated in an internship, had a mentor, or completed an IDP—each of which was captured using the PTS.
- **YCC cohort.** We identified three cohorts of students: one that entered the YCC program about nine months after the YCC grant awards (cohort A in Table II.4, Chapter II), one that entered about two years after awards (cohort B), and one that entered about three years after awards (cohort C).

1. Defining the treatment and comparison group analytic samples for the subgroup analysis

The analytic samples for estimating impacts for particular subgroups defined by student characteristics, YCC program experiences, and YCC cohorts were obtained by restricting the treatment and comparison samples to those in the particular subgroup. For example, to estimate impacts for those with low academic achievement at baseline, we compared the outcomes of low achievers in the treatment and comparison groups. For these analyses, we used the IPW weights constructed for the primary analysis.

For the subgroup analysis based on YCC program experiences, the specific service subgroups could only be defined for the treatment group. Treatment students who receive each specific service could systematically differ from those who do not. Thus, to balance characteristics between the comparison group and subsets of treatment students who did or did not receive each specific service, we estimated separate propensity score models specific to each subgroup. We used the same methods that were used to create propensity scores for the primary analysis (described in Section A.1. above) for estimating the propensity scores with one exception—to increase sample sizes we pooled across cohorts and included cohort indicators in each model. For each type of service, we created an indicator variable equal to one for treatment group members who received that service and zero for all comparison group members and estimated propensity score models using this indicator as the outcome and the baseline covariates used for the primary analysis. Balancing tests indicate that this process resulted in well-balanced samples: across all districts, service groups, and covariates, the largest effect size differences were about 0.10.

Table III.20 summarizes the analytic samples for each subgroup. The analysis for a particular subgroup was conducted using only students with available data to determine their subgroup designation (that is, we did not impute subgroup designations for students with missing data on their subgroup status).

Table III.20. QED analytic sample for each subgroup

	Credit accumulation		School attendance		ELA test scores		Algebra progression	
Subgroup	T	C	T	C	T	C	T	C
Student characteristics								
Academic achievement								
Low prior math score	4,223	4,171	5,354	5,304	3,876	3,108	5,639	5,636
Low prior reading score	4,280	4,206	5,410	5,331	3,933	3,138	5,647	5,627
Income subgroups	4,219	4,156	5,270	5,209	3,887	3,092	5,504	5,498
Program experience								
Received an internship	5,058	4,712	6,198	5,808	4,628	2,902	6,588	6,571
Had a mentor	6,574	6,131	8,634	8,176	6,016	4,251	9,168	9,232
Completed an IDP	7,214	6,650	9,104	8,558	6,534	4,647	9,594	9,685
YCC Cohorts								
YCC cohort subgroups	4,319	4,257	5,457	5,395	3,968	3,175	5,713	5,707

Source: School records, Participant Tracking System.

C = comparison; ELA = English language arts; IDP = individual development plan; T= treatment.

2. Constructing outcomes for the subgroup analysis

Outcomes for the subgroup analysis were identical to those used in the primary analysis (see Section A.2).

E. Impact estimation methods

All impacts were estimated using regression models. The analysis was conducted using the free RCT-YES software (www.rct-yes.com) that estimates impacts using design-based theory developed using the building blocks of experiments (see Schochet 2015, 2016). In this section, we discuss impact models used for the primary analysis and the secondary analysis.

1. Primary impact analysis

The primary impact analysis addressed the question: What is the impact of the YCC program on school attendance, credit accumulation, proficiency in English language arts, and algebra progression? Our main strategy for answering this question was to estimate regression models using school records for each of the 16 districts while controlling for indicators for treatment status, district effects, cohort effects, and baseline covariates of the students from school records. Of note, we cannot identify students in the treatment group in the QED-based primary analysis, high school graduation analysis, and subgroup analysis who were *offered* a spot in the YCC program. Instead, we can only identify students who actually *participated* in the program. As a result, we cannot estimate an intention-to-treat (ITT) effect among the QED sample. Instead, these analyses estimated a treatment-on-the-treated effect (that is, the effect among students who chose to enroll in YCC) using the following weighted regression model, in which an impact of the YCC program was calculated for each district and then averaged to obtain a pooled estimate:

(1) $$y_i = \sum_{k=1}^{n} \beta_k * Block_{i,k} + \sum_{k=1}^{n} \delta_k YCC_{i,k} * Block_{i,k} + \sum_{g=1}^{G} \psi_g Cohort_{i,g} + X_i\gamma + e_i$$

In this model, y_i is the outcome (school attendance, credit accumulation, ELA, or algebra progression) for student *i*; *n* is the number of districts; $Block_{i,k} = 1$ for students enrolled in district *k* and 0 otherwise; $YCC_{i,k} = 1$ for students participating in YCC (QED treatment group) and 0 for others (comparison group); $Cohort_{i,g}$ is an indicator equal to 1 if student i was in 9th grade cohort *g* (where cohorts are groups of students entering 9th grade together); X_i is a vector of students' demographic characteristics and prior achievement, which were identified from the LASSO procedure described in Section A.1.a, e_1 is the error term; β_k, δ_k, and ψ_g are estimated parameters, and γ is a vector of estimated parameters.

We estimated Equation (1) for each outcome separately, including only sample members with nonmissing data for the outcome under investigation. We estimated all models using the IPW weights, with the weights equal to 1 for treatment students and $\frac{\hat{p}_i}{1-\hat{p}_i}$ for comparison group students. In other words, comparison group students were weighted to resemble treatment students along observable dimensions (see Section B.2.b).

Our benchmark approach calculated the average impact of YCC across districts using $\hat{\delta} = \sum_{k=1}^{n} \frac{\hat{\delta}_k}{n}$, where each district was weighted equally. However, to assess the robustness of study findings, we examined the district-level impact estimates ($\hat{\delta}_k$) to gauge whether the pooled impact estimates were driven by a small number of districts with very large or small impacts. The variation in impacts across districts was assessed using a joint *F*-test and by examining the sign and magnitude of the 16 impacts. Relatedly, for sensitivity, we also conducted the analysis weighting students equally (see Chapter IV) to estimate impacts for the average student rather than the average district (the two sets of impacts could differ if district size is related to the impact estimates). We did not adjust *p*-values for multiple comparisons because our primary analysis focuses on only one outcome for each domain.

As discussed in Section A.1.a, we created five imputed data sets for each district, containing separate imputations for the model covariates (but not outcomes). Thus, we estimated impacts using RCT-YES for each imputed data set and then accounted for the variation in the estimated impacts both within and across datasets using the following variance formula (Rubin 2004):

(2) $$Var_{Total}\left(\hat{\delta}\right)=\frac{1}{m}\sum_{i=1}^{m}Var_i\left(\hat{\delta}_i\right)+\left(1+\frac{1}{m}\right)\left(\frac{1}{m-1}\right)\sum_{i=1}^{m}\left(\hat{\delta}_i-\hat{\delta}\right)^2$$

where $\hat{\delta}$ is the average of estimated impacts across imputed data sets, $\hat{\delta}_i$ is the estimated impact using the i^{th} imputed data set, and *m* is the number of imputed data sets, which was 5.

We examined the *p*-value associated with the *t*-statistic or chi-squared statistic for each estimated impact, and we reported findings for statistically significant impacts ($p \leq 0.05$). We noted marginally significant findings, where $p \leq 0.10$, when they contributed to a consistent pattern of impacts across multiple outcomes, cohorts, or subgroups. In addition, we examined the pattern of effects across districts to ensure that the pooled results were not driven by a few districts with outlying impacts. Further, we examined the magnitude of the significant impact estimates to assess their policy relevance. We also converted the impact estimates into common effect size (standard deviation) units, which facilitates interpreting the impacts across outcomes and gauging the magnitude of impacts using common thresholds across research areas (see, for example, Lipsey et al. 2012; Cohen 1988, 1977).

Table III.21 presents the realized minimum detectable effect sizes for our outcomes in the primary analysis. These are based on a 5 percent significance level (so that a true impact of zero would result in a significant finding 5 percent of the time) and 80 percent power (that is, an effect as large or larger than the realized minimum detectable impact would be significant 80 percent of the time). The study was powered to detect a 0.64 percentage point change in school attendance; a 0.06 standard deviation change in cumulative credits; a 0.04 standard deviation change in ELA scores; and a 2.6 percentage point change in algebra progression.

Table III.21. Realized minimum detectable effects for primary outcomes

Primary outcome	Standard error	Realized MDE
School attendance (percent of attended days)	0.23	0.64
Credit accumulation (*z*-score)	0.02	0.06
Algebra progression (percent progressed)	0.93	2.60
English language arts test score (*z*-score)	0.02	0.04

Source: School records.

MDE = minimum detectable effect.

2. Secondary analyses

a. RCT impact analysis

The RCT impact analysis used school records to compare impact results using the RCT and QED samples (using aligned samples across districts and cohorts). To do this, we compared the $\hat{\delta}_k$ estimates, the district-specific impacts, for the aligned RCT and QED samples. We compared the signs and magnitudes of the two sets of estimates and conducted *t*-tests to statistically test for differences. We excluded Chicago Public Schools from the analysis due to small samples and the associated lack of statistical power for comparing the RCT and QED findings.

For this analysis, we estimated Equation (1) separately for LAUSD, Metropolitan School District of Pike Township, and Pulaski Public Schools, and separately for the RCT and QED samples. When estimating impacts using the RCT samples in the Metropolitan School District of Pike Township and Pulaski Public Schools, we added additional covariates that were available from the BIFs, which enabled us to expand the youth characteristics (X_i) included in the estimation (Table III.22). To better align the RCT and QED impact estimates, we calculated complier average causal effect (CACE) impact estimates for the RCT analysis rather than the intention-to-treat (ITT) estimates produced by Equation (1). We did this to adjust for treatment students who did not receive YCC services (no-shows) and for control students who did receive YCC program services (crossovers) (see Table III.14). The CACE estimates the effect of YCC among students willing to participate in YCC (and who therefore participated in the lottery or listed YCC as one of their ranked choices in LAUSD) who would have enrolled in YCC only if assigned to receive an offer to enroll.

To estimate impacts for the CACE parameter, we used an instrumental variable approach, replacing the $YCC_{i,k}$ indicator in Equation (1) with an indicator variable $Participate_{i,k}$ that equals 1 for those who ever enrolled in YCC, and zero for those who did not, and used $YCC_{i,k}$, the indicator for random assignment, as an instrumental variable for $Participate_{i,k}$ (Angrist et al. 1996; Bloom 1984). Intuitively, the approach inflates the ITT estimates of the effect of the offer of services generated by Equation (1) to reflect impacts for the smaller group of treatment students who could have benefited because of their program participation. This approach is valid when the indicator for random assignment sufficiently explains variation in participation. To explore this, we regressed $Participate_{i,k}$ on $YCC_{i,k}$ and the full set of covariates included in the impact model. For each outcome sample, the coefficient on $YCC_{i,k}$ was statistically significant at the 0.001 percent level, suggesting that $YCC_{i,k}$ explains sufficient variation in $Participate_{i,k}$. For these analyses, we estimated the models using weights to account for differences in the probability of assignment to YCC.

In our RCT impact analysis using *FUS outcomes*, we further modified equation (1) to adjust for potential survey nonresponse bias by estimating all models using survey nonresponse weights (see Section B.2.b).

Table III.22. Covariates in the RCT impact analysis with FUS outcomes

Variable type	Measure	Source
School attendance, 7th grade	Students' school attendance in 7th grade	School records
Low-income status, 8th grade	Equals 1 if the student was eligible for the free and reduced price lunch program or, where that was not available, if the student's census block had a poverty rate of 20 percent or higher	School records
Race/ethnicity	Students' race or ethnicity	School records
Repeated grade 7 or 8	Equals 1 for students who repeated 7th or 8th grade and 0 for students who did not	School records
Reading assessment scores, 7th grade	Students' 7th grade reading achievement *z*-scores, standardized using district, year, and grade-level means and standard deviations	School records
Reading assessment score, 8th grade	Students 8th grade reading achievement *z*-scores, standardized using district, year, and grade-level means and standard deviations	School records
Never drank alcohol	Equals 1 for students who said they never drank alcohol and 0 for students who said they have tried alcohol	Student baseline information form
Positive school behavior	Equals the sum of five separate indicator variables that captured students' self-reported positive school behaviors in the past three months they were in school: never late; never cut or skipped classes; never had an unexcused absence; never got in trouble for not following rules; and never was suspended or put on probation	Student baseline information form
Ever worked for pay	Equals 1 if the student reported ever having worked for pay and 0 if they did not	Student baseline information form
Talked to child about education after high school	Equals 1 if the parent reported having talked to the child about education after high school at least twice and 0 if they did not	Parent baseline information form
Expects child to receive a vocational certificate	Equals 1 if the parent expected the child to receive a vocational certification and 0 if they did not	Parent baseline information form

b. High school graduation analysis

To estimate impacts on high school graduation, we used methods identical to those in primary impact analysis (see Section E.1). We conducted this analysis for three of the cohorts of students in our primary analysis (cohorts 9A, 10A, and 10B) where high school graduation could be measured using school data available over the study period.

c. Subgroup analysis

We estimated several subgroup analyses for the samples in the QED on the four primary outcomes, using different approaches for subgroups defined by pre-YCC characteristics and those defined by post-YCC program experiences.

To estimate the effects for subgroups defined by pre-YCC characteristics, we created subgroup indicators $S_i = 1$ if student i was in the subgroup and 0 otherwise. We did not use imputed values for any subgroup indicators. We then estimated a modified version of Equation (1) in which S_i was fully interacted with the block and block by treatment indicators. This model used the same IPW weights that we used in the primary analysis. We conducted F-tests to test for differences across subgroup impacts (such as across cohorts).

To estimate impacts for a subgroup defined by whether a treatment group student received a particular YCC program service (a post-YCC characteristic), we estimated Equation (1) restricted to those treatment group members who received the YCC service and the full comparison group using the service-specific IPW weights discussed in Section D.1.

For each type of program experience, we used *t*-tests to gauge whether the program experience improved students' outcomes. The service-related impact findings must be interpreted carefully as they capture both the effects of the service component and the types of students who chose or had the opportunity to receive the service and other associated ones. We did not conduct statistical tests to gauge differences in subgroup impacts across different types of YCC services that were received (for example, mentoring and internships).

IV. SENSITIVITY ANALYSIS OF IMPACT ESTIMATES

Chapter III outlined the set of benchmark analytic decisions made to estimate the impacts of the YCC program on the four primary outcomes. These decisions were based on a host of assumptions, only some of which are testable. This chapter presents findings from a series of sensitivity analyses conducted to check the robustness of our primary impact findings to alternative assumptions. The goal of making these analyses was to assess whether the findings from the primary analysis are sensitive to the assumptions underlying the analysis.

Key finding

In all but one case, changes in the assumptions used for our benchmark analysis approach lead to the same conclusions about the impacts of the YCC program on key milestones and momentous points achievable in high school. Participating in the YCC program improved school attendance and credit accumulation but had no effect on algebra progression. However, the conclusion that can be drawn about the effects of YCC program participation on ELA test scores is sensitive to the approach we use to weight students in the analysis—specifically, it depends on whether we give equal weights to students or to districts.

The benchmark approach for our primary impact analysis, described in detail in Chapter III, compared the outcomes of 6,207 treatment group students identified in the PTS as having enrolled in the YCC program and 109,541 comparison group students across the 16 QED districts. In this chapter, we present findings from the following six sensitivity analyses:

1. **Estimating models without baseline covariates.** The benchmark approach included baseline covariates in the impact models. By estimating the models without these covariates, this sensitivity analysis yielded a simple-differences-in-means estimator. Although models without covariates are less precise than those with covariates, if covariates do not differ between treatment and comparison group students, including them in the impact model does not affect the estimated impacts, but does affect standard errors.
2. **Excluding students with missing covariates.** In the benchmark approach, we used multiple imputation by chained equations to impute missing covariates. This sensitivity analysis—the complete case analysis—excluded students with any missing covariate values, even if outcome data were available. This approach reduces the sample size for the analysis but avoids use of imputed covariates for impact estimation.
3. **Estimating impacts for each of the five imputed datasets.** The multiple imputation approach created five imputed datasets for each district and estimated impacts using each imputed dataset. The benchmark approach averaged the impact estimates across those datasets and constructed standard errors that incorporated variation both within and across the five sets of estimates. This sensitivity analysis examined the impact findings for each dataset individually to ensure that a single dataset did not have undue influence on the findings.

4. **Weighting each student equally to form the pooled estimates across districts.** Our benchmark approach weighted districts equally to obtain the pooled estimates across the 16 QED districts. This sensitivity analysis estimated impacts by weighting students equally, which gives more weight to districts with larger samples and yields more precise impact estimates.
5. **Matching using a nearest neighbor matching approach.** Our benchmark approach used IPW methods for obtaining the comparison group. This sensitivity analysis matched (with replacement) each treatment student to a single comparison student based on the closeness of their propensity scores. This approach yields a smaller comparison group and yields less precise impact estimates, but is one commonly used for QED studies because it provides an easy-to-understand pairing of a treatment group member with a single comparison group member.
6. **Adjusting standard errors for clustering for the whole-school YCC program models.** Our benchmark approach selected a comparison group in the four districts with a whole-school model from similar non-YCC schools in the same district, which assumes that the student-level error term is independent across students. This sensitivity analysis assumed school-level effects might be random components of the error term, stemming from correlated outcomes for students in the same school (due to shared school environments, for example). These clustering effects reduce the precision of estimates (that is, increase standard errors) by reducing the number of independent observations in the sample.

Table IV.1 summarizes the findings from each analysis. The sample size corresponds to the maximum sample size across outcomes.

Table IV.1. Estimated impacts on primary outcomes using alternative model specifications and samples

Outcome	School attendance (percent)	Credit accumulation (z-score)	ELA test score (z-score)	Algebra progression (percent)	Sample size
Benchmark impact estimate	0.714* (0.233)	0.107* (0.020)	0.014 (0.016)	1.112 (0.965)	102,965
Sensitivity analyses:					
1. No covariates in model	0.572* (0.257)	0.097* (0.022)	-0.022 (0.022)	0.966 (1.028)	102,491
2. Excluding students with missing covariates	0.780* (0.281)	0.092* (0.022)	0.008 (0.019)	-0.967 (1.398)	42,772
3. Impacts for each of the five imputed datasets					
Imputed dataset 1	0.668* (0.229)	0.108* (0.020)	0.008 (0.015)	1.015 (0.927)	102,491
Imputed dataset 2	0.778* (0.229)	0.107* (0.020)	0.012 (0.015)	0.905 (0.921)	102,356
Imputed dataset 3	0.691* (0.227)	0.103* (0.020)	0.020 (0.015)	1.166 (0.916)	102,643
Imputed dataset 4	0.692* (0.227)	0.104* (0.020)	0.016 (0.015)	0.953 (0.912)	102,298
Imputed dataset 5	0.741* (0.227)	0.113* (0.020)	0.014 (0.015)	1.572+ (0.914)	102,965
4. Equal student weighting	0.699* (0.164)	0.130* (0.015)	0.039* (0.012)	-0.428 (0.729)	102,965
5. Nearest neighbor matching	0.669*539+ (0.321316)	0.105096* (0.030029)	-0.012019 (0.021020)	-0.204136 (1.301268)	10,255263
6. Clustering for the whole-school models	0.710* (0.242)	0.102* (0.036)	0.010 (0.017)	1.118 (1.168)	102,936

Source: School records, Participant Tracking System.

Note: Each row represents a separate regression with standard errors in parentheses. The sample size refers to the outcome with the largest sample. Benchmark impact estimates weighted districts equally, included baseline covariates, and pooled across the five multiple imputed datasets using Rubin's rule to account for variation in estimated impacts within and across datasets. All impact estimates are average treatment effects on the treated. In all IPW models, weights used to balance the treatment and comparison group are defined to be one for all students in the treatment group and $\frac{\hat{p}_i}{1-\hat{p}_i}$ for the comparison group students.

Sensitivity check #5 (nearest neighbor matching) was conducted with replacements and used imputed dataset 1.

See Chapter III for details on how outcomes are defined. Data for school attendance and algebra progression were available in 16 districts, data on ELA test scores was available in 15 districts, and data on credit accumulation was available in 14 districts.

* Indicates significant differences at the 5 percent level.

\+ Indicates significant differences at the 10 percent level.

ELA = English language arts.

A. Estimating models without baseline covariates

Our benchmark estimation model controlled for a host of baseline covariates, such as baseline (from 7th and 8th grade) student demographic, family income, and academic characteristics (see Chapter III, Table III.3). The IPW method yielded balanced treatment and comparison groups, but we included baseline covariates in the impact estimation models to reduce potential remaining differences between the two research groups and to improve the precision of the impact estimates.

Relative to our benchmark approach (top row in Table IV.1), the estimated impacts changed little when we excluded covariates from the model (second row in Table IV.1). This sensitivity analysis confirmed that the IPW procedure was successful in creating balanced treatment and comparison groups. (This conclusion also is supported by the baseline equivalence results discussed in Chapter III.) It suggests also that the covariate imputation procedures did not slant the results. Further, overall conclusions about statistical significance did not change because standard errors did not materially increase when covariates were excluded.

B. Excluding students with missing covariates and estimating separate impacts for each imputed dataset

In our benchmark approach, we imputed missing data for over 60 percent of students who were missing at least one covariate but who had available outcome data (Chapter III, Section A). We imputed these missing records using multiple imputation by chained equations to maximize the number of students included in the analysis and to use information from students' other covariates and outcomes that were not missing. This imputation approach involved creating and calculating impacts on five imputed datasets for each district and then averaging the five sets of impact estimates and estimating standard errors to account for the variation in the impacts both within and across datasets (Rubin 2004).

To examine the extent to which this imputation procedure influenced our results, we conducted two types of sensitivity analyses. First, we excluded from the analysis students with any imputed covariates. This reduced the maximum primary sample size of 102,965 students by roughly 58 percent to 42,772. Second, we estimated impacts separately for each of the five imputed datasets. In each case, the overall conclusions about program effects on the four primary outcomes did not change (Table IV.1): school attendance improved by about 0.6 to 0.8 standard deviations, credit accumulation improved by about 0.10 to 0.12 standard deviations across all models, and impacts on ELA test scores and algebra progression remained statistically insignificant.

C. Impacts weighting students equally

In our benchmark approach, we weighted districts equally to obtain pooled (average) impact estimates across the 16 QED districts. We adopted this approach because we believe that, for purposes of using study results to inform future replication of similar programs as YCC, it is most relevant to policymaking decisions to focus on program effects for the average district (and the distribution of impacts across them). Nonetheless, because sample sizes and impacts varied across districts (and are somewhat correlated), we assessed the sensitivity of the impact findings to how districts are weighted to obtain the overall impact estimates.

To address this issue, the main report (Maxwell et al. 2019) presents impacts when each of the 16 districts, in turn, is omitted from the analysis. The main report also presents information on the distribution of impacts across the 16 districts (such as the number of impact estimates with a positive sign).[11] Here, we present results when students rather than districts were weighted equally to calculate the pooled impact estimates and standard errors. This approach gives more weight to districts with larger treatment group samples and yields more precise impact estimates (by reducing design effects due to unequal weighting). It provides estimates that pertain to the average student rather than the average district.

Table IV.1 reports the impact findings when students are weighted equally. The results provide support for the benchmark impact findings on school attendance, credit accumulation, and algebra progression. The gain in school attendance from YCC program participation remained at 0.7 percentage points and the increase in credit accumulation remained at 0.1 standard deviations. The average student also experienced no statistically significant change in algebra progression. As expected, across all outcomes standard errors were also smaller (over 25 percent smaller in the weighted student compared to weighted district models).

The impact findings on ELA test scores, however, increased and became statistically significant when students are weighted equally. The impact estimate increased from 0.01 to 0.04 standard deviations, and the standard error decreased from 0.02 to 0.01 (a 50 percent decline), together yielding statistical significance at the 5 percent level. Further, impacts were positive in 10 of 15 districts (presented in the main report). The key reason the pooled findings change when students are weighted equally is that impacts on ELA scores were negative in the smallest districts. Thus, these smaller districts had less influence over the pooled estimates when students are weighted equally, yielding impact estimates that are more positive. In sum, the ELA results provide some evidence that YCC program moved the needle on improving ELA scores. However, we view this result as tentative because it is sensitive to whether districts or students are weighted equally.

D. Nearest neighbor matching

As discussed in Chapter III, for the benchmark IPW approach, we constructed weights for the comparison group to minimize preexisting, observable differences between the treatment and comparison groups. The weights were based on predicted probabilities from a logistic regression model where an indicator of treatment or comparison group status was regressed on baseline covariates, separately by cohort and district.

An alternative approach is nearest neighbor matching, which matches each treatment group student to the comparison group students with the closest propensity score. To do this, we used the technique of matching with replacement so that a comparison group student could match to more than one treatment group student, and for simplicity we matched each treatment student to a single comparison student. This approach led to a maximum sample about one-tenth the size of the IPW sample (10,255 compared to 102,936). Thus, the nearest neighbor approach produced less precise impact estimates, even after adjusting the IPW estimates for design effects due to unequal weighting.

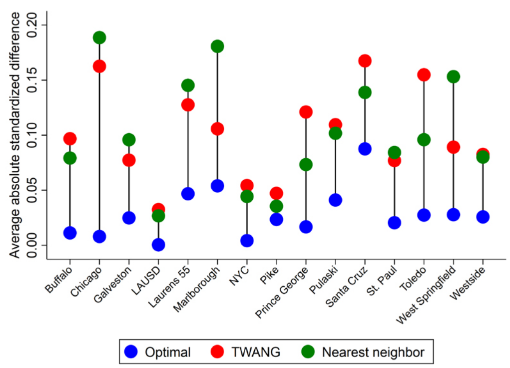
[11] We did not report district-level impacts due to small sample sizes. In addition, data sharing agreements with some districts prohibited data disclosure.

As discussed, the benchmark logistic IPW approach performed better on our matching metrics than the machine learning approach, implemented using the toolkit of weighting and analysis of nonequivalent groups (TWANG) (described in Griffin et al. 2014). Figure IV additionally confirms that the IPW approach yielded smaller average absolute standardized differences in the matching covariates compared to the nearest neighbor approach. Nonetheless, it is worthwhile to compare the impact findings using the nearest neighbor approach to those from our benchmark approach (controlling for observable treatment-comparison differences in the estimation models), because nearest neighbor matching is commonly used in the literature for QED designs.

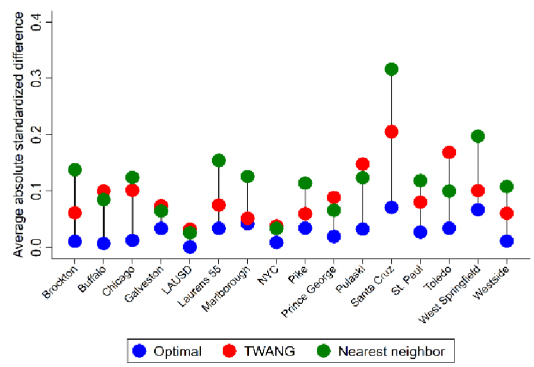
Impact findings using the nearest neighbor matching approach were consistent with those from our benchmark approach (Table IV.1). The impacts on school attendance and credit accumulation remained statistically significant—even though standard errors increased by about 35 and 50 percent, respectively—and the impacts on ELA test scores and algebra progression remained statistically insignificant.

Figure IV.1. Standardized differences in matching covariates using benchmark and alternative matching approaches

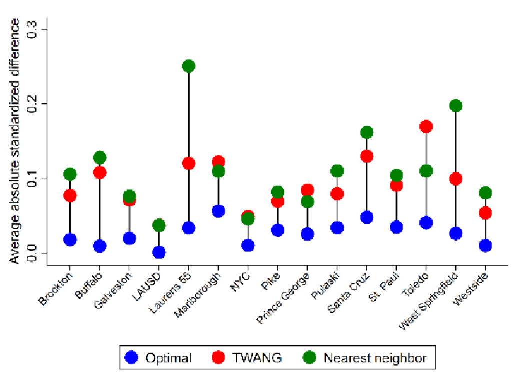
A. Students entering the 9th grade in 2014–2015



B. Students entering the 9th grade in 2015–2016



C. Students entering the 9th grade in 2016–2017



Source: School records, Participant Tracking System.

Note: Each dot shows the average standardized difference in matching covariates for the three specifications. "Optimal" refers to our preferred logit model using IPW. TWANG refers to the machine learning approach that used generalized boosted models to calculate propensity scores. Optimal and TWANG models are trimmed to remove portions of the distribution with poor overlap using the approach in Crump et al. (2009).

E. Adjusting standard errors for clustering for the whole-school YCC program models

In the four districts that used a whole-school model, in which all students in the school received YCC program services, we selected comparison students from similar non-YCC schools in the same district. In our benchmark approach, we assumed that the student-level error term is independent across students. However, school-level effects could also be considered as random components of the error term if schools are treated as the sampling unit rather than students. In this case, the outcomes of students in the same schools could be correlated due to shared school environments (for example, the same teachers and student peer effects) or other factors, such as neighborhood effects outside of the school. These clustering effects could reduce precision by reducing the number of independent observations in the sample, but they will not change the impact estimates themselves under our least squares estimation strategy.

We found that incorporating school-level clustering increases standard errors across all impact estimates (Table IV.1). Clustered standard errors for school attendance increased by roughly 10 percent and more than doubled for credit accumulation. Nonetheless, the impacts on school attendance and credit accumulation remain statistically significant at the 5 percent level.

V. DETAILED DATA TABLES

In this chapter, we collect detailed data tables that support information presented in the text, figures, and tables of the impact report *Building College and Career Pathways for High School Students: Youth CareerConnect* (Maxwell et al. 2019) and that support information presented in Chapter III of this report. We present the tables in the order in which they are referenced in the text of the impact. Table V.1 supports material in Chapter I in the impact report; Tables V.2 and V.3 support Chapter II in the impact report; Tables V.4 and V.5 support Chapter III; in the impact report Tables V.6 through V.13 support Chapter IV in the main report, and Tables V.14 through V.16 support Chapter III of this report.

We used several guidelines when developing the tables in this chapter:

- Tables include the maximum number of respondents (where appropriate), even though item-specific nonresponse might reduce that number in some cells.
- We use *italics* to identify cells in which fewer than 75 percent of respondents who were asked a question actually answered it.
- Percentages may not sum to 100 because of rounding.
- When we present information on the districts included in the RCT, we use Chicago to designate the Chicago Public School system, LA for the Los Angeles Unified School District, Pike for the Metropolitan School District of Pike Township, and Pulaski for the Pulaski County School District.
- * Indicates significant differences at the 5 percent level.

  + Indicates significant differences at the 10 percent level.
- The grade we assign in the Participant Tracking System is based on the student grade at enrollment and assumes that students make standard academic progress. For example, a student who enrolled in YCC as a grade 10 student in the 2014–2015 school year is considered a grade 11 student in the 2015–2016 school year.
- Acronyms include the following:

AJC	American Job Center
ACT	American College Test
AP	advanced placement
BIF	baseline information form
CACE	complier average causal effect
CPR	cardiopulmonary resuscitation
CTE	career and technical education
FRPL	Free and reduced price lunch
FAFSA	Free Application for Federal Student Aid

FUS	follow-up survey
GED	General Educational Development
HS	high school
IDP	Individual development plan
IEP	Individualized Education Program
IT	information technology
ITT	intention-to-treat
n.a.	not applicable
NA	not available
NR	not reported (cell contains fewer than 9 individuals)
OSHA	Occupational Safety and Health Administration
PTS	Participant Tracking System
QED	quasi-experimental design
RCT	randomized controlled trial
SE	Standard error
SLC	small learning community
WBL	work-based learning
YCC	Youth CareerConnect

Table V.1. Characteristics of participants, September 30, 2018 (percentage unless otherwise stated)

			RCT sample	
	All YCC students	QED sample	Chicago, LA, Pike, Pulaski	Chicago, Pike, Pulaski
Characteristics				
Female	44.0	41.5*	51.3*	51.5*
Ethnicity				
Hispanic	42.9	39.8*	31.8*	15.9*
Race				
Black	23.4	35.6*	44.7*	55.9*
White	57.4	41.8*	51.6*	41.0*
Other	8.6	10.5*	3.5*	3.1*
Age at enrollment (in years)	15.0	14.7*	14.6*	14.8^{+}
Eligible for FRPL	46.7	60.2*	70.6*	67.1*
English language learner	12.0	8.1*	9.6	7.8*
Had a disability	6.5	6.5	9.4*	7.8
Grade at enrollment				
9th	47.3	61.2*	65.8*	56.6*
10th	23.8	20.3*	31.0*	39.3*
Number of students	**29,724**	**9,159**	**374**	**295**

Source: PTS as of the last day of YCC program enrollment, September 30, 2018.

Notes: The percentages for race do not add to 100 because race was not disclosed in all cases. Statistical significance is based on two-tailed *t*-tests differences between each subsample and the rest.

Table V.2. Services YCC participants received (percentage unless otherwise stated)

	All YCC students		Analytic samples		
	2016	2018	QED	RCT Chicago, LA, Pike, Pulaski	RCT Chicago, Pike, Pulaski
Left YCC	21.7	47.2	49.6*	15.3*	13.9*
Career focus area[a]					
Industry					
Health care and social assistance	23.5	27.2	22.9*	20.6*	9.5*
Professional, scientific, and technical services	20.1	22.3	19.0*	35.4*	35.0*
IT	9.9	12.1	17.7*	24.4*	31.0*
Manufacturing	8.6	10.7	10.1*	11.5	14.6*
Management of companies and enterprises	7.5	4.7	10.5*	0.0*	0.0*
Other services (except public administration)	3.0	9.2	3.5*	0.0*	0.0*
Unclassified	10.5	8.3	9.8*	7.2	9.2
Occupation focus area					
Architecture and engineering	20.5	25.3	27.6*	11.1*	23.1
Computer and mathematical	15.2	20.3	19.5+	19.4	0.0*
Health care practitioners and technicians	13.8	17.0	13.5*	50.0*	33.8*
Health care support	6.7	8.3	12.9*	0.0*	0.0*
Business and financial operations	5.0	5.5	5.8	0.7*	1.5
Student has not chosen	8.9	9.6	9.3	18.1*	40.0*
Obtained industry or occupational credential	9.9	8.0	8.1	32.9*	42.5*
Took industry-specific courses	70.7	80.0	84.0*	94.1*	95.9*
If took industry-specific courses, enrollment restrictions:					
Course open only to YCC students	65.8	69.7	85.4*	80.6*	77.3*
Course open to non-YCC students	34.2	30.3	14.6*	19.4*	22.7*
WBL					
At school (career fairs, career exploration talks, and mock interviews)					
Percentage with employer providing a service	37.4	45.2	56.1*	63.2*	80.1*
If employer-provided service:					
Average months in YCC before first employer service	7.4	8.4	6.6	6.6	7.4
Average number of quarters employer service provided	2.5	3.0	2.8*	2.8*	2.5
Mentoring	40.1	50.9	51.9*	49.1*	40.1
If received mentoring:					
Average months in YCC before first service	10.8	10.6	13.6*	9.5+	7.1*
Average number of quarters	2.1	2.8	3.1*	2.0*	2.3*
At workplace					
Internship	14.1	19.1	5.2*	14.2*	17.3

	All YCC students		Analytic samples		
	2016	2018	QED	RCT Chicago, LA, Pike, Pulaski	RCT Chicago, Pike, Pulaski
If received internship:					
Average months in YCC before first internship	12.5	15.7	22.6*	12.1*	12.2*
Completed an internship	92.5	96.7	95.1*	92.5+	92.2+
Average number of quarters participated in an internship	1.2	1.3	1.3*	1.4+	1.4*
More than one internship	21.5	25.7	30.0*	32.1	33.3
A paid internship	45.5	46.0	67.1*	75.5*	74.5*
An unpaid internship	57.0	58.2	38.3*	32.1*	33.3*
An internship with an employer partner	52.5	53.6	71.1*	90.6*	90.2*
An internship in student's field/industry	63.8	60.3	45.7*	56.6	54.9
An internship in student's occupation focus	17.9	15.0	26.0*	3.8*	3.9*
Other work-based experiences (job shadowing, exposure to various aspects of an industry, and other exposures to the world of work)	50.4	62.8	68.7*	67.3+	83.3*
If received other work-based experience:					
Average number of quarters received work experience	1.9	2.4	2.9*	4.3*	4.4*
Average months in YCC before first work experience	6.8	7.5	9.8*	4.3*	4.1*
Counseling services					
Completed initial IDP	43.5	53.3	52.4*	81.2*	84.7*
Completed FAFSA	8.7	15.6	14.2*	0.5*	0.7*
Received career/academic counseling	84.4	90.2	97.1*	98.4*	97.9*
If received career/academic counseling:					
Average months in YCC before first service	3.9	3.4	4.4*	2.5*	1.5*
Average number of quarters	3.8	4.7	5.3*	4.7	5.3*
Percentage of participants receiving support services	35.2	52.4	60.2*	68.1*	66.2*
If received support services:					
Average months in YCC before first service	7.3	9.2	12.5*	6.8*	6.6*
Average number of quarters	2.0	2.2	2.2*	2.6*	2.4*
Number of students	**13,073**	**29,724**	**9,159**	**374**	**295**

Source: PTS for the quarters ending June 30, 2016, and September 30, 2018.

Notes: Statistical significance is based on two-tailed *t*-tests differences from the all YCC students in 2018.

[a] YCC programs were required to report an industry and/or occupation focus.

Table V.3. Services and activities that schools offered to YCC students, 2015 and 2017 (percentage of grantees)

	2015	2017	Difference
Preparing for both college and career			
Integrated academic and career-focused coursework			
Standards and assessments	100.0	100.0	0.0
Academic curriculum aligned to state career and college-ready standards	95.8	100.0	4.2
Curriculum and instructional materials in career-related classes were based on industry standards	100.0	100.0	0.0
Academic courses	100.0	100.0	0.0
Graduates expected to complete coursework successfully to attend two-year college or apprenticeship training programs	100.0	100.0	0.0
Flexibility provided to students with special needs	100.0	100.0	0.0
Coursework reached high levels of English and mathematics (four years in each)	100.0	90.9	-9.1
Graduates expected to complete coursework successfully in order to attend four-year colleges	81.3	81.8	0.5
CTE courses	100.0	100.0	0.0
Distinctive career theme integrated across all years of the program	100.0	100.0	0.0
CTE courses sequenced to build technical skills from year to year	100.0	100.0	0.0
Students took courses for a career ladder in H-1B industry or occupation	100.0	100.0	0.0
Aimed to develop career-specific skills needed to enter the field	100.0	100.0	0.0
Aimed to develop technological (for example, computer) skills	100.0	100.0	0.0
Sequence of CTE courses enabled students to obtain skill certifications recognized by employers	95.5	95.8	0.3
Students able to demonstrate knowledge of a variety of careers and related educational requirements in career field	90.5	86.4	-4.1
Curriculum integration	100.0	100.0	0.0
Academic courses used examples related to career theme	85.0	100.0	15.0
Students were shown how their academic subjects relate to each other and apply in the context of adult professional work	95.8	95.7	-0.1
Students engaged in projects that applied skills from several courses (for example, senior or capstone projects)	95.0	95.2	0.2
Career-focused classes also taught academic skill building	100.0	94.7	-5.3
Integrated academic and career skill building			
Instruction (project-based learning used in courses, occupational skills training, students complete a capstone course)	95.8	100.0	4.2
Project-based learning used in courses	95.7	100.0	4.3
Occupational skills training	70.8	82.6	11.8
Students complete capstone course that brings together knowledge learned	38.1	73.9	35.8
Certifications and credentials	75.0	100.0	25.0
Courses leading to industry-recognized credential	73.9	100.0	26.1
Preparation for certification examination	60.9	95.8	34.9
Stackable credentials	50.0	70.8	20.8
Skill badges	13.6	25.0	11.4

	2015	2017	Difference
Postsecondary education supports			
College visits	79.2	100.0	20.8
College faculty or representatives visited HS classes	70.8	91.7	20.9
Campus visits to two-year colleges	70.8	100.0	29.2
Campus visits to four-year colleges	62.5	91.7	29.2
Postsecondary preparatory coursework	79.2	100.0	20.8
Courses articulate to a two- or four-year college program	62.5	95.7	33.2
Dual-enrolled coursework	65.2	100.0	34.8
College entrance examinations preparation courses	41.7	75.0	33.3
AP coursework	50.0	66.7	16.7
Postsecondary financial assistance	45.8	100.0	54.2
Financial aid planning assistance	37.5	95.8	58.3
Assistance with completion of the FAFSA	37.5	95.8	58.3
Tuition or financial assistance	33.3	82.6	49.3
Work-readiness training			
Assessment	100.0	100.0	0.0
Workplace skills were incorporated and assessed	95.8	100.0	4.2
Competency-based assessments were offered	95.5	100.0	4.5
Several assessments reflected practices in career field	80.0	95.0	15.0
Soft skills training	83.3	100.0	16.7
Work-readiness assessments (for example, WorkKeys)	69.6	83.3	13.7
Citizenship training	69.6	75.0	5.4
Training in decision making and determining priorities	68.2	87.5	19.3
Peer-centered activities (peer mentoring or tutoring)	65.2	79.2	14.0
Community service learning	65.2	87.5	22.3
Organizational and teamwork training	60.9	91.3	30.4
Workplace behavioral expectations	100.0	100.0	0.0
About work expectations for attendance and the need to adhere to them	100.0	100.0	0.0
About work expectations for punctuality and the need to adhere to them	100.0	100.0	0.0
To dress appropriately for a position and duties	100.0	95.8	-4.2
Workplace culture and communication	100.0	100.0	0.0
To speak clearly and communicate effectively–orally and non-orally	100.0	100.0	0.0
To accept direction, feedback, and constructive criticism with a positive attitude and use information to improve work performance	95.5	100.0	4.5
To understand requirements for career pathways (for example, that they need to attend a two- or four-year college or earn a certificate)	90.9	100.0	9.1
To demonstrate understanding of workplace culture and policy	91.3	91.7	0.4
Workplace performance expectations	95.7	100.0	4.3
To relate positively with coworkers and work productively with individuals and in teams	95.7	100.0	4.3
To participate fully in a task or project from initiation to completion	91.3	100.0	8.7
To meet quality standards	87.0	100.0	13.0
To exercise sound reasoning and analytic thinking to solve workplace problems	82.6	95.8	13.2

	2015	2017	Difference
Connecting students with career track employment			
School-based career activities			
Connecting to employers: Mentoring	87.0	100.0	13.0
Group mentoring	65.2	87.0	21.8
Individual mentors	56.5	87.5	31.0
Connecting to employers: Other school-based activities	91.7	95.8	4.1
Speakers to describe workplaces and careers	91.7	95.8	4.1
WBL activities			
Connecting to employers: Internships	58.3	95.8	37.5
Unpaid internships	39.1	83.3	44.2
Paid internships	37.5	79.2	41.7
Internships at a place of work, but not required	27.3	62.5	35.2
Required internships at a place of work	21.7	37.5	15.8
Virtual internships	14.3	16.7	2.4
Connecting to employers: Other WBL	91.7	100.0	8.3
Field trips to workplaces	87.5	100.0	12.5
Job shadowing for individual students	69.6	83.3	13.7
Group job shadowing	60.9	79.2	18.3
Other workforce preparation activities	79.2	100.0	20.8
Résumé-writing workshops	52.2	87.5	35.3
Mock interviews staged by industry professionals	50.0	87.5	37.5
Attendance at trade associations or professional conferences	56.5	75.0	18.5
Connecting students to a training program	43.5	75.0	31.5
Referral to programs at an AJC	9.5	41.7	32.2
Apprenticeships	4.5	16.7	12.2
Offering academic and nonacademic supports			
SLC			
SLCs for students	87.5	91.3	3.8
Students attend a school within a school	66.7	54.6	-12.1
Students take classes together as a cohort at each grade level	52.2	82.6	30.4
Students have a physical space available only to them	41.7	65.2	23.5
Students attend a separate small school	4.3	9.1	4.8
SLCs for teachers	87.0	91.3	4.3
Teachers scheduled to work with a specific group of students	78.3	82.6	4.3
Teachers have a regularly scheduled common planning period	66.7	78.3	11.6
Individual counseling			
IDP	95.5	100.0	4.5
Working with students to develop an IDP	95.5	100.0	4.5
Reviewing and updating a student's IDP	95.5	100.0	4.5
Educational and career goals	100.0	100.0	0.0
Helping students identify feasible educational and career goals	100.0	100.0	0.0
Providing career interest inventories	85.7	91.7	6.0
Assessing students' ability to identify and obtain employment in chosen career	66.7	83.3	16.6
Providing occupational information based on local labor markets	50.0	87.5	37.5

	2015	2017	Difference
Educational and career planning and preparation	100.0	100.0	0.0
Assisting in selecting courses that meet career and educational objectives	100.0	100.0	0.0
Identifying WBL experiences to complement career aspirations	77.3	95.8	18.5
Assisting in selecting and applying to postsecondary education	77.3	100.0	22.7
Assisting with résumé preparation or interview skills	75.0	95.8	20.8
Determining ways to finance postsecondary education or training	71.4	100.0	28.6
Assisting in selecting and applying to postsecondary training	70.0	100.0	30.0
Helping with job search and placement	65.0	83.3	18.3
Facilitating a relationship with or identifying resources at AJCs	36.8	54.6	17.8
Special populations support	100.0	100.0	0.0
Providing for unique needs of students with physical or learning disabilities	100.0	95.8	-4.2
Encouraging and supporting low-income and underrepresented students to enroll in YCC	100.0	100.0	0.0
Providing for unique needs of English language learners	90.0	87.5	-2.5
Academic and nonacademic supports			
Academic support	82.6	100.0	17.3
Developmental or special education	81.8	79.2	-2.6
Individualized tutoring	72.7	100.0	27.3
Homework assistance	66.7	91.7	25.0
Acceleration strategies to get lower-performing students up to speed by graduation	57.1	91.7	34.6
Financial support	83.3	100.0	16.7
Transportation	70.8	95.8	25.0
School supplies	60.9	66.7	5.8
Work clothes or uniforms	52.2	70.8	18.6
Costs related to credential attainment for individual participants (for example, fees for certification examinations)	50.0	91.7	41.7
Work-related equipment (for example, personal computer)	45.5	70.8	25.3
Fees associated with other tests or examinations (for example, ACT)	37.5	70.8	33.3
Child care	13.6	8.3	-5.3
Other dependent care (for example, elder care)	0.0	0.0	0.0
Health and well-being support	77.3	66.7	-10.6
Psychological counseling (in-house or as referral)	71.4	58.3	-13.1
Health care services/referrals	63.6	66.7	3.1
Support for special populations	83.3	87.5	4.2
Services for students from low-income families	83.3	83.3	0.0
Services for students with disabilities	83.3	87.5	4.2
Services for English language learners	75.0	79.2	4.2
Services for pregnant and parenting students	68.2	66.7	-1.5
Number of respondents	**24**	**24**	**n.a.**

Source: 2015 and 2017 grantee surveys.

Table V.4. Baseline characteristics by cohort (percentage unless otherwise stated)

	Cohort		
Baseline characteristic	**2014**	**2015**	**2016**
Age at entry into 8th grade (in years)	14.1	14.1	14.1
Female	41.6	40.7	43.4
Race/ethnicity			
American Indian	0.4	0.3	0.4
Asian	5.7	5.5	6.6
Black	36.6	34.5+	36.1
Hispanic	23.1	25.5*	24.2
White	32.5	30.9	31.1
Multiracial	1.7	3.3*	1.6
Low -income status, 7th grade	64.5	67.3+	66.7
Low-income status, 8th grade	64.1	65.8	65.6
School attendance, 7th grade	94.3	94.7	94.7
School attendance, 8th grade	95.0	94.6+	94.8
Ever suspended, 7th grade	12.9	14.3	10.3*
Ever suspended, 8th grade	11.7	12.6	12.0
Math assessment scores, 7th grade (*z*-score)	0.1	0.0	0.1
Math assessment score, 8th grade (*z*-score)	0.1	0.1	0.1
Reading assessment scores, 7th grade (*z*-score)	0.0	0.0	-0.0
Reading assessment score, 8th grade (*z*-score)	0.0	0.0	0.1
English language learner, 8th grade	7.1	8.8*	10.4*
Received special education services, 8th grade	13.2	14.9	11.3*
Repeated 7th or 8th grade	6.0	7.0	7.3+
Sample size	**45,457**	**33,121**	**35,735**

Source: School records, PTS.

Notes: The table shows averages among YCC students by entering cohort. Only the 15 districts with students entering in each year are included in the analysis. Means give equal weight to each district.

*Indicates significant difference from the 2014 cohort at the 5 percent level.

+ indicates significant difference from the 2014 cohort at the 10 percent level.

Table V.5. Districts included in subgroup analyses of program services

	In subgroup analysis of program service		
District	Internship	Mentor	IDP
Brockton Public Schools			
Buffalo Public Schools		X	X
Chicago Public Schools			
Galveston Independent School District	X	X	
Laurens County School District 55		X	
Los Angeles Unified School District	X	X	X
Marlborough Public Schools			
Metropolitan School District of Pike Township		X	X
New York City Department of Education	X	X	X
Prince George's County Public Schools	X	X	X
Pulaski Public Schools			
Santa Cruz Valley Unified School District			
St. Paul Independent School District 625			X
Toledo Public Schools		X	X
West Springfield School District			X
Westside Community Schools			X
Count	**4**	**8**	**9**

Note: Districts were excluded from the analysis if fewer than 50 treatment students either did or did not receive the service. An X indicates that the district was included in the subgroup analysis. A blank cell indicates that it was not.

Table V.6. Preparing students for both college and career (percentage of students)

	Treatment	Control	Overall
Integrated academic and career-focused coursework and skill building			
Had a career focus in two or more classes	81.3*	67.1	74.2
Completed a capstone course	*44.8*	*45.4*	*45.1*
Took a dual-enrollment course	72.2	69.4	70.8
Took an AP course	62.6	54.5	58.5
Postsecondary education supports			
Received assistance with financial aid planning	39.8	42.8	41.3
Received assistance with completing a FAFSA	37.0	36.7	36.8
Received assistance with learning how to apply to college	56.8	57.3	57.1
Visited one or more two-year college campuses	49.1	54.7	51.9
Visited one or more four-year college campuses	54.9	58.2	56.5
Had someone from college come talk to their HS classes	82.5	76.3	79.3
Work readiness training			
Worked in a school-based enterprise	27.8	34.5	31.2
Practiced interviewing	58.2	50.6	54.4
Worked on developing a résumé	68.3	68.7	68.5
Learned how to negotiate a salary for a job	29.7	38.2	34.0
Learned how to work on a team	95.0	97.3	96.1
Learned how to make decisions	92.7	90.0	91.3
Learned how to lead a team	84.2	77.1	80.7
Learned how to handle conflict	85.6	85.8	85.7
Learned how to be a good citizen	91.3	89.7	90.5
Did community service learning	68.0	63.9	65.9
Took a test to see what career interests they had	81.2	84.5	82.8
Took a test for readiness for work (for example, WorkKeys)	43.6	41.7	42.7
Earned a badge for a specific skill, talent, or other achievement	38.6	39.1	38.9
Took courses that led to an industry-recognized credential	37.6	38.5	38.1
Prepared for a certification exam	39.7	38.7	39.2
Earned a degree, certificate, or license at school that would help them get a job	26.9	28.9	28.0
Leadership development opportunities	58.9	63.2	61.1
Training in peer counseling	15.1	16.4	15.8
Number of respondents	**279**	**157**	**436**

Source: FUS.

Table V.7. Connecting students with career-track employment through employer engagement (percentage of participation)

	Treatment	Control	Overall
School-based			
Mentoring: Regularly talked…			
One-on-one about jobs with someone outside school	47.2	48.5	47.9
As a group about jobs with someone from outside school	38.0	36.7	37.3
One-on-one about school with someone from school (not counselor)	57.9	54.5	56.2
As part of a group about school with someone from school (not counselor)	52.8	56.4	54.6
Workplace preparation: Participated in activities or classes…			
That improved computer skills	75.2	80.7	77.9
On how to do better in school	71.6	73.6	72.6
About what is needed for work success	77.0+	85.6	81.4
That taught technical skills that could be used in a job	69.8	74.6	72.2
That prepared for college entrance exams	73.4*	86.6	80.1
Work-based			
Field trips to workplaces	69.1*	54.3	61.7
Job shadowing			
One-on-one at work to learn what someone does	50.2	45.3	47.8
As part of a group at work to learn what someone does	53.0	46.1	49.5
Internships			
Paid	16.0	13.4	14.7
Unpaid	10.9	9.2	10.0
Apprenticeship	6.9	6.0	6.4
Number of respondents	**279**	**157**	**436**

Source: FUS.

Table V.8. Offering student supports (percentage of students)

	Treatment	Control	Overall
Individualized academic and career counseling			
Was referred to and enrolled in a training program outside school	24.1	22.1	23.1
Was referred to a program at a local AJC	10.2	6.5	8.3
Talked to a counselor about which classes to take	88.4	87.5	87.9
Talked to a counselor about going to college or education goals	78.3	79.7	79.0
Talked to a counselor about work or career goals	68.7	70.5	69.6
SLCs			
Had a physical space to gather	89.9	90.7	90.3
Had two or more classes with the same group of students	79.3	72.6	75.9
Took two or more classes with the same teacher	37.1	39.9	38.5
Had projects that counted toward a grade in more than one course	79.6	78.1	78.9
Academic and nonacademic supports			
Academic support services at school			
Individualized tutoring	41.8+	54.1	48.1
Homework assistance	60.8*	72.7	66.8
Special education programs or services, such as an IEP	27.1	24.2	25.6
Help with making up credit for classes you didn't take or pass	46.8	50.8	48.8
Nonacademic supports			
Services provided at school			
Health care services or referrals	27.5	26.0	26.7
Psychological counseling either at school or referred for services outside school	20.7	28.0	24.5
Services for English language learners	24.8	20.4	22.6
Services for students with physical disabilities	19.6	18.1	18.8
Services for students from low-income families	42.6	34.5	38.5
Services for pregnant and parenting students	12.7	8.2	10.4
Financial assistance provided by school			
Test fees, for example, for SAT or ACT, certification exams	50.6	50.8	50.7
School supplies, such as laptops or textbooks	74.9	67.4	71.1
Work clothes or uniforms	19.8	15.5	17.6
Work-related equipment, such as drafting tools or personal computer	37.2	40.5	38.9
Transportation, such as bus transportation or passes	76.4	73.9	75.2
Childcare	4.7	3.8	4.2
Other dependent care, such as elder care	*4.4*	*2.6*	*3.5*
Number of respondents	**279**	**157**	**436**

Source: FUS.

Table V.9. Knowledge and expectations (percentage of students)

	BIF			FUS		
	Treatment	Control	Overall	Treatment	Control	Overall
Education knowledge						
Courses to attend a four-year college	NA	NA	NA	77.2	79.8	78.5
Courses to attend a two-year college	NA	NA	NA	75.9	76.2	76.1
Courses to graduate from HS	NA	NA	NA	97.1	98.4	97.7
Education/training needed beyond HS for desired career	NA	NA	NA	88.3	84.4	86.4
Education expectations						
Vocational certificate						
Yes	46.5	47.0	46.7	17.0	15.1	16.1
No	11.3*	20.5	14.6	46.9	51.1	49.0
Don't know	42.2*	32.4	38.7	36.1	33.8	35.0
Level of education						
Less than HS degree	0.0	0.0	0.0	0.6	0.6	0.6
HS diploma or GED	4.6	4.6	4.6	9.6	5.7	7.6
Technical or trade school	0.0*	1.7	0.6	2.0	1.9	2.0
Two-year college degree	6.9	9.2	7.8	9.2	7.0	8.1
Four-year college degree	38.6	38.2	38.4	40.2	48.9	44.5
Advanced degree, such as a master's degree or Ph.D.	49.8	46.2	48.5	38.5	35.8	37.2
Employment expectations						
Expect to be working at age 30	NA	NA	NA	*98.5*	*100.0*	*99.2*
If yes, expected job/occupation at age 30						
Health diagnosing and treating practitioners	NA	NA	NA	*29.5*	*33.4*	*31.3*
Engineers	NA	NA	NA	*13.3*	*16.2*	*14.7*
Health technologists and technicians	NA	NA	NA	*8.1*	*8.4*	*8.2*
Computer occupations	NA	NA	NA	*5.7*	*5.6*	*5.7*
Other	NA	NA	NA	*43.4*	*36.3*	*40.1*
Certainty about job/occupation						
Very certain	NA	NA	NA	44.1	46.9	45.4
Fairly certain	NA	NA	NA	51.9	43.5	48.0
Not certain	NA	NA	NA	4.0+	9.6	6.6
Number of respondents	**338**	**189**	**527**	**279**	**157**	**436**

Source: Student BIF and FUS.

Table V.10. Employment outcomes (percentage unless otherwise stated)

	BIF			FUS		
	Treatment	Control	Overall	Treatment	Control	Overall
Work readiness skills[a]						
Learned how to…						
Work on a team	NA	NA	NA	95.0	97.3	96.1
Make decisions	NA	NA	NA	92.7	90.0	91.3
Lead a team	NA	NA	NA	84.2	77.1	80.7
Handle conflict	NA	NA	NA	85.6	85.8	85.7
Be a good citizen	NA	NA	NA	91.3	89.7	90.5
Participated in activities or classes for						
Computer skills	NA	NA	NA	75.2	80.7	77.9
Understanding what is needed to be successful at work	NA	NA	NA	77.0[+]	85.6	81.4
Technical skills	NA	NA	NA	69.8	74.6	72.2
Earned						
License or certificate for a job	NA	NA	NA	26.9	28.9	28.0
Badge	NA	NA	NA	38.6	39.1	38.9
Took courses that led to an industry-recognized credential	NA	NA	NA	37.6	38.5	38.1
Degrees, certificates, and licenses						
Earned degree, certificate, or license through HS	NA	NA	NA	6.8	8.3	7.6
If yes, what certificate, degree, or license?						
CPR	NA	NA	NA	*31.6*	*50.4*	*43.0*
IT/tech support	NA	NA	NA	*20.9*	*0.0*	*8.2*
Microsoft	NA	NA	NA	*20.6*	*6.0*	*11.7*
Adobe	NA	NA	NA	*6.5*	*21.7*	*15.7*
OSHA	NA	NA	NA	*7.5*	*20.4*	*15.3*
Paid work history						
Ever worked for pay	20.7	17.0	19.4	66.8	69.5	68.1
Currently working, if ever worked	41.8	34.4	39.4	40.6	33.9	37.3
If ever worked:						
Timing of work						
Both summer and school year	36.5	45.2	39.4	62.4	58.3	60.3
Summer only	44.4	45.2	44.7	22.9	30.7	26.9
School year only	19.0	9.7	16.0	14.7	11.0	12.8
Had a job arranged through school	NA	NA	NA	22.5	18.1	20.2
Average number of hours worked per week[b]	*11.4*	9.8	*10.8*	21.1	17.9	19.5
Occupation (current or most recent)[c]						
Personal care and service workers, other	*30.8*	28.6	*30.0*	8.7	4.8	6.7
Grounds maintenance workers	*17.3*	21.4	*18.8*	1.8	3.7	2.8
Construction trades workers	*5.8*	10.7	*7.5*	0.5	1.9	1.2
Food and beverage serving workers	*5.8*	3.6	*5.0*	20.6	21.1	20.9

	BIF			FUS		
	Treatment	Control	Overall	Treatment	Control	Overall
Retail sales workers	*1.9*	0.0	*1.3*	28.7	18.3	23.5
Other	*38.5*	35.7	*37.5*	39.7	50.1	44.9
Industry (current or most recent)[d]						
Food services and drinking places	*5.8*	7.1	*6.3*	34.5	25.0	29.6
General merchandise stores	*0.0*	0.0	*0.0*	13.4	5.0	9.0
Food and beverage stores	*0.0*	0.0	*0.0*	6.4	3.8	5.1
Administrative and support services	*19.2*	17.9	*18.8*	2.5	0.9	1.7
Other	*75.0*	75.0	*75.0*	43.2*	65.3	54.6
Number of student respondents	**338**	**189**	**527**	**279**	**157**	**436**

Source: Student BIF and FUS.

[a] Students were asked about learning and participation at school.

[b] Average hours worked per week include the number of hours worked at all paid jobs; if not currently working, respondents provided the number of hours per week worked in their most recent job.

[c] Jobs are categorized according to three-digit Standard Occupational Coding system. Occupation codes that represent less than 5 percent of student responses on both the BIF and FUS are not shown.

[d] Jobs are categorized according to three-digit North American Industry Classification system. Industry codes that represent less than 5 percent of student responses on both the BIF and FUS are not shown.

Table V.11. Education outcomes (percentage unless otherwise stated)

	BIF			FUS		
	Treatment	Control	Overall	Treatment	Control	Overall
Graduation						
Enrolled in HS in 2018–2019	NA	NA	NA	94.0	92.8	93.4
Plan to get HS diploma or GED						
Spring 2018	NA	NA	NA	1.8	1.6	1.7
Fall 2018	NA	NA	NA	0.8	0.0	0.4
Spring 2019	NA	NA	NA	43.1	45.8	44.5
Fall 2019	NA	NA	NA	0.3	0.7	0.5
Spring 2020	NA	NA	NA	53.1	50.5	51.8
Fall 2020	NA	NA	NA	0.4	1.4	0.9
Behavior at school						
Late for school						
Ever happened	45.2	46.0	45.5	55.8	57.6	56.7
Happened three or more times	14.3[+]	8.5	12.2	17.0	13.6	15.3
Cut or skipped class						
Ever happened	7.4	6.4	7.0	8.5	13.4	10.9
Happened three or more times	1.5	2.1	1.7	1.4	0.5	0.9
Unexcused absence						
Ever happened	36.3	34.0	35.5	55.0	55.3	55.1
Happened three or more times	7.4	7.4	7.4	15.1[+]	7.5	11.4
Got in trouble for not following school rules						
Ever happened	23.8	22.5	23.3	16.5	14.3	15.4
Happened three or more times	5.1	4.3	4.8	3.7	1.6	2.6
Suspended or put on probation						
Ever happened	5.9	6.4	6.1	6.6	3.7	5.2
Happened three or more times	1.2	0.0	0.8	0.9	0.9	0.9
School satisfaction and engagement						
Percentage that say they						
Like school a lot	35.7	37.8	36.5	32.8	35.9	34.3
Like school	43.5	42.6	43.1	47.9	38.9	43.5
School is okay	18.5	18.1	18.3	18.9	25.2	22.0
Don't like school at all	2.4	1.6	2.1	0.3	0.0	0.2
Percentage that say grades are						
Very important	79.3	77.8	78.7	75.5	74.5	75.0
Important	18.6	20.1	19.2	21.4	22.3	21.9
Somewhat important	1.8	1.6	1.7	3.1	3.2	3.2
Not important at all	0.3	0.5	0.4	0.0	0.0	0.0
Average student grit score[a]	3.7	3.7	3.7	3.5[+]	3.7	3.6
Average weekly hours on homework						
During school hours	2.2	2.3	2.2	3.6	3.2	3.4
Weekdays before or after school	3.9	3.6	3.8	5.2	5.5	5.4
During weekend	2.7	2.3	2.6	3.2	2.9	3.1
Participated in a school-sponsored activity	86.5	83.3	85.4	87.2	90.3	88.7

	BIF			FUS		
	Treatment	Control	Overall	Treatment	Control	Overall
Sports	57.9	53.6	56.4	50.6	58.4	54.4
Number, if participated	2.0	1.8	1.9	2.3	2.0	2.1
Music or drama	50.0	52.5	50.9	33.5	41.8	37.6
Number, if participated	1.4	1.5	1.5	2.0	1.7	1.8
Student government	9.3	9.7	9.4	14.9	15.9	15.4
Number, if participated	*1.3*	*1.9*	*1.5*	2.0	1.4	1.7
Honor society	17.0	20.5	18.2	23.3	17.2	20.3
Number, if participated	*1.5*	*1.3*	*1.4*	1.6	1.8	1.7
Clubs	41.1	36.9	39.6	54.0	51.0	52.5
Number, if participated	2.1	2.1	2.1	2.2	2.3	2.3
Vocational education club or student organization	10.6	10.9	10.7	21.6	17.3	19.5
Number, if participated	*1.9*	*1.8*	*1.9*	2.4	1.8	2.1
Other school activity	24.0	*25.0*	*24.4*	5.8	7.0	6.4
Number, if participated	*2.3*	*1.6*	*2.0*	NR	NR	NR
Criminal justice involvement						
Never arrested or taken into custody for a crime/offense	96.9	98.4	97.5	95.6	98.0	96.5
Ever arrested or taken into custody for a crime/offense	3.1	1.6	2.5	4.4+	2.0	3.5
Substance abuse						
Never drank alcohol	97.3	97.9	97.5	86.1	83.4	85.1
Ever drank alcohol	2.7	2.1	2.5	13.9	16.6	14.9
Drank last month, if ever drank	NR	NR	NR	16.1	16.0	16.1
Never used or tried marijuana	95.5	96.3	95.8	84.6	87.5	85.6
Ever used or tried marijuana	4.5	3.7	4.2	15.4	12.5	14.4
Used marijuana last month, if ever tried	NR	NR	NR	40.0	52.6	44.4
Never used or tried another type of drug	99.4	98.9	99.2	99.3	97.4	98.6
Ever used or tried another type of drug	0.6	1.1	0.8	0.7	2.6	1.4
Used another drug last month, if ever tried	NR	NR	NR	NR	NR	NR
Postsecondary education/training						
Took a dual-enrollment course	NA	NA	NA	72.9	71.4	72.4
Took an AP course	NA	NA	NA	63.7	58.8	61.9
Number of respondents	**338**	**189**	**527**	**279**	**157**	**436**

Source: Student BIF and FUS.

[a] Grit score is computed by using Angela Duckworth's short (eight-item) grit scale (Duckworth and Quinn 2009). Students answer eight questions, each of which is scored from 1 to 5. A student's overall grit score is the average of scores across all eight questions. Scores range from 1 ("not at all gritty") to 5 ("extremely gritty"). The table excludes students who did not answer all eight grit questions. For the questions and information about scoring, see https://examinedexistence.com/wp-content/uploads/2014/09/grit-vs-iq-angela-duckworth.pdf.

Table V.12. Impacts of YCC on HS behaviors, postsecondary preparation, and employment readiness (ITT) (percentage unless otherwise stated)

	Treatment group mean	Control group mean	Impact estimate	*p*-value of impact estimate
Milestone				
Enrolled in HS in 2018–2019	94.7	92.8	1.9	0.470
Momentum Points				
HS behaviors				
School activities				
Participated in a school-sponsored activity	87.0	90.3	-3.2	0.308
Engagement and satisfaction				
Believe grades are very important	75.7	74.5	1.2	0.808
Like school a lot	35.9	35.9	0.0	0.993
Number of hours spend on homework per week	11.9	11.6	0.3	0.721
Positive school behavior index (0–5)	3.5	3.5	-0.0	0.926
Substance abuse				
Never drank alcohol	85.2	83.9	1.3	0.755
Never used or tried marijuana	80.8	88.2	-7.4+	0.053
Postsecondary preparation				
Positive education expectations and knowledge				
Expect to receive a two- or four-year college degree	88.3	91.8	-3.5	0.283
Expect to receive a vocational certificate	18.7	15.2	3.6	0.430
Took an AP course	61.7	54.5	7.2	0.184
Took a dual-enrollment course	72.2	69.3	2.9	0.607
Understand courses needed to attend a four-year college	78.1	79.9	-1.8	0.661
Understand education or training needed for desired career	89.5	84.3	5.2	0.298
Employment success				
Work readiness skills				
Earned a badge that leads to an industry-recognized credential	50.8	51.6	-0.8	0.891
Earned a degree, certificate, or license at school	28.7	29.0	-0.4	0.950
Grit score (0–8)	3.6	3.7	-0.1	0.142
Holds a credential	5.5	8.2	-2.6	0.367
Work-readiness index (0–8)	6.5	6.6	-0.1	0.525
Paid work experience				
Ever worked for pay	68.9	69.8	-1.0	0.827
If ever worked, had a job arranged through school	26.0	19.5	6.5	0.313
Number of respondents	**279**	**157**	**n.a.**	**n.a.**

Source: FUS and school records.

Note: The table shows regression-adjusted treatment group and unadjusted control group means. The ITT estimates measure impacts of the offer of the YCC program.

Table V.13. Impacts of YCC on HS behaviors, postsecondary preparation, and employment readiness (CACE) (percentage unless otherwise stated)

	Treatment group mean	Control group mean	Impact estimate	*p*-value of impact estimate
Milestone				
Enrolled in HS in 2018–2019	99.1	95.1	4.1	0.473
Momentum Points				
HS behaviors				
School activities				
Participated in a school-sponsored activity	85.4	92.3	-6.9	0.303
Engagement and satisfaction				
Believe grades are very important	77.4	74.9	2.5	0.807
Like school a lot	34.9	34.7	0.1	0.992
Number of hours spend on homework per week	11.8	11.0	0.7	0.721
Positive school behavior index (0–5)	3.5	3.6	-0.0	0.927
Substance abuse				
Never drank alcohol	91.7	88.9	2.8	0.755
Never used or tried marijuana	88.6	100.0	-15.6[+a]	0.065
Postsecondary preparation				
Positive education expectations and knowledge				
Expect to receive a two- or four-year college degree	89.6	97.3	-7.7	0.287
Expect to receive a vocational certificate	15.0	7.6	7.4	0.428
Took an AP course	73.1	58.2	14.9	0.187
Took a dual-enrollment course	77.1	70.7	6.4	0.604
Understand courses needed to attend a four-year college	75.5	79.3	-3.9	0.662
Understand education or training needed for desired career	91.2	80.0	11.2	0.297
Employment success				
Work readiness skills				
Earned a badge that leads to an industry-recognized credential	45.5	47.2	-1.7	0.891
Earned a degree, certificate, or license at school	29.6	30.4	-0.8	0.950
Grit score (0–8)	3.6	3.8	-0.2	0.144
Holds a credential	0.0	2.7	-6.0[a]	0.376
Work-readiness index (0–8)	6.4	6.6	-0.2	0.529
Paid work experience				
Ever worked for pay	67.0	69.0	-2.0	0.827
If ever worked, had a job arranged through school	42.6	27.5	15.1	0.315
Number of respondents	**279**	**157**	**n.a.**	**n.a.**

Source: FUS and school records.

Note: The table shows regression-adjusted treatment group and unadjusted control group means. The CACE estimates measure impacts for those who complied with their research assignments (roughly, treatment group members who participated in YCC).

[a] Impact estimate does not equal the treatment-control group difference due to estimation error.

Table V.14. Baseline equivalence for the QED treatment and matched comparison group sample excluding imputed data (percentage unless otherwise stated)

Baseline characteristic	Treatment group mean	Comparison group mean	Difference in means (treatment – control)	Effect size
Age at entry into 8th grade (in years)	14.1	14.1	-0.00	-0.000
Gender	46.8	44.5	2.33	0.043
Race/ethnicity [a]				
American Indian	0.3	0.4	-0.08	-0.012
Asian	6.0	5.6	0.43	0.017
Black	37.0	35.8	1.17	0.023
Hispanic	30.0	31.2	-0.22	-0.024
White	24.3	24.6	-0.37	-0.008
Multiracial	2.4	2.4	0.07	0.004
Low-income status, 7th grade	69.1	68.9	0.30	0.006
Low-income status, 8th grade	67.2	67.0	0.19	0.004
School attendance, 7th grade	95.6	95.6	0.00	-0.005
School attendance, 8th grade	95.2	95.2	0.00	-0.004
Ever suspended, 7th grade	11.3	10.8	0.55	0.016
Ever suspended, 8th grade	12.6	11.5	1.06	0.031
Math assessment scores, 7th grade (*z*-score)	0.0	0.1	-0.01	-0.011
Math assessment scores, 8th grade (*z*-score)	0.2	0.2	0.00	0.001
Reading assessment scores, 7th grade (*z*-score)	0.0	0.1	-0.01	-0.012
Reading assessment scores, 8th grade (*z*-score)	0.1	0.1	0.01	-0.009
Received special education services, 8th grade	10.1	10.7	-0.66	-0.020
English Language Learner, 8th grade	9.1	9.0	0.08	0.003
Repeated a grade in middle school	2.5	2.8	-0.35	0.020
Number of districts	**14**	**14**	**n.a.**	**n.a.**
Sample size	**3,766**	**45,267**	**n.a.**	**n.a.**

Source: School records.

Note: Weighted comparison group means weight each comparison student by $\frac{\hat{p}_i}{1-p_i}$, where $\hat{p}_i$ is the estimated propensity score. Districts are weighted equally. Effect sizes are calculated by dividing the differences in means by the standard deviation of the comparison group.

[a] We conducted an *F*-test to assess the joint baseline equivalence across all race and ethnicity categories; differences were not statistically significant at the 5 percent level (*p*-value=0.658).

Table V.15. Baseline equivalence for the QED sample by primary outcome domain

Baseline characteristic	School attendance effect size (SE)	Credit accumulation effect size (SE)	ELA test score effect size (SE)	Algebra progression effect size (SE)
Age at entry into 8th grade	0.011 (0.020)	0.015 (0.024)	0.018 (0.023)	0.011 (0.019)
Gender	-0.005 (1.753)	-0.005 (2.037)	-0.020 (2.005)	-0.002 (1.703)
Race/ethnicity [a]				
American Indian	0.021 (0.168)	0.027 (0.183)	0.027 (0.188)	0.012 (0.172)
Asian	-0.003 (0.614)	0.005 (0.638)	0.012 (0.800)	-0.006 (0.621)
Black	0.005 (0.978)	0.013 (1.215)	-0.010 (1.132)	0.007 (0.972)
Hispanic	-0.000 (0.884)	-0.005 (1.006)	0.016 (1.074)	-0.005 (0.908)
White	-0.005 (1.073)	-0.010 (1.113)	-0.015 (1.138)	-0.001 (1.081)
Multiracial	-0.004 (0.545)	-0.011 (0.662)	-0.000 (0.660)	0.002 (0.536)
Low-income status, 7th grade	0.009 (1.526)	0.016 (1.717)	0.019 (1.713)	0.007 (1.547)
Low-income status, 8th grade	0.010 (1.438)	0.014 (1.594)	0.015 (1.631)	0.008 (1.479)
Attendance rate, 7th grade	0.001 (0.547)	-0.000 (0.670)	-0.015 (0.442)	-0.010 (0.492)
Attendance rate, 8th grade	-0.012 (0.244)	-0.027 (0.307)	-0.027 (0.271)	-0.003 (0.231)
Ever suspended, 7th grade	0.001 (1.121)	-0.018 (1.372)	0.024 (1.129)	-0.001 (1.082)
Ever suspended, 8th grade	0.002 (1.195)	0.000 (1.440)	0.027 (1.203)	0.001 (1.155)
Math assessment scores, 7th grade	-0.014 (0.042)	-0.016 (0.049)	-0.022 (0.048)	0.007 (0.040)
Math assessment scores, 8th grade	-0.008 (0.042)	-0.016 (0.048)	-0.023 (0.044)	0.008 (0.040)
Reading assessment scores, 7th grade	-0.006 (0.044)	-0.012 (0.051)	-0.028 (0.049)	0.012 (0.040)
Reading assessment scores, 8th grade	-0.012 (0.040)	-0.020 (0.046)	-0.032 (0.045)	0.012 (0.037)
Received special education services, 8th grade	0.005 (1.382)	0.012 (1.525)	0.009 (1.545)	-0.008 (1.243)
English Language Learner, 8th grade	-0.020 (0.793)	-0.013 (0.827)	-0.005 (0.891)	-0.027 (0.795)
Repeated a grade in middle school	0.017 (0.897)	0.034 (1.115)	0.009 (1.002)	0.000 (0.908)
Number of districts	**16**	**14**	**15**	**16**
Sample size	**85,932**	**80,169**	**66,619**	**102,491**

Source: School records.

Note: Weighted comparison group means weight each comparison student by $\frac{\hat{p}_i}{1-\hat{p}_i}$, where $\hat{p}_i$ is the estimated propensity score. Districts are weighted equally. Effect sizes are differences in means divided by the pooled standard deviation of the treatment and comparison groups.

[a] We conducted an *F*-test to assess the joint baseline equivalence across all race and ethnicity categories; differences were not statistically significant at the 5 percent level.

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