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Do Innovative Career Pathways in Massachusetts High Schools Promote Equitable Access to Higher Education?

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Abstract

Two persistent shortcomings of the American labor market are the wage gaps and unequal unemployment rates that exist between racial groups. More specifically, Black and Latinx high school graduates earn less and are more likely to be unemployed than their White counterparts, on average. Likewise, students from low-income families are much more likely to be low-income themselves in adulthood. One of the ways Massachusetts seeks to address this is by offering Innovation Career Pathways, optional career and technical education (CTE) programs within traditional public high schools that are attended by students from historically disadvantaged backgrounds, to grant them access to preparation for in demand careers through technical courses and hands-on learning experiences. In addition to being conducive to economic opportunity directly by promoting career readiness, literature suggests that CTE programs may also do so indirectly by having a positive effect on educational attainment, which has a positive relationship with employment as well as earnings. This study investigates the effects of participation in the Massachusetts Innovation Career Pathways (ICP) on college readiness, college enrollment, and college persistence of racial minority and low-income students using Inverse Probability of Treatment Weighting, as determined by propensity scores. Given the findings that program participation has positive effects on college enrollment and persistence across racial and economic groups, increased recruitment of Black, Latinx, and low-income students into the program may be a way to promote equitable access to higher education in the state of Massachusetts.

Introduction

The U.S. labor market has persistently featured an unemployment gap between White and Black or Latinx Americans, with unemployment rates being an average 6.1 percentage points lower for White Americans, dating back to records from the 1970's (The White House, 2023). An equally defining feature of the U.S. labor market is the racial inequality that exists in income, which has worsened since the 1970's. The median hourly salary of Black employees was 24% less than that of their White counterparts in 2019, compared to having been 16% less in 1979 (Wilson & Darity, 2022). This national issue manifests itself locally in the state of Massachusetts, where employees of color earn 73 cents for each dollar their White counterparts earn (Cristantiello, 2023).

In the United States, inequality in income is not just by racial group but also by socioeconomic background. Wagmiller and Adelman (2009) longitudinally investigated the relationship between exposure to poverty in childhood and poverty in adulthood using a nationally representative sample consisting of 67,271 parents and their adult children. Their finding was that 46% of children who had low-income parents were low-income earners in adulthood, while less than 1% of children who did not have low-income parents became low-income earners in adulthood (Wagmiller & Adelman, 2009). In Massachusetts, 12% of children live in poverty while 26% of children live in a household where guardians lack secure employment (Annie E. Casey Foundation, 2022). Without intervention, there is risk of perpetuating economic inequality by socioeconomic background.

To address existing and the risk of perpetuating inequities in employment and earnings in the state, the Massachusetts Department of Elementary and Secondary Education (DESE) launched Innovation Career Pathways (ICP) as part of its suite of High-Quality College and Career pathways in autumn of 2018 (DESE, 2020). The objective is to provide students historically disadvantaged in the state a supportive and rigorous academic experience and career development that is relevant to their interests, so that they may graduate high school with a well-designed postsecondary plan and ultimately be gainfully employed. Designated Innovation Career Pathways programs are structures within Massachusetts public high schools that connect student learning to in-demand industry sectors—e.g., information technology, healthcare, environmental sciences—in their respective region and the state broadly (DESE, 2020).

Participating schools collaborate with the MassHire State Workforce Board (MSWB) and local employers to provide students with career awareness activities, work-based learning experiences, and courses that lead to industry recognized credentials (DESE, 2020). The MSWB is a committee that advises the Governor on workforce development, career-related education policies, and state economic goals (Mass.gov, n.d.). Moreover, ICP participants receive advising from school counselors, via the My Career and Academic Plan (MyCAP) tool, to support them in identifying areas of aptitude and interest, exploring career opportunities, and establishing a transition path to college, apprenticeship, and/or employment training (Massachusetts Department of Elementary and Secondary Education, n.d.). Given ICP's focus on the recruitment of Black, Latinx, and low-income students as part of its guiding principle of equitable access (DESE, 2020) and the positive effects of career preparation on educational attainment (Brodersen et al., 2021; Lindsay et al., 2024 ; Witzen, 2018; Dougherty et al., 2019), it is particularly appropriate to investigate whether ICP is an intervention that can also reduce inequitable educational outcomes.

This study gauges the relationship between Innovation Career Pathways participation and educational attainment, for which variation may contribute to the disparity in income and employment status by race and socioeconomic status. Specifically, the research questions are:

1. What is the effect of participating in Innovation Career Pathways on students' likelihood of being college ready, where college readiness is approximated by the completion of MassCore (a recommended program of study that aligns high school coursework with college and workforce expectations)?
2. What is the effect of participating in Innovation Career Pathways on students' likelihood of enrolling in college within 6 months of high school graduation?
3. What is the effect of participating in Innovation Career Pathways on students' likelihood of persisting to a second year in college?
4. How do these effects vary by racial background and socioeconomic status?

While the effects of Innovation Career Pathways participation on college completion and earnings are of interest, the data will not be available in time for this study, so this will be investigated in the future.

Literature Review

Effects of CTE on Educational Attainment

Although the aims of public education are broad and far reaching, most agree that adequate employment and income should be among the outcomes. As such, career and technical education (CTE) was introduced in U.S. education in the early 20th century (Imperatore & Hyslop, 2017). In addition to its intentions to prepare citizens for the work force, recent studies have found that CTE in high school is related to higher education outcomes (Brodersen et al., 2021; Lindsay et al., 2024; Witzen, 2018; Dougherty et al., 2019), the subject of interest for this research project. This is because the aims of CTE have evolved to include the promoting of college readiness as well as workforce development. For example, the U.S. Department of Education has redefined CTE from a narrow focus on low-wage job attainment for non-college bound youth to programs of study that prepare students for college and career readiness (Fletcher & Dumfor, 2021). Likewise, Massachusetts currently defines CTE as programs that combine high academic standards with career exploration and technical training to qualify students for entry level employment in a competitive field and provide them a strong foundation for college (Massachusetts Department of Elementary and Secondary Education, n.d.).

Not only is enrolling in CTE courses in high school predictive of course enrollment and performance in college (Plasman et al., 2019), but studies found that students who participate in CTE programs are more likely to graduate high school on time and more likely to enroll in a postsecondary institution. Using a multivariate logistic regression controlling for student demographic information, baseline achievement, and school level demographics, Brodersen et al. (2021) found that CTE concentrators were 10 percentage points more likely than non-participants to enroll at a higher education institution within two years of high school graduation, in American states of Nebraska and South Dakota.

Lindsay et al. (2024) conducted a meta-analytic review across 8 studies and determined that CTE participants were more likely to enroll in 2-year colleges, compared to students who did not take CTE courses in high school, with a small but statistically significant g effect size of 0.142. They caution that "causal association between CTE and college enrollment is nuanced," (p. 8) because of minimal and non-significant effects on enrollment at 4-year colleges. Using propensity-score matching to eliminate bias caused by systematic differences between CTE participants and non-participants in the Maryland Longitudinal Data System, Witzen (2018) found that CTE completers are 7.8 percentage points more likely to be enrolled in college immediately after graduating from high school. It should be noted that all CTE participants in the Witzen (2018) study were in healthcare programs. Although not the focus of this study, but of interest, Dougherty et al. (2019) also found that students who complete high school CTE are more likely to earn a college degree.

Offering CTE as a means to promote educational attainment does not come without reservations. Smith (2019) asserts that in many instances, CTE training can help high school graduates in the short term but may provide fewer long-term benefits for students who do not take upper-level coursework. Furthermore, Dougherty (2023) explains that while completing a CTE program in engineering or information technology may direct a student to college, many CTE programs, like those for the skilled trades, do not promote traditional postsecondary education institutions. Ecton and Dougherty (2023) investigated heterogeneity that may exist within the array of academic programs that fall under CTE, via descriptive analysis, and found substantial differences in outcomes, including educational attainment, for students in different fields, e.g., health care compared to construction. Likewise, Mellor and Lin (2021) found that the percentage of CTE program completers who enroll in and graduate from college varies by career cluster, their area of concentration.

Inequitable Access to CTE

Despite the knowledge that CTE may promote educational attainment, Black and Latinx students still have unequal access to high-quality CTE programs in the United States. While 22 percent of White students participate in CTE as concentrators—enrolling in and completing three CTE courses—18 percent of Black students and 16 percent of Latinx students do so nationally (Center for American Progress, 2023). Among those who do participate in CTE, White students are more likely than Black and

Latinx students to take classes in STEM, with Black students particularly more likely to take courses in hospitality and tourism, which are lower paying (Butrymowicz, 2021). The present impact evaluation on Massachusetts Innovation Career Pathways contributes dually to the literature, by adding to the literature on the efficacy of CTE and presenting an argument that it is a means to promote equitable educational attainment—namely readiness for, access to, and success in higher education.

Theory of Change

The literature suggests a few mechanisms as to how and why CTE may promote college going after high school. Via career exploration, which tends to be a component of CTE, a student may discover their desired job or profession requires a college degree (Hughes et al., 2001). Kemple and Willner (2008) indeed argue that integrating academic content with applied learning activities, as done in CTE, not only improves student achievement, but also that CTE partnerships with employers offer students insight on education and skill requirements of various jobs and careers, which in turn may increase students' aspirations and motivate them to pursue postsecondary education.

Moreover, the applied learning emphasized in CTE programs may engage, stimulate, and retain students who might have otherwise dropped out and encourage them to pursue further studies after they graduate high school (Advisory Committee for the National Assessment of Vocational Education, 2003). It is also possible that CTE programs connect students to employers who provide tuition reimbursement as an employee benefit (DeLuca, 2006). Sixty percent of American employers offer tuition reimbursement and corporations spend $28 billion on tuition assistance annually (Glover, 2017).

With a randomized controlled trial, via lottery admissions to CTE high schools in North Carolina, Hemelt et al. (2017) determined that a mediator for positive effects of CTE participation on college enrollment is improved attendance in the early high school years. Visher and Stern (2015) suggest that one of the reasons certain CTE programs may promote educational attainment is because participants receive more personal, academic, and social support, when a small team of teachers shares responsibility for the same cohort of students for multiple years. Edmunds et al. (2022) argue that it is the increasingly widespread practice of Dual Enrollment—simultaneous taking of high school and college courses by students—in CTE programs, which in turn promotes college readiness, that is driving the relationship between CTE participation and college enrollment.

In addition to allowing some students to be dually enrolled in high school and college courses, another way CTE may be promoting college enrollment could be necessity to complete courses beyond high school to earn the certification. Ecton and Dougherty (2023) explain that the expectation of attending community college is built into various CTE programs in high school, whose certification curricula include college colleges, which may extend beyond high school graduation. Such clusters include but are not limited to information technology (IT) and healthcare related professions.

Another closely related, but separate mechanism by which CTE may be promoting college enrollment is through high school CTE and college CTE course pipelines. Using the Education Longitudinal Study of 2002, Plasman et al. (2019) employed logistic regression, school fixed effects, and instrumental variable analysis to determine that CTE course taking in high school linked to overall CTE course taking throughout college. They specifically found that the relationship between high school and 4-year college CTE course taking was statistically significant.

Theoretical Framework

This study is framed by Human Capital Theory, which suggests that any deliberate embedding of resources in activities that render individuals more knowledgeable or skilled in a manner conducive to an economic return, such as schooling, is an investment (Schultz, 1961; Becker, 1962). Becker (1962) further explains that human capital investments may differ in their perceived connection to the return. While the connection between college preparation in high school and educational attainment is clear, career preparation in high school has evolved to include the promoting of college enrollment as well as workforce development (Fletcher & Dumfor, 2021). Sweetland (1996) suggests that the return on human capital investments may be intermediately measured by years of schooling. Therefore, this paper argues that by offering Innovation Career Pathways, Massachusetts, knowingly or unknowingly, made a human capital investment which may not only yield a return via job placement, but also by having a positive effect on educational attainment, which has a positive relationship with earnings (Lobo & Burke-Smalley, 2018). Determining the effects of Innovation Career Pathways on college readiness, access, and success is analogous to a return-on-investment analysis.

In addition to the theoretical framework, this study is structured by Perna and Thomas' (2006) Framework for Reducing the College Success Gap and Promoting Success for All. According to Perna and Thomas (2006), the four key transitions in a success process are college readiness, college enrollment, college achievement, and post-college attainment. Furthermore, there are four layers of context to understanding student success—internal, family, school, and sociopolitical. The framework maps on to this research project in direct and substantive ways. Specifically, the outcomes of interest—college readiness as approximated by MassCore completion, college enrollment, and college persistence—align with three of the four transitions in Perna and Thomas' (2006) student success process. Covariates for regression models that estimate the propensity scores, the probability of receiving treatment assignment, as well as the post-weighting regression models that estimate effects of program participation correspond to Perna and Thomas' (2006) layers of context.

Intervention Description

After the receipt of the New Skills for Youth (NSFY) grant from the Council of Chief State School Officers (CCSSO) to address the national need for greater career preparation and access to high quality careers, Massachusetts launched Innovation Career Pathways (ICP) in select high schools in autumn 2018, via a designation process that ensures ICP programs grant equitable access to students, offer guided academic pathways that are connected to careers, provide support services that promote success, and have partnerships with the local workforce (DESE, 2020). In sum, ICPs are interventions intended to connect student learning to in demand careers in the local and state economy. As such, ICP offering schools work with their local workforce board and local employers to determine employment prospects of present and future students, and subsequently expose and train student participants for said careers (DESE, 2020).

The exposure and training include a career immersion experience in either an internship or capstone project—a practical experience culminating in a performance or a product—offering structured work readiness activities and work-based learning experiences (DESE, 2020). Student participants must complete at least one hundred hours of activity outside of the classroom, in the form of research, service-learning, or other related activity, as part of their internship or in completing their capstone project (DESE & DHE, 2020). Furthermore, student participants must complete a series of courses and experiences relevant to achieving industry recognized credentials. Participation in this kind of pathway can lead students to opportunities for meaningful careers in that industry sector upon completion of the needed education and training (DESE, 2020).

Massachusetts ICP program designs are informed by the six core components for high quality career pathways that CCSSO identified for its NSFY initiative —career advising, labor market information, integrated instruction, work-based learning, credential preparation, and post-secondary linkages (DESE, 2020). As such, Massachusetts ICP uses a tool called My Career and Academic Plan (MyCAP) to advise students on the completion of a college and career plan during high school, which promotes identifying areas of aptitude and interest, the exploration of career opportunities, and the establishment of a transition path to college, apprenticeship, and/or employment (DESE, 2020).

In terms of being informed by labor market information, the pathway options are attuned to work force needs as recommended and supported by the MassHire State Workforce Board and local employers. Regarding integrated instruction, students participate in a sequence of career-oriented courses relevant to their pathway, including both academic and technical subjects. Work-based learning is covered in their one-hundred-hour internship or capstone experience, while credential preparation is imbedded in the course taking, as they are sequenced such that they lead to professional certifications. Lastly, post-secondary linkages are such that many of the courses are college level and contribute to the attainment of an associate or bachelor's degree (DESE, 2020).

It should be noted that Innovation Career Pathways is distinct from the already existing Chapter 74 CTE programs in Massachusetts, which meet the definition of vocational technical education contained in Massachusetts General Law Chapter 74 and meet the Perkins Act definition of career and technical education (DESE, 2022). The signature learning experiences for Chapter 74 CTE programs are: safety and essential industry credential opportunities; immersive work-based learning such as co-op; and at least 900 hours of immersive coursework/learning. The signature learning experiences for Innovation Career Pathways are: at least 100-hour Internship or work-based learning capstone experience; and at least 2 advanced courses related to continued study in industry area, which may include dual enrollment courses (DESE, 2024).

Data and Methods

Data Sources

This study draws from four sources of administrative data that capture information about students enrolled in the Massachusetts public secondary school system—the Student Information Management System (SIMS), the Massachusetts Comprehensive Assessment System (MCAS), the School Safety and Discipline Report (SSDR), and the National Student Clearinghouse (NSC) Student Tracker. Per the Massachusetts DESE website (2023), SIMS is a student-level data system that enables the collection and analysis of information to meet federal and state reporting requirements, and to inform decisions making, policy and practice. SIMS contains fifty-two data elements, or variables, which detail each student's demographic profile as well as their enrollment and attendance. MCAS is a series of statewide assessments that help parents, students, educators, and policymakers determine where districts, schools, and students are meeting expectations and where they need additional support (DESE, 2023). SSDR collects student removals from class or school, including suspensions and expulsions (DESE, 2023).

NSC is a nonprofit organization that provides reporting, verification, and research services to educational institutions in the United States. The NSC network comprises nearly all colleges and universities in the United States, representing 97 percent of postsecondary education enrollment in the country (Dunbar & Shapiro, 2016). NSC provides a service called the Student Tracker for High Schools, which enables all secondary schools in the United States to follow their graduates' transition to college by querying participating institutions' postsecondary enrollment and degree records (Dunbar & Shapiro, 2016). This is the data that is used to determine whether graduates from Massachusetts public secondary schools enrolled and persisted in college.

Sample Selection

Innovation Career Pathways is a school level designation, meaning that the state designates which schools may offer the program. Even though student selection into the program is informed by the same guiding principles throughout the state, the specific processes are not uniform across schools. Per the Designation Criteria, participating schools prioritize students underrepresented in high demand industry sectors (DESE, 2020) to receive designation. To meet those ends, the schools are further asked to enroll students without regard to prior academic performance, provide student supports, scalability, multiple entry points for students, and preparation for entry into the program (DESE, 2020,). If they operate within those guidelines, schools can select students however else they think best and retain their designation. A school may enroll a large or small share of the student body in the program. For example, 28 Massachusetts high schools offered ICP to 12th graders in 2022. In terms of count of 12th grade ICP enrollment in the 28 schools, the range was from 1 student to 155 students, with a mean of 21 students. In terms of share of the school enrolled in ICP, the range was from 0% to 96% of the 12th graders in the school, when rounded, with a mean of 13%.

There were two interventions launched as part of the Massachusetts High Quality College and Career Pathway programs in 2018, Innovation Career Pathways and Early College. Although no student can participate in both interventions during the years of the study, there is some school overlap, which results in 1,882 Early College students attending schools that also offer Innovation Career Pathways. Those 1,882 students were excluded from this study. Therefore, the treatment students used in this study are the 1,354 grade 12 Innovation Career Pathways participants that schools enrolled in the four years of the study, in adherence to state guidelines. The untreated students are the 25,630 remaining 12th grade students across the 2018-19 and the 2021-22 school years, who attend a school that offers Innovation Career Pathways, but do not participate in the program, minus the 1,882 who participate in Early College. The analysis starts with the 2018-19 school year because it is the first year for which there are grade 12 students in the programs (Table 1).

Program Participation

There were 43 unique high schools in the state of Massachusetts that offered the Innovation Career Pathways program to 12th graders at any point during the 2018-19 to the 2021-22 academic years. There were 7 schools that offered the program in 2018-19, the first year in the study, which increased to 40 by 2021-22, the last year in the study, due to additional programs being designated each year. There were 26 high schools participating in 2019-20 and 39 in 2020-21. There were 24 ICP participants in the 12th grade in 2018-19, making up 1.3 percent of 12th graders at those schools. In 2019-20, there were 315 ICP participants in the 12th grade, and they made up 4.9 percent of 12th graders in the ICP offering schools. In 2020-21, there were 440 ICP participants in the 12th grade, with a school participation rate of 4.4 percent. Lastly, there were 575 ICP participants in the 12th grade in 2021-22, with a participation rate of 6.6 percent. On aggregate, participants made up 5 percent of 12th graders in their schools and 0.5 percent of 12th graders in the state during those 4 years (Table 1).

Table 1. Innovation Career Pathways Participation in 12th Grade

School Year	Student Group			
	Innovation Career Pathways	Rest of School	Rest of State	Total
2019	24	1757	70204	71985
2020	315	6136	65212	71663
2021	440	9552	62570	72562
2022	575	8185	63261	72021
Total	1354	25630	261247	288231

Given the ICP guiding principle of equitable access, which encourages the recruitment of Black, Latinx, and Low-income students, schools that were designated to offer the program have overrepresentation of these groups, relative to the rest of the state, on average. Furthermore, the programs enrolled such students at parity with the school during the four years. More specifically, 15% of ICP participants were Black, compared to 15% of the remaining students in the ICP offering schools and 9% of the rest of the state; 24% of ICP participants were Latinx, compared to 25% of the remaining students in the ICP offering schools and 18% of the rest of the state; while 43% percent of ICP participants were low-income, compared to 42% of the remaining students in the ICP offering schools and 30% of the rest of the state.

Table 2. Participation of Underrepresented Students in ICP

	Percent Black	Percent Latinx	Percent Low-Income
Innovation Pathway	15%	24%	43%
Rest of School	15%	25%	42%
Rest of State	9%	18%	30%

ICP participants are slightly more likely to be proficient or advanced in English Language Arts (ELA) and Math than their school peers. Looking at the 8th grade standardized test scores for the 12th graders from the 2018-19 to the 2021-22 academic years, 42% of ICP participants were proficient or advanced in Math, compared to 37% of the rest of their peers at the ICP offering schools, and 47% of their remaining state peers, mutually exclusively. At 49% and 46%, respectively, ICP participants were proficient or advanced in ELA at a rate comparable to the rest of their peers at the ICP offering schools. 58% of their remaining state peers were proficient or advanced in ELA. In terms of baseline achievement, participation in the program within the schools is more reflective of the school, relative to the rest of the state.

Table 3. MCAS Performance Levels

	Proficient or meeting expectations in Math	Proficient or meeting expectations in ELA	Advanced or exceeding expectations in Math	Advanced or exceeding expectations in ELA
Innovation Pathway	32%	41%	10%	8%
Rest of School	28%	38%	9%	8%
Rest of State	31%	44%	16%	14%

Dependent Variables

Given the outcomes of interest—college readiness, college access, and college success—the dependent variables are MassCore completion, college enrollment within six months of graduating high school, and persistence to a second year in college. MassCore is a recommended program of study that aligns high school coursework with college and workforce expectations. This entails performing satisfactorily in four years of English, four years of mathematics, three years of a lab-based science, three years of history, two years of the same world language, and one year of the arts (DESE, 2022). For this study, the completion of MassCore serves as a proxy for college readiness. It should be noted that the criteria for meeting MassCore reflects the national literature on college readiness. For example, DeAngelo and Franke (2016, p.1596) define college ready students as having "completed four years of English, three years of math, two years of a foreign language, one year each of biological and physical sciences, plus an additional year of one or the other (in total three years of science), one year of history/government, and one year of art" in high school. For all four cohorts included in this study, the MassCore completion information is available in the Student Information Management System (SIMS) while the college enrollment information is available in the detailed National Student Clearinghouse (NSC) report. College success, defined as second year persistence in this study, is also drawn from the annual college enrollment data from NSC. Second year persistence is an intermediate measure, as college completion is the ultimate measure of college success, however such data is not available in time to be included.

Independent Variables

The primary independent variable is program participation, for which there is an indicator variable in SIMS. Additionally, a correct specification of covariates is crucial to propensity score calculation. In education, covariates representing students' prior achievement, gender, race, disability status, and socioeconomic background, can play a role in determining selection into interventions and influence the outcomes of interest (Fisher, 2019). As such, the Student Information Management System (SIMS) covariates that will be used in this study are race, gender, disability status and socioeconomically disadvantaged status, as well as English learner status.

Race is a seven-value nominal variable indicating whether a student is Asian, Black, Latinx, Multiracial, Native American, Pacific Islander, or White. For the purposes of this study, which investigates the effect of program participation overall and particularly for Black and Latinx students, racial groups of Asian, Multiracial, Pacific Islander, and Native American were collapsed as Other Race. Black, Latinx, and Other Race are compared against White as the reference group. Findings for Other Race are not substantively meaningful, as the small groups collapsed may have quite different historical patterns of performance, but collapsing was a statistical necessity, as the individual groups were too small to draw stable inferences. It should also be noted that the term racial minority students in this paper refers to students who identified as Black or Latinx.

Gender is a categorical variable indicating if a student is male, female, or non-binary. Although nonbinary is a gender option, it is not present the sample, thus gender is operationally a binary variable in this study. Socioeconomically disadvantaged status is a binary variable indicating whether a student's "household is eligible for free or reduced-price lunch, or if they receive Transitional Aid to Needy Families benefits" (DESE, 2023, p.26). Disability status is a binary variable indicating when a student meets criteria to receive disability support services and accommodations. English learner students are defined as "children who have indicated a language other than English on the Home Language Survey, are less than proficient on an English language proficiency assessment and are unable to perform ordinary classroom work in English" (DESE, 2023, p.32).

After retrieving demographic and program participation information, the data was merged with math and reading standardized test scores from grade 8. Grade 8 scores are being used in lieu of grade 10 scores because some Early College programs start preparatory activities in grade 9, which disqualifies grade 10 test scores as baseline. Massachusetts administered 3 different standardized tests during the years subjects of the study were in grade 8—Partnership for Assessment of Readiness for College and Careers (PARCC), Legacy MCAS, and Next Generation MCAS—all of which were graded on different scales. While the test scores are on different scales, the test results all come with four performance levels—failing, needs improvement, proficient, and advanced for PARCC and Legacy MCAS; and not meeting expectations, partially meeting expectations, meeting expectations, and exceeding expectations for Next Generation MCAS. Performance levels across tests were numerically coded one through four, with missingness given the value of 0, to be included as five factor variables for the calculations of propensity scores.

Methods

This study estimates the effects of Innovation Career Pathways on participants using propensity score weighting, namely, the inverse probability of receiving the treatment weighting. The propensity score is the conditional probability of being assigned a treatment given a vector of observed covariates (Rosenbaum & Rubin, 1983). It is the likelihood that each person in a population would be assigned to treatment based on available variables within the data set. After calculating propensity scores, there are four methods a researcher may use to remove the effects of confounding variables when estimating the effects of treatment: propensity score matching, stratification on the propensity score, inverse probability of treatment weighting, and covariate adjustment using the propensity score (Austin, 2011). There are different advantages and challenges to using one propensity score analytic method over another, such as weighting over matching, stratification, and covariate adjustment.

Although propensity score matching eliminates a greater proportion of the systematic differences in baseline characteristics than the others (Austin, 2011), the Rosenbaum Bounds Sensitivity Analysis, which allows a researcher to calculate how strongly an unobserved confounder must affect treatment assignment to be able to undermine the results from a matching analysis (DiPrete & Gangl, 2004), determined that the model specified for this study was highly sensitive to a confounder (See Table 5). Inverse probability of treatment weighting is not only second to propensity score matching by a small margin, when it comes eliminating systematic differences (Austin, 2011), but it retains all observations from the study population in the outcome analysis (Guo & Fraser, 2015), as opposed to the dropping of unmatched records that happens with the propensity score match. Inverse probability weighting was thus chosen for this study.

Analytically, Inverse Probability of Treatment Weighting (IPTW) involves two steps. Firstly, the propensity score is calculated, based on an individual's observable and research question relevant characteristics. Secondly, the inverse of the propensity score is calculated, which will serve as sampling weights in the regression model (Guo & Fraser, 2015). The use of the weights in a regression including the entire study's population creates a synthetic sample in which the distribution of measured baseline covariates is independent of treatment assignment, analogous to how survey sampling weights are used to weight survey samples so that they are representative of specific populations (Austin, 2011).

By weighting each individual in the population by the inverse probability of receiving the treatment, IPTW balances baseline characteristics in the treated and untreated groups (Chesnaye et al., 2021). Weights are calculated for each individual as 1/propensity score for the treated group and 1/(1−propensity score) for the untreated group. Subsequent inclusion of the weights in the analysis renders assignment to either the treated or untreated group independent of the covariates included in the propensity score calculating logistic regression (Chesnaye et al., 2021). The weighted sample may then be used in multivariate regression analyses to estimate the average treatment effect (ATE).

Balance between treated and untreated groups was assessed across all baseline characteristics as appropriate following weighting (Chesnaye et al., 2021). The approach taken follows Austin and Stuart (2015), using the weighted standardized difference to compare the mean and prevalence of continuous and binary variables, respectively, between treated and untreated subjects in the weighted sample. Austin and Stuart (2015) further explain that if, in the sample weighted by the estimated inverse probability of treatment, systematic differences persist between treated and control subjects, this may be an indication that the specification of the propensity score model requires modification.

Diagnostic Tests

The first step for any propensity score based analytic approach entails a logistic regression (Guo & Fraser, 2015), with treatment assignment as the binary outcome and a set of pertinent covariates as predictors (D'Agostino, 1998) to determine the probability of receiving the treatment based on the observable characteristics. Below is the output for the propensity score calculating regression:

Table 4. Propensity Score Calculating Logistic Regression

	Logistic Regression Odds Ratios	(SE)
Black	1.236*	(0.117)
Other Race	1.426***	(0.142)
Latinx	1.303**	(0.108)
Economically. Disadvantaged/Low Income	1.134	(0.078)
Male	0.828**	(0.051)
Disability	0.639***	(0.077)
English Learner	1.141	(0.173)
Chronically Absent in G8	0.819	(0.094)
Suspended in G8	0.838	(0.116)
Missing ELA Test	1.577	(0.406)
Needing Improvement/Partially Meeting Expectations in ELA	0.872	(0.103)
Proficient/Meeting Expectations in ELA	0.888	(0.116)
Advanced/Exceeding Expectations in ELA	0.834	(0.144)
Missing Math Test	0.230*	(0.166)
Needing Improvement/Partially Meeting Expectations in Math	1.229	(0.138)
Proficient/Meeting Expectations in Math	1.419**	(0.180)
Advanced/Exceeding Expectations in Math	1.569**	(0.247)
School Year=2019	0.289***	(0.062)
School Year=2021	0.915	(0.080)
School Year=2022	1.302**	(0.110)
Observations	21070	

Exponentiated coefficients; Standard errors in parentheses
$^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

Because the principal aim of all propensity score models is to achieve balanced covariates between treated and untreated groups, a good propensity score calculating logistic regression is not necessarily one that best predicts treatment assignment (Shiba & Kawahara, 2021). As such, reporting measures of model fit that assess the predictive performance of a propensity model is of limited value (Westreich et al., 2011). Whether matching, weighting, stratifying, or covariate adjusting, with propensity scores, the concern is whether balance is achieved after the application of propensity scores.

The first method attempted was a propensity score matching, with nearest neighbor (Stone & Tang, 2013) set at a caliper of .2 standard deviations of the logit of the propensity score, to minimize the mean square error of the resultant estimated treatment effect (Austin, 2011). However, according to the Rosenbaum bounds test on this propensity score match, the critical level of gamma at which we would have to question our conclusion of a positive effect is 1, as its corresponding sigma value is greater than .05 (Table 5). In other words, it would require a hidden bias of gamma no greater than 1 to render spurious the conclusion of a positive effect of program participation on college enrollment. These gamma values, which are in odd ratios units, correspond to the odds ratios of the covariates from the logistic regression from which the propensity scores were calculated. Half of the covariates have odds ratios that are greater than 1 (Table 4), which means the confounder is likely predict participation as much as half of the covariates. Therefore, the researchers interpret the match to be sufficiently sensitive to a confounder to not use propensity score matching as the method of choice.

Table 5. Rosenbaum Bounds for Delta

Gamma	Sig +
1	0.145476
1.1	0.474456
1.2	0.799918
1.3	0.95309
1.4	0.992864
1.5	0.99925
1.6	0.999942
1.7	0.999997
1.8	1
1.9	1
2	1

As a result of this concern, the same propensity score calculating regression model was used to calculate inverse probability weights to conduct propensity score weighting instead of matching, since the match was sensitive to a confounding covariate. The overidentification test, which determines whether the model-adjusted means of the covariates are the same between groups, has a p-value higher than .05 (Table 6), which means we do not reject the null hypothesis that the covariates are balanced and that this model may be used.

Table 6. Weighting Overidentification Test

Iteration 0:	criterion = .03487247
Iteration 1:	criterion = .03567228
Iteration 2:	criterion = .03623506
Iteration 3:	criterion = .03756787
Iteration 4:	criterion = .0380361
Iteration 5:	criterion = .03824145
Iteration 6:	criterion = .03834134
Iteration 7:	criterion = .03841706
Iteration 8:	criterion = .03846804
Iteration 9:	criterion = .03850337
Iteration 10:	criterion = .03852164
Iteration 11:	criterion = .03852683
Iteration 12:	criterion = .0385299
Iteration 13:	criterion = .03853315
Iteration 14:	criterion = .03853537
Iteration 15:	criterion = .03853652
Iteration 16:	criterion = .03853713
Iteration 17:	criterion = .03853746
Iteration 18:	criterion = .03853773
Iteration 19:	criterion = .03853805
Iteration 20:	criterion = .03853819
Iteration 21:	criterion = .03853827
Overidentification test for covariate balance	
H0: Covariates are balanced:	
chi2(21) = 24.9482	
Prob > chi2 = 0.2494	

To gauge balance when using inverse probability weighting, one must look at pre-weighted (raw) and post-weighted standardized mean differences across covariates (Austin & Stuart, 2015). In addition to comparing standardized means, one should also compare variance ratios, as it enables a researcher to obtain a broader characterization of the similarity of the distribution of a covariate between groups (Austin, 2009). If the covariates are perfectly balanced, the standardized mean difference between the treated and untreated should be 0 and the variance ratio should be 1. As shown on table 7, all the standardized differences between the treated and untreated are smaller in the weighted sample than in the unweighted sample. Furthermore, the weighted standardized differences are all nearly 0, and weighted variance ratios are all nearly 1. Although there is no consensus among researchers, Austin (2009) suggests that an absolute standardized difference of less than 0.10 is an indication that covariates are balanced between groups and Stuart (2010) argues that regression adjustments yielding variance ratios between 0.5 and 2 are trustworthy. All weighted standardized differences and weighted variance ratios for the variables that were included in the propensity score model meet those criteria.

Table 7. Standardized differences and Variance Ratios

	Standardized Differences		Variance Ratio	
	Raw	Weighted	Raw	Weighted
Black	0.036	0.010	1.079	1.022
Other Race	0.089	-0.023	1.268	0.933
Latinx	0.050	-0.033	1.070	0.953
Economically. Disadvantaged/Low Income	0.075	-0.017	1.033	0.991
Male	-0.103	0.014	0.996	0.999
Disability	-0.159	0.020	0.657	1.045
English Learner	0.033	-0.010	1.143	0.956
Chronically Absent in G8	-0.061	0.035	0.835	1.099
Suspended in G8	-0.064	0.006	0.787	1.021
Missing ELA Test	0.070	-0.014	1.868	0.859
Needing Improvement/Partially Meeting Expectations in ELA	-0.029	0.010	0.980	1.007
Proficient/Meeting Expectations in ELA	0.027	-0.007	1.006	0.999
Advanced/Exceeding Expectations in ELA	-0.011	-0.005	0.971	0.985
Missing Math Test	-0.122	-0.003	0.146	0.971
Needing Improvement/Partially Meeting Expectations in Math	0.005	-0.014	1.003	0.995
Proficient/Meeting Expectations in Math	0.074	0.002	1.052	1.001
Advanced/Exceeding Expectations in Math	0.019	0.012	1.052	1.033

Weighting not only causes balance across relevant variables, as shown in Table 7, but also in observation counts between treated and non-treated groups. The difference in frequencies of treated and untreated in the pre-weight population is 18,670 while the difference is the post weight synthetic sample is 70, where the treated and untreated records are nearly equally represented in the latter but not the former. Looking at the observation balance summary (Table 8), the raw data is such that the ratio of non-treated to treated observations is nearly 17 to 1 while the weighted data has a near 1:1 ratio.

Table 8. Observation Balance Summary

Observation Counts	Raw	Weighted
Number of total observations	21,070	21,070.0
Number of Treated observations	1,200	10,570
Number of non-treated observations	19,870	10,500

Results/Findings

Effects of ICP on College Readiness

Weighted regression models estimate that ICP participation has a positive effect on college readiness, as approximated by MassCore completion (Table 9). The first model, which is a multivariate logistic regression weighting the inverse probability of participating in ICP, estimates that ICP participants have 1.55 times the odds of being college ready relative to non-participants. The second model is the weighted multivariate logistic regression from model one with school fixed effects, which estimates that ICP participants have 1.53 times the odds of being college ready than non-participants. Similar estimates from the first and fourth model suggest that there isn't a lot of variation in impact of Innovation Career Pathways participation by school, when it comes to college readiness. The third and fourth models incorporate interactions between program participation and race, and program participation and family income status. There are statistically significant odds ratios of 0.44, 0.62, and 0.68 for interactions of program participation and being Black, Latinx, and low-income, respectively. This means that although Innovation Career Pathways participation increases the odds of completing MassCore for all students on average, the effects may be less pronounced for Black, Latinx, and low-income students. These interactions are graphed in probability units in Figures 1 and 2. Per Figure1, although the interaction term for being Black and being an ICP participant is statistically significant when estimating effects on college readiness, there is no evidence for a practical difference between Black ICP participants and Black non-participants, at a less than one percentage point difference. When it comes to Latinx students, Figure 1 suggests that ICP does indeed make a positive difference, but to a lesser extent than it does for White students. Likewise, according to Figure 2, program participation is associated with an increase in the probability of being college ready for low-income students, but the increase in probability is smaller than that of non-low-income students. Other race in this model is not substantively meaningful, as it's an aggregation of different groups with variable historical patterns of achievement, so not much is made of the interaction. No significant interactions were found between program participation and underrepresented groups of interest—Black, Latinx, and low-income—when school fixed effects are included (Appendix 2A), so models three and four do not include school fixed effects.

Table 9. Effects on MassCore Completion/College Readiness

	Weighted Regression	(SE)	With School Fixed Effects	(SE)	With Race Interaction	(SE)	With Low Income Interaction	(SE)
Innovation Pathway	1.550***	(0.136)	1.533**	(0.226)	2.219***	(0.356)	1.852***	(0.243)
Black	0.311***	(0.035)	0.884	(0.142)	0.456***	(0.028)	0.308***	(0.035)
Other	0.473***	(0.059)	0.744	(0.154)	0.647***	(0.042)	0.468***	(0.059)
Latinx	0.739**	(0.075)	0.875	(0.133)	0.909	(0.057)	0.729**	(0.074)
Low Income	0.660***	(0.055)	0.657***	(0.069)	0.649***	(0.054)	0.782***	(0.044)
Male	0.721***	(0.059)	0.725**	(0.079)	0.716***	(0.058)	0.714***	(0.058)
Disability	0.554***	(0.073)	0.422***	(0.065)	0.560***	(0.073)	0.556***	(0.073)
English Learner	1.366	(0.240)	0.852	(0.188)	1.363	(0.237)	1.362	(0.237)
Chronically Absent in G8	0.623***	(0.080)	0.554**	(0.102)	0.614***	(0.077)	0.629***	(0.080)
Suspended in G8	1.273	(0.182)	0.747	(0.135)	1.238	(0.169)	1.266	(0.181)
Missing Test Score (ELA)	0.566*	(0.136)	1.280	(0.287)	0.586*	(0.139)	0.568*	(0.134)
Partially Meeting Expectations (ELA)	1.711***	(0.248)	1.995***	(0.319)	1.705***	(0.246)	1.686***	(0.244)
Proficient/Meeting Expectations (ELA)	2.027***	(0.333)	2.587***	(0.430)	2.025***	(0.334)	2.021***	(0.332)
Advanced/Exceeding Expectations (ELA)	1.592	(0.414)	2.665**	(0.857)	1.673	(0.448)	1.598	(0.419)
Missing Test Score (Math)	4.370**	(2.190)	1.365	(0.379)	4.026**	(1.862)	4.445**	(2.321)
Partially Meeting Expectations (Math)	1.099	(0.140)	1.256	(0.196)	1.084	(0.137)	1.095	(0.139)
Proficient/Meeting Expectations (Math)	1.418*	(0.217)	1.903***	(0.350)	1.413*	(0.217)	1.415*	(0.218)
Advanced/Exceeding Expectations (Math)	0.964	(0.220)	1.148	(0.348)	0.934	(0.217)	0.952	(0.219)
School Year =2019	1.040	(0.260)	0.398*	(0.148)	1.020	(0.260)	1.024	(0.254)
School Year =2021	1.701***	(0.179)	2.790***	(0.421)	1.687***	(0.175)	1.706***	(0.180)
School Year =2022	2.087***	(0.219)	3.508***	(0.508)	2.111***	(0.220)	2.095***	(0.220)
ICP and Black Interaction					0.439***	(0.106)		
ICP and Latinx Interaction					0.619*	(0.145)		
ICP and Low-Income Interaction							0.681*	(0.121)
Constant	2.331***	(0.445)	1.834**	(0.423)	2.048***	(0.390)	2.198***	(0.416)
Observations	21070		20295		21070		21070	

Exponentiated coefficients; Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 1. Innovation Career Pathways and Race Interaction for College Readiness

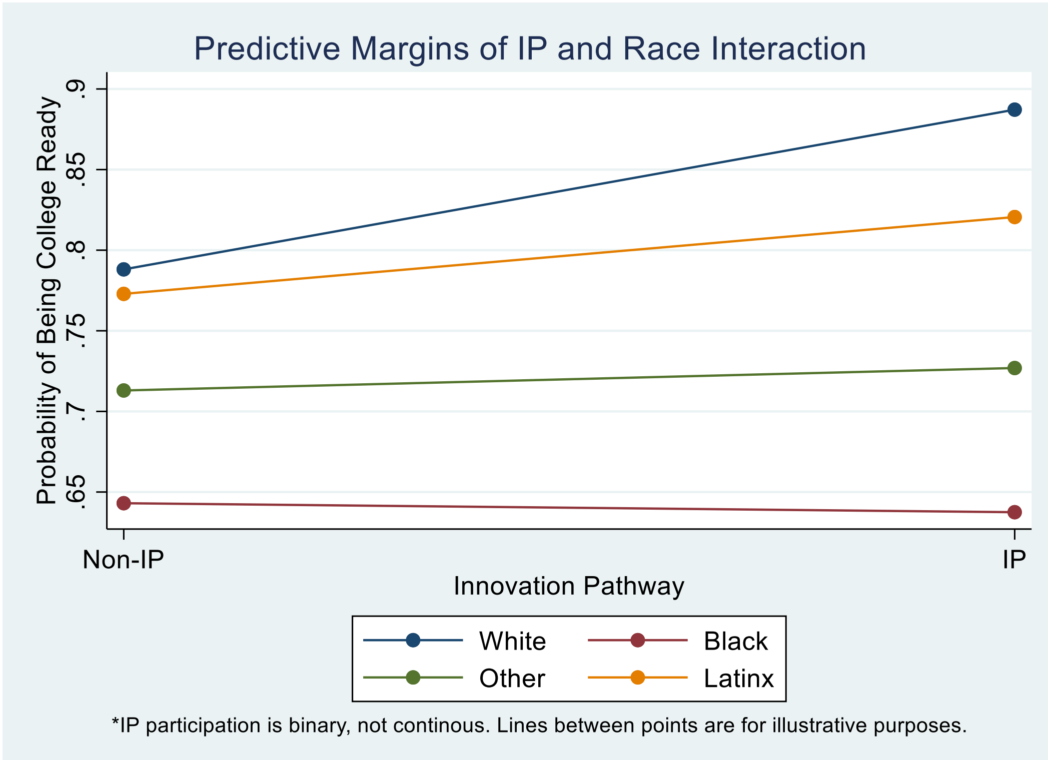
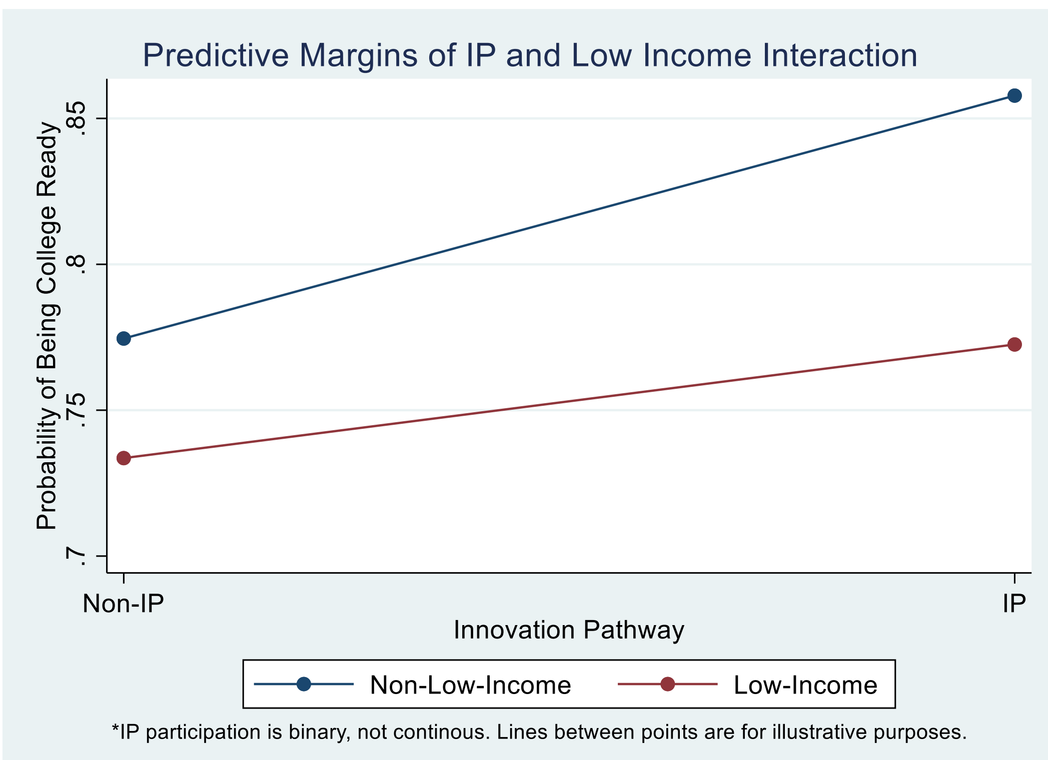


Figure 2. Innovation Career Pathways and Low-income Interaction for College Readiness



Effects of ICP on College Access

Innovation Career Pathways participation is likewise estimated to have positive effects on college enrollment (Table 10). Per the multivariate logistic regression weighting the inverse probability of participating in ICP, participants have 1.34 times the odds of enrolling in college the year after completing high school, relative to non-participants. No interactions were found for ICP participation and being Black, Latinx, or a student from a low-income background for college enrollment (Appendix 2B). This means that there is no evidence of heterogeneity of effects by racial and economic groups. Including school fixed effects in the second model increased the estimate to 1.45 times the odds of enrolling in college for ICP participants, relative to non-participants. Overall, accounting for school fixed effects doesn't really change the estimate substantially, which suggests there is not a lot of variation in impact of Innovation Career Pathways participation on college enrollment by school.

Table 10. Effects on College Enrollment/College Access

	Weighted Regression	(SE)	With School Fixed Effects	(SE)
Innovation Pathway	1.337^{***}	(0.103)	1.449^{***}	(0.156)
Black	1.092	(0.130)	1.393^{*}	(0.210)
Other	0.853	(0.097)	0.928	(0.114)
Latinx	0.580^{***}	(0.056)	0.711^{**}	(0.079)
Low Income	0.586^{***}	(0.046)	0.638^{***}	(0.051)
Male	0.652^{***}	(0.048)	0.628^{***}	(0.046)
Disability	0.743^{*}	(0.108)	0.763	(0.114)
English Learner	0.659^{*}	(0.125)	0.657^{*}	(0.130)
Chronically Absent in G8	0.576^{***}	(0.084)	0.572^{***}	(0.082)
Suspended in G8	0.458^{***}	(0.082)	0.456^{***}	(0.084)
Missing Test Score (ELA)	1.631	(0.432)	1.745^{*}	(0.463)
Partially Meeting Expectations (ELA)	1.798^{***}	(0.264)	1.768^{***}	(0.269)
Proficient/Meeting Expectations (ELA)	2.753^{***}	(0.427)	2.766^{***}	(0.448)
Advanced/Exceeding Expectations (ELA)	4.359^{***}	(1.025)	4.479^{***}	(1.087)
Missing Test Score (Math)	5.310^{**}	(3.316)	4.722^{**}	(2.759)
Partially Meeting Expectations (Math)	1.195	(0.164)	1.179	(0.166)
Proficient/Meeting Expectations (Math)	1.965^{***}	(0.307)	1.853^{***}	(0.298)
Advanced/Exceeding Expectations (Math)	2.698^{***}	(0.607)	2.593^{***}	(0.582)
School Year =2019	1.323	(0.376)	1.352	(0.371)
School Year =2021	1.455^{***}	(0.159)	1.440^{**}	(0.161)
School Year =2022	1.193	(0.124)	1.137	(0.122)
Constant	0.736	(0.141)	0.708	(0.146)
Observations	21070		21070	

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Effects of ICP on College Success

With a smaller sample, due to needing an additional year of data to calculate, Innovation Career Pathways made an estimated positive difference on second-year persistence (Table 11). Looking at the multivariate logistic regression weighting the inverse probability of participating in ICP, participants had 1.37 times the odds of persisting to a second year in college, relative to non-participating students. There are no significant interactions between program participation and being Black, Latinx, or a student from a low-income background (Appendix 2C). Lastly, incorporating school fixed effects to the post-match regression model yields an estimate of 1.33 times the odds of persisting to a second year in college for ICP participants, relative to non-participants. It is worth noting that school fixed effects do not substantially change the estimate, again indicating no evidence of variation by school.

Table 11. Effects on Second-year Persistence/College Success

	Weighted Regression	(SE)	With School Fixed Effects	(SE)
Innovation Pathway	1.368**	(0.134)	1.334*	(0.179)
Black	1.188	(0.182)	1.508*	(0.270)
Other	0.807	(0.107)	0.901	(0.135)
Latinx	0.526***	(0.067)	0.639**	(0.094)
Low Income	0.598***	(0.061)	0.659***	(0.069)
Male	0.578***	(0.056)	0.562***	(0.054)
Disability	0.718	(0.154)	0.717	(0.154)
English Learner	0.782	(0.245)	0.790	(0.263)
Chronically Absent in G8	0.623*	(0.150)	0.623*	(0.150)
Suspended in G8	0.393***	(0.098)	0.385***	(0.099)
Missing Test Score (ELA)	1.184	(0.527)	1.144	(0.519)
Partially Meeting Expectations (ELA)	2.325***	(0.562)	2.193**	(0.530)
Proficient/Meeting Expectations (ELA)	3.689***	(0.912)	3.496***	(0.875)
Advanced/Exceeding Expectations (ELA)	6.887***	(2.142)	6.622***	(2.063)
Missing Test Score (Math)	6.933**	(4.786)	6.722**	(4.345)
Partially Meeting Expectations (Math)	1.286	(0.241)	1.323	(0.247)
Proficient/Meeting Expectations (Math)	2.043***	(0.417)	2.000***	(0.405)
Advanced/Exceeding Expectations (Math)	3.082***	(0.767)	3.069***	(0.757)
School Year =2019	1.180	(0.309)	1.255	(0.331)
School Year =2021	1.479***	(0.162)	1.447**	(0.165)
Constant	0.329***	(0.099)	0.352***	(0.109)
Observations	14049		14049	

Exponentiated coefficients; Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Robustness Check

As a robustness check, the researcher limited the data to the 2020-21 and 2021-22 academic years, when all the 12th graders would have only taken the Next Generation MCAS in 8th grade, in order to use the continuous test scores as opposed to the test performance levels in the regression models that calculate propensity scores as well as those that estimate the main effects. All other aspects of the models remained the same. As shown in Table 12, this approach estimates that Innovation Career Pathways Participants have 1.72 higher odds of being college ready, 1.35 higher odds of enrolling in college, and 1.42 higher odds of persisting to a second year in college, relative to non-participants in their schools, excluding those who participate in Early College. All models across the two approaches, continuous tests scores or factor test performance levels, estimate that Innovation Career Pathways participation has a positive effect on all three outcomes. Notably, the 1.35 odds estimated effect on college enrollment from this main effect model using continuous test scores is similar in magnitude to the 1.34 odds estimated effect from the main effect model in Table 10, which uses test performances levels.

Table 12. Estimated Effects Using Continuous Test Scores from 2020-21 and 2021-22

	Effects on College Readiness	(SE)	Effects on College Access	(SE)	Effects on College Success	(SE)
Innovation Career Pathways	1.715***	(0.180)	1.345***	(0.113)	1.416**	(0.173)
Black	0.381***	(0.052)	1.202	(0.163)	1.458	(0.309)
Other	0.718*	(0.099)	0.944	(0.126)	1.034	(0.179)
Latinx	0.883	(0.111)	0.634***	(0.072)	0.612**	(0.105)
Low Income	0.636***	(0.065)	0.584***	(0.053)	0.540***	(0.073)
Male	0.638***	(0.060)	0.706***	(0.060)	0.720**	(0.091)
Disability	0.544***	(0.079)	0.772	(0.124)	0.796	(0.215)
English Learner	1.207	(0.254)	0.833	(0.190)	1.081	(0.468)
Chronically Absent in G8	0.557***	(0.079)	0.475***	(0.075)	0.285***	(0.078)
Suspended in G8	1.413*	(0.248)	0.366***	(0.079)	0.270**	(0.109)
Next Gen ELA	1.011***	(0.003)	1.013***	(0.003)	1.018***	(0.004)
Next Gen Math	1.005	(0.003)	1.021***	(0.003)	1.020***	(0.005)
School Year 2022	1.158	(0.108)	0.820*	(0.068)	1.000	(.)
Observations	14114		14114		7210	

Exponentiated coefficients; Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Discussion

Dougherty (2018), who investigated the causal impact of participating in CTE on secondary school success in Massachusetts, the setting of this very study, has argued that the research on how well CTE programs prepare students for postsecondary education is emergent; that CTE's impact on college readiness, access, and success are less clear (Dougherty, 2023); and that this should be explored in further research. Although Innovation Career Pathways is a CTE program within a traditional high school, whilst Dougherty's (2018, 2023) work focuses on whole-school CTE programs, this investigation on the effects of ICP participation on college readiness, enrollment, and persistence in Massachusetts speaks directly to his suggestion.

Furthermore, this paper corresponds with and contributes to the emergent literature on the effects of CTE participation on college access and success. Similar in direction to the findings of Brodersen et al. (2021) and Witzen (2018) on the effects of CTE on college enrollment, we find that students who participate in Innovation Career Pathways have higher odds – than students in their schools who do not participate – of enrolling in college, on average. The odds ratios from the multivariate logistic regression weighting the inverse probability of participating in ICP, without and with the school fixed effects, translate to 5.6 and 6.7 percentage point increases in college enrollment, respectively, relative to non-participants when using a linear probability model. These are smaller than the 10 and 7.8 percentage points positive differences found by Brodersen et al. (2021) and Witzen (2018), so our effect estimates are not of the same magnitude.

Although we do not yet have the college completion information for ICP participants, we also find that participants have higher odds of persisting to a second year in college, which corresponds with Dougherty et al. (2019) who find that students who complete a CTE program in high school are more likely to earn a post-secondary degree. Given the findings, which are that ICP participation generally has positive effects on college readiness, access, and success across racial and economic groups—even considering slightly less pronounced effects on college readiness for Black, Latinx, and Low-income students—we argue that more targeted recruitment of students historically underrepresented in higher education to participate in ICP may be a way to promote equitable educational attainment in Massachusetts.

It should be noted that the slightly less pronounced effects of ICP on college readiness for Black, Latinx, and Low-income students may be about the relationship between ICP and the measure of college readiness used in the study, as opposed to college readiness itself, which is unknown. Unlike the two other outcomes of college enrollment and college persistence which are observed, college readiness is approximated by the taking and completion of certain courses. The fact that ICP participants have higher odds of enrolling and persisting in college, across racial and economic groups, suggests that Black and low-income ICP participants are not necessarily meaningfully less college ready. Hypothetically speaking, if a student enrolled in a rigorous course that was more conducive to their career of choice in lieu of an equally rigorous course on the MassCore curriculum, they would not necessarily be less well prepared for college, although the measure of college readiness in this study would suggest that.

Although the within-school feature is what distinguishes ICP from the whole school CTE offerings in the state of Massachusetts, a final point of discussion is the variation in the count and share of 12th graders who participate in the ICP program at each ICP offering school. With some schools having less than 5% of 12th graders participating while others have more than 95%, some interesting questions emerge. While variation by school is addressed in the regression models that estimate impact with school fixed effects, what are the implications for implementation? Can a school deliver Innovation Career Pathways as well for 95% of the 12th grade cohort as it does for 5 %, or for n=10 versus n=200? In light of these questions, Massachusetts may need to consider issues around implementation and program quality for schools, perhaps through an implementation evaluation.

With the framing of offering Innovation Career Pathways as a human capital investment, as defined by Shultz (1961) and Becker (1962), and the years of schooling as an outcome measure (Sweetland, 1996), the positive effects of program participation on college enrollment suggest that the return is very promising. It is the positive effects on college persistence that makes this return concrete, as it indicates an additional year of schooling. Using the Mincer equation, which estimates of the average monetary returns of one additional year of education, the World Bank estimates that each additional year of education produces a private rate of return to schooling of about 5–8% per year, with the highest returns being for tertiary education (Patrinos, 2016). This means that every year of learning generates about a 5-8% increase in annual income for the individual. For students who persisted to second year in college as a result of participating in this intervention, this theoretical return on investment may very well become very real.

Limitations

There are two concerns that arise from using performance levels across three tests. Firstly, the four performance levels of one test do not directly correspond to the four performance levels of the other tests. For example, a student who is proficient (PARCC/Legacy MCAS) does not exactly correspond to a student who is meeting expectations (Next Generation MCAS). The multivariate logistic regression model that calculates propensity scores as well as the regressions that estimate effect sizes all include cohort fixed effects, via the school years, so comparisons across years, and therefore across tests, is not a concern. While PARCC and Legacy MCAS tests were administered in the same years, the Massachusetts Department of Elementary and Secondary Education provided a conversion table by which all PARCC scores were converted to Legacy MCAS scores, after which their performance level was determined, so the performance levels for PARCC test takers correspond with performance levels of Legacy MCAS test takers.

The second concern is that the performance levels are not granular enough to sufficiently capture variation that may exist between treated and untreated subjects. For example, a student on the high end of proficient (PARCC/Legacy MCAS) or meeting expectations (Next Generation MCAS) may have performed substantially differently from a student on the low end of that same performance level. Although they were speaking about test scores as an outcome variable, as opposed to a predictor variable, May et al. (2009) argue in their Institute for Education Sciences (IES) technical methods report that while scale scores provide greater precision, performance levels are not just categorized continuous scores, but rather judgments about what cutoff points indicate substantively meaningful attainment of knowledge or skills, and thus may be used in impact evaluations, so long as caution is exercised when interpreting results. Nevertheless, the robustness check indicates that a model using continuous test scores yields similar results to those using factor test performance levels, when looking at college enrollment. While MassCore completion and college persistence are proxies for college readiness and success, college enrollment is a direct measure, so it is of principal interest in this study.

Methods that address bias by controlling for confounding variables, including inverse probability of treatment weighting, may do well in balancing observed covariates between groups, but they do not necessarily balance unmeasured characteristics (Nuttall & Houle, 2008). Oftentimes, the best a researcher can do is include all relevant covariates for which there are measures, as well as proxies for other measures of interest, as this study uses attendance and discipline measures for non-cognitive skills. In addition to the risk of omitted confounders, which is a limitation of all propensity score methods, inverse probability weighting can be additionally susceptible to unstable weights, when there are observations in the data with low or high probability of receiving the treatment (Austin, 2011).

Furthermore, while the effects of ICP on college readiness, access, and success may be positive on average, it is unclear what variation may exist between ICP career sectors or if the effects are being driven up or down by certain career tracks. Ecton and Dougherty (2023) found substantial heterogeneity across outcomes for students in different fields. More specifically, Mellor and Lin (2021) found that the percentage of CTE program completers who enroll in and graduate from college varies by career cluster, their area of concentration. For example, Dougherty (2023) found that while healthcare CTE participants pursue further education beyond high school, participants in skilled trade CTE programs do not. For the years in this study, Massachusetts did not consistently collect the ICP sector of participants. This should be investigated in future research.

Conclusion

While the United States is mythologized as the land of economic opportunity, two recurrent shortcomings of the American labor market are the wage gaps and unequal unemployment rates that exist between racial groups and socioeconomic groups. This is the case nationally and also in the state of Massachusetts, where Black and Latinx high school graduates are more likely to be unemployed and earn less when they are employed, relative to White high school graduates. We investigated whether the offering of Innovation Career Pathways, an optional career and technical education (CTE) program within traditional public high schools that are primarily attended by students from historically disadvantaged backgrounds, promotes educational attainment for their participants, which the literature suggests has a positive relationship with employment as well as earnings.

Although the literature on the impact of CTE on college outcomes is emergent, the findings summarized in the literature review for this study suggest that the effects are generally positive, with CTE participants being more likely to graduate high school, enroll in a postsecondary institution shortly after, and completing a post-secondary credential. This is quite a shift from the historical intentions of CTE, which previously narrowly focused on preparing non-college bound youth for low-wage job attainment.

Using Inverse Probability of Treatment Weighting, as determined by propensity scores, we find that ICP participants have higher odds of being college ready, enrolling in college, and persisting to a second year in college and thus argue that more targeted recruitment of Black, Latinx, and low-income students to participate in ICP may be a way to promote equitable access to higher education. Although this study uses college readiness, enrollment, and persistence as outcomes, they are somewhat of a secondary objective of Innovation Career Pathways; the primary objective is eventual gainful employment. Therefore, in addition to looking at college completion data, rates of employment and earnings are outcomes of high interest for Innovation Career Pathways in future research.

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