

The Returns of College and Career Preparation as Human Capital Investments in Massachusetts

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Dedication

First and foremost, I dedicate this doctoral thesis to my mother and father, Anne Marie Ange Wagnac-Lucien and Pierre Joazar Lucien, who not only gave me the gift of life but sacrificed their livelihoods by relocating from Haiti to the United States so that my brothers and I could have better educational opportunities. Ever the believer in the transformative power of education, my mother not only pushed and supported us in our educational pursuits but also modeled the behavior she wanted us to emulate by returning to school and earning an associate, a bachelor's, and a master's degree after arriving to the United States at the age of 38 with three children. My father, who was born in abject poverty to parents with limited literacy in rural Haiti, became the laureate in his section at the State University of Haiti Faculty of Sciences, when he earned his bachelor's degree in 1986. He later started his own architecture and civil engineering firm in my hometown of Les Cayes. My parents have inspired me from the moment I was born, and that is perhaps my superpower.

I further want to dedicate the thesis to the people of Haiti—Haitian citizens, the Haitian diaspora, and all people of Haitian ancestry. I don't know how many Haitians have earned a doctorate degree from Oxford, but I would not be surprised if I was the first or one of a few. It was 220 years ago in 1804, when Haiti gained its independence from France. Ever since, the people of Haiti have had to endure economic instability, political turmoil, and a slew of natural disasters. As an example of each, Haiti currently has the lowest GDP in the Western Hemisphere, the Haitian President was assassinated in July 2021, and the earthquake in January 2010 was the second most destructive event in the world in 21st century, fatalities-wise. During the writing of this very dedication, Haitian refugees and migrant workers in Springfield, Ohio are being targeted by a United States presidential candidate as not adding value and causing harm, suggesting they're unbelonging and unworthy. All this to say, we are worthy, hardworking, and when given the opportunities, even capable of earning advanced degrees from universities like Oxford.

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Thesis Abstract

Framed by Human Capital Theory (Schultz, 1961; Becker, 1962) and structured by the Research Framework for Reducing the College Success Gap (Perna & Thomas, 2006), this thesis gauges the effects of participation in the Early College (EC) and Innovation Career Pathways (ICP) programs on educational attainment for students in Massachusetts using propensity score methods across three papers. It further investigates interactions between program participation and students being Black, Latinx, or low-income, given the underrepresentation of those groups in higher education.

The first paper is an impact evaluation of EC, which uses propensity scores to match program participants with non-participants and compare differences in college readiness, access, and success via post-match regressions incorporating school fixed-effects and interactions. Among other findings, this study estimates that EC participation has a 14-percentage point impact on college enrollment, with positive interaction effects for low-income students. This finding is consistent in direction and magnitude with the 15.6-percentage point impact estimate found by Edmunds et al. (2017; 2020).

The second paper is an impact evaluation of ICP, which uses inverse probability of treatment weighting (IPTW) to create a synthetically balanced sample consisting of all students in ICP offering schools, from which average treatment effects are calculated via weighted regressions incorporating school fixed-effects and interactions. Among other findings, this study estimates that ICP participation has a 7-percentage point impact on college enrollment. This finding is consistent in direction and magnitude with the 7.8-percentage point impact estimate found by Witzen (2018).

The third paper is a comparative impact evaluation of EC and ICP, which uses inverse probability of treatment weighting based on generalized propensity scores (GPS). Consistent with the former two impact evaluations, this study finds that both EC and ICP positively affect college enrollment, with EC having positive interaction effects for low-income students, among other findings.

Chapter 1: Introduction

Research suggests that educational attainment, namely pursuing and earning a college degree, is associated with a variety of positive outcomes for individuals and the communities in which they live. For the individual, this can mean higher earnings (Lobo & Burke-Smalley, 2018), better health and lower mortality rates (Trostel, 2015; Hummer & Lariscy, 2011), and personal development (Rose, 2013). For society, this can mean increased civic engagement (Levin-Waldman, 2013), reduced incarceration rates (Cunningham, 2006), and less spending on social programs (Baum & Payea, 2005). Collectively, these findings substantiate and serve as a premise for Human Capital Theory, which posits that the deliberate pursuit of knowledge and skills that yield an economic return, such as attending school, is a human capital investment (Schultz, 1961; Becker, 1962). It should be noted that better health and lower incarceration rates are cost savings and therefore indirect economic returns.

Although the returns from the human capital investment of educational attainment for the individual and society are well documented, there is persistent and pervasive inequity in access and outcomes when it comes to education in the United States (Gamoran, 2001; 2015). Black, Latinx, and low-income students historically and presently have less access to quality education and have worse outcomes, including lower rates of educational attainment (Goldrick-Rab et al., 2016; Murnane et al., 2014; Jeffrey, 2020). This shortcoming of American education does not just persist temporally, but is also pervasive spatially, as it is observed throughout the country. One such settings is the Commonwealth of Massachusetts (National Center for Education Statistics, 2022; The College Board, 2022), which is one of the 50 states in the American Union.

The Need to Intervene in Massachusetts

Massachusetts consistently ranks highly when comparing its standardized test scores, high school completion rates, and college enrollment rates to the remaining forty-nine states in the last two

decades (National Center for Education Statistics, 2022). However, when the data is disaggregated, there remain sizeable disparities that separate racial minority students and socioeconomically disadvantaged students from their peers. Inequities in Massachusetts secondary education are that racial minority and socioeconomically disadvantaged students are less likely to meet post-secondary-readiness benchmarks on reading and math exams; are less likely to complete a state recommended sequence of courses that aligns with post-secondary and workforce readiness; and are under-represented among students completing post-secondary credit bearing courses (Massachusetts Education Equity Partnership, 2018).

Once in college, these issues persist. Some inequities in Massachusetts higher education are that performance gaps between White and racial minority students in post-secondary math and reading are higher than the national average; the gap between the number of White and Black students at post-secondary institutions who must take remedial courses continues to grow; and that post-secondary completion rates for racial minority and socioeconomically disadvantaged students remain lower than those of their White and non-disadvantaged peers, with minimal change from year to year (Massachusetts Department of Higher Education, 2016). Such inequities have negative consequences not only for the individual students and their families, but also for the economy of the state, as educational attainment—secondary and post-secondary completion—is associated with employment status and income, and the state demographics are shifting, with the share of the citizenry that identify as Black or Latinx increasing (Massachusetts Education Equity Partnership, 2018).

Considering the demographic shifts, Massachusetts expanded college and career pathway programs to include Early College (EC) and Innovation Career Pathways (ICP), to further provide students in the state a supportive and rigorous academic experience and career development relevant to their interests, so that they may graduate secondary school with a well-designed post-secondary plan. Per the Early College designation criteria, EC seeks to promote post-secondary school enrollment by

allowing secondary school students to experience and complete post-secondary courses on a clearly articulated pathway and gain exposure to a variety of career opportunities (Massachusetts Department of Higher Education & Massachusetts Department of Elementary and Secondary Education, 2017). Furthermore, by providing the courses at no cost to students, EC would reduce the time and expense of earning a degree while increasing the likelihood of completion.

Per the Innovation Career Pathways Designation Criteria, ICPs are structures within secondary schools that connect student learning to an in-demand industry sector—e.g., information technology, engineering, or healthcare—in the regional and state economy (Massachusetts Executive Office of Education & Massachusetts Department of Elementary and Secondary Education, 2020). More specifically, schools leverage partnerships with local career centers and employers to provide students career awareness and work-based learning activities. The students also participate in a series of courses, which are often post-secondary level, and experiences relevant to achieving industry recognized credentials. The top guiding principle for EC and IP is Equitable Access, which is defined as prioritizing students underrepresented in post-secondary education enrollment and completion. To meet the Equitable Access criterion, schools must demonstrate outreach and recruitment of racial minority, socioeconomically disadvantaged, first-generation, and otherwise underrepresented students.

By offering Early College and Innovation Career Pathways so that its citizens may acquire useful knowledge and skills that will produce the desirable outcomes of higher educational attainment and gainful employment, Massachusetts is making human capital investments, as are the students who choose to participate. Thus, the papers that comprise this integrated thesis seek to investigate the returns on these human capital investments. More specifically, the research questions across the three papers are: 1) What is the effect of participating in Early College or 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 Early College or Innovation Career Pathways on students' likelihood of enrolling in college within 6 months of on-time secondary school completion? 3) What is the effect of participating in Early College or Innovation Career Pathways on students' likelihood of persisting to a second year in college? 4) How do these effects vary by racial and socioeconomic background? 5) How do these effects vary by intervention? Given the relationship between educational attainment and earnings (Lobo & Burke-Smalley, 2018) and the prevalent use of educational attainment as an outcome measure in Human Capital literature (Sweetland, 1996), college readiness, college enrollment, and persistence to a second year in college are appropriate outcomes for the three papers of the integrated thesis.

American Education

To make sense of the contents of this thesis, it is helpful if the reader is lightly oriented to the organization and structure of American education. Depending on the state, compulsory education starts at age five, six, or seven and runs for nine to thirteen consecutive years, with a grade corresponding to the year in school. Schooling is mandatory to the age of at least sixteen in all states and no state requires a student to be in school passed the age of nineteen (National Center for Education Statistics, 2017). Schools are generally categorized as early childhood, elementary, middle, and high schools. High schools, known elsewhere as secondary schools, generally enroll students from grades nine to twelve—age fourteen to eighteen—and are at least partly compulsory in every state (US Department of Education, 2008). In Massachusetts, education is compulsory from age six to age sixteen.

Upon completion of twelfth grade, at around age eighteen, a student may choose to pursue tertiary education at a post-secondary institution. These institutions vary widely in terms of type, ownership,

and governance arrangements. For the sake of this paper, it's most helpful to know that a student may attend career and technical school or an institution of higher education. Per the US Department of Education (2008), Career and technical schools, which are mostly private, provide short training courses and sometimes specialized degree programs while higher education institutions, which may be public or private, are typically degree granting colleges or universities. Overall, postsecondary education includes non-degree programs that lead to certificates and diplomas plus 6 degree levels: associate, bachelor, first professional, master, advanced intermediate, and research doctorate (US Department of Education, n.d.). Associate's degrees are only granted at 2-year colleges, also known as community or junior colleges, which also do not offer the remaining degree levels.

Primary, Secondary, and Tertiary Education in Massachusetts

There are 1,837 public schools in Massachusetts—1,093 elementary schools, 320 middle schools, and 414 high schools (Department of Elementary and Secondary Education, n.d.). During the 2021-22 academic year, the last year in this study, there were 875,392 students in those schools. That is 91.4% of all students in Massachusetts, as 7.2% attended private or parochial schools and 1.4% were home schooled. During that year, 43.85 of students identified as low-income, 9.3% were Black, 23.1% were Latinx, and 55.7% were white. 51.3% identified as male, 48.6% identified as female, and 0.1% identified as non-binary. Of all the students in public schools, 73,817 were in grade nine; 73,468 were in grade ten; 71,883 were in grade eleven; and 68,770 were in grade twelve, totaling 287,938 students in Massachusetts public high schools, the context in which Early College and Innovation Career Pathways take place.

The Massachusetts public higher education system consists of 29 total colleges—15 community colleges, 9 state universities, and 5 autonomous University of Massachusetts campuses. At the beginning of 2021-22 school year, enrollment of all undergraduate students at Massachusetts public

colleges & universities totaled 153,929 (Massachusetts Department of Higher Education, 2021). Massachusetts has numerous private higher education institutions as well, which include the like of Massachusetts Institute of Technology (MIT) and Boston College. Including the students enrolled in public colleges and universities, there were 472,056 students enrolled in 106 institutions of higher learning in the state of Massachusetts in autumn 2020 (Carnegie Classification of Institutions of Higher Education, 2023).

History of Promoting Educational Attainment in Massachusetts

Covering the history of promoting educational attainment in the state of Massachusetts helps to contextualize the human capital investments of Early College and Innovation Career Pathways. Not only is Massachusetts presently a top performer across various measures at all levels of education (National Center for Education Statistics, 2023), it is the birthplace of American public elementary and secondary education, as well as American higher education. In April 1635, more than a century before the 1776 American Declaration of Independence, the all-boys Boston Latin School (BLS) in Massachusetts became first public school in what would become the United States (Crooks, 2023). Modeled after the Free Grammar School of Boston, England, BLS taught Latin, Greek, and other humanities subjects for the express purpose of preparing students for college.

Just a year later, in 1636, Harvard University—perhaps the best known in the United States today—was founded in Massachusetts, serving as the first college in the American colonies (Harvard University, n.d.). In 1839, Massachusetts led the way in what one could argue is the precursor to the modern American community college, with the opening of the first public normal school in the country, in the city of Lexington, which offered a two-year course beyond secondary school (Paterson, 2021). Massachusetts therefore has a relatively long and unprecedented history of preparing students for and offering opportunities to attend college in the United States.

Early College and Innovation Career Pathways were designated by the Massachusetts Board of Elementary and Secondary Education as well as the Massachusetts Board of Higher Education. The board model of public education governance, which is now the norm across the United States, was first implemented in Massachusetts. In 1837, Horace Mann, commonly referred to as "the father of American education," was elected as the inaugural Secretary of the new Massachusetts Board of Education (PBS, n.d.). This was the first of its kind in the country and Mann used his position to enact major educational reform, such as the aforementioned opening of public normal school in Lexington, Massachusetts. Therefore, Massachusetts also has a relatively long and unprecedented history of promoting educational attainment, i.e., making human capital investments, in the United States.

History of Inequity in Massachusetts Education

Despite being a pioneer in many aspects of promoting educational attainment in the United States, Massachusetts educational endeavors and institutions have historically been marred by inequity, whereas White students have had better access to quality schools than racial minority students, via segregation. Dating back to 1787, Black residents of Boston—the largest and capital city of Massachusetts—were petitioning the Massachusetts Legislature for access to quality public schools in which White students enrolled (Saimprevil, 2022). Although the African School was started by Black Boston parents to educate their children in 1798, the conditions remained poor with deterioration and overcrowding, relative to schools attended by White students (National Park Service, n.d.). Consequently, the city of Boston commissioned the construction of the Abiel Smith school for Black students in 1835, but the conditions in that school were markedly inferior to those of the White schools (Grover & Da Silva, 2002).

Segregation in Massachusetts education remains prevalent nearly two centuries later, despite the 1965 passing of the Racial Imbalance Act, which outlawed segregated schools, defined as those with

a student body comprised of more than 50% of any racial group (Boston Research Center, n.d.). In 2018, the year that Early College and Innovation Career Pathways policy interventions were launched, it was found that 60% of Boston schools were segregated, by the Racial Imbalance Act definition (Miller, 2020). Even when not using this definition, some schools are segregated in that they exclude Black, Latinx, and low-income students. For example, enrollment at the aforementioned Boston Latin School, which is one the best public schools in the country (U.S. News and World Report, 2024) in addition to being the first, is majority wealthy White and Asian students (Arshad, 2022).

Because a student's school district is defined based on their neighborhood of residence and community residents must pay for education with taxes, neighborhoods with wealthier homeowners generate greater tax revenue to finance public education (Chaaraoui, 2024). This structure is a major driver behind the segregated schools and their negative impact on Black, Latinx, and low-income students, who then end up enrolling at lesser resourced schools. In many ways, "education policy is constrained by housing policy," as Rothstein (2014) from the Economic Policy Institute puts it. Human capital investments targeting Black, Latinx, and low-income students, as indicated on the designation criteria for Early College and Innovation Career Pathways, may be a way extend the Massachusetts legacy of promoting educational attainment to those who are historically underrepresented.

Massachusetts Economy and Demographics

Other, and perhaps equally important, motivations for the offering of Early College and Innovation Career Pathways by the state of Massachusetts in 2018 were the labor market projections and demographic shifts, corroborating that these interventions are indeed intentional human capital investments. The Georgetown University Center on Education and the Workforce projected that by 2018, the year both Early College and Innovation Career Pathways were launched, Massachusetts would be ranked first among the 50 states, in terms of the proportion of its jobs that will require a

post-secondary degree at 70% (Carnevale et al. 2010). Conversely, Massachusetts was ranked 39th in states that would have job openings for people who did not graduate high school. When looking at the highest mean annual wages from 2023 in Massachusetts, all the occupations that pay six figures, $100,000 or more, require at least a bachelor's degree (Massachusetts Department of Economic Research, 2024).

Alongside those labor market projections and the higher wages of college graduates, Massachusetts Department of Higher Education (2016) projected that by 2022, the overall rate at which young adults in Massachusetts earn college degrees will pivot from growth to decline due to demographic shifts and the lower rates at which racial minority students earn degrees, resulting in the demand for qualified graduates with degrees in high-need fields outpacing the supply that they could provide. The population of Massachusetts is changing such that it is one of just six states in the United States that can attribute all its population growth between 2000 and 2010 to the increase in its Latino population (Massachusetts Education Equity Partnership, 2018). With such projections and demographic shifts, government action needed to be taken.

Thesis Rationale and Outline

The seven chapters of this integrated thesis answer a vital policy question for the state of Massachusetts—do the human capital investments of Early College and Innovation Career Pathways yield the desired returns, via their effects on student outcomes—while engaging and contributing to the literature in multiple ways. For example, experimental research on Early College has shown that this type of intervention has positive effects on college readiness, access, and success (Berger et al., 2013; Edmunds et al., 2017). However, their respective studies only included whole school Early College programs, where the entire school participated in the intervention. Edmunds et al. (2017) list

the evaluation of early college strategies within traditional comprehensive high schools, such as those of Massachusetts, as a suggestion for further research.

Likewise, there is evidence that career and technical education, the type of intervention Innovation Career Pathways are, have positive effects on college readiness, access, and success (Witzen, 2018; Brodersen et al., 2021). Yet, Dougherty (2018) argues that the research on how well Career Technical Education (CTE) programs prepare students for college is emergent; that CTE's impact on college readiness, access, and success are less clear (Dougherty, 2023); and that those questions should be investigated in further research. This thesis speaks to Edmunds (2017) and Dougherty (2018; 2023), and to the emergent joint literature of college and career readiness. The thesis also engages Human Capital Theory, as defined by Shultz (1961) and Becker (1962), whilst employing Perna and Thomas' (2006) Framework for Reducing the College Success Gap and Promoting Success for All.

The thesis comprises 7 chapters— Chapter 1: Introduction; Chapter 2: Literature Review; Chapter 3: Research Methods; Chapter 4: Effects of Early College Participation on Educational Attainment for All in Massachusetts (Integrated Thesis Paper 1); Chapter 5: Do Innovative Career Pathways in Massachusetts High Schools Promote Equitable Access to Higher Education? (Integrated Thesis Paper 2); Chapter 6: The Comparative Effects of Early College and Innovation Career Pathways on Educational Attainment in Massachusetts (Integrated Thesis Paper 3); and Chapter 7: Discussion and Conclusion. The contents of the chapters are as follows:

Chapter 1: Introduction

This chapter first introduces public education and educational attainment in Massachusetts, highlighting the state's high performance relative to the rest of the country. Secondly the chapter summarizes the inequity by racial and socioeconomic background that persists at all levels of education in the state. Thirdly, the chapter introduces and briefly describes Early College and

Innovation Career Pathways, the two interventions launched by the state of Massachusetts to address said inequity. Lastly the chapter presents the research questions and justifies the need for these studies to be conducted. The chapter also orients the reader to the structure American and covers the relatively long history of education in Massachusetts to further contextualize the problem and interventions.

Chapter 2: Literature Review

This Chapter covers the long history of inequity in educational outcomes by racial and socioeconomic groups in the United States. Pertinent to this study, the chapter then covers the financial and social returns of educational attainment for the individual and for society at large, with a focus on historically marginalized groups in the United States. The chapter then outlines the role that policy interventions may play in addressing social problems such as inequity in education and provides some examples that have been deployed to improve education outcomes elsewhere, including Early College and career and technical education. Lastly, the chapter concludes with a summary and justification for the theoretical and research frameworks that inform and structure the thesis.

Chapter 3: Research Methods

This chapter starts with a primer on causal inference and non-experimental causal research, followed by a description of the propensity score methods used to evaluate the two interventions in this study. The conceptual underpinnings as well as the mathematical operations of propensity score methods are explicated. Steps to be taken, including how to calculate the propensity score with a logistic regression, matching or weighting with the propensity score, and post-match or post-weight regressions featuring fixed effects and interactions are described. The remainder of the chapter focuses on the data—where they come from, how they were prepared, the dependent and independent variables included in the study, and how they are being stored securely.

Chapter 4: Effects of Early College Participation on Educational Attainment for All in Massachusetts (Integrated Thesis Paper 1)

This chapter is an impact evaluation of Early College, which uses propensity scores to match program participants one-to-one with non-participants in Early College offering schools, to compare differences in college readiness, access, and success via post-match multivariate regressions incorporating school fixed effects and interactions. Findings and connections to existing literature are presented and discussed. Sections covering literature review, theoretical framework, methods, and conclusion are also included. The various choices made by the researcher in terms of the specifications are outlined. The justification for the use the method for this paper and the limitations of the method are also presented.

Chapter 5: Do Innovative Career Pathways in Massachusetts High Schools Promote Equitable Access to Higher Education? (Integrated Thesis Paper 2)

Covering recent literature that shows career preparation in high school promotes educational attainment, this chapter is an impact evaluation of Innovation Career Pathways, which uses the inverse probability of treatment weighting (IPTW) to create a synthetically balanced sample consisting of all students in ICP offering high schools, from which average treatment effects are calculated from post-weighted multivariate regressions incorporating school fixed effects and interactions. A comprehensive description of the intervention is provided, as well as typical paper sections, including theoretical framework, methods, and conclusion. The justification for the use of the method for this paper and various robustness checks are presented before the findings and discussion.

Chapter 6: The Comparative effects of Early College and Innovation Career Pathways on educational attainment in Massachusetts (Integrated Thesis Paper 3)

This chapter is a comparative impact evaluation of Early College and Innovation Career Pathways, which uses inverse probability of treatment weighting based on generalized propensity scores. (GPS). Although the two previous chapters evaluate Early College and Innovation Career Pathways, respectively, the estimates from those two studies should not be directly compared, as they were derived from different subsets of the sample and thus do not represent the same populations. Likewise, college preparation in high school and career preparation in high school have their distinct literatures, but there is an emergent joint college and career readiness literature that this chapter engages. Given that some Massachusetts schools choose between offering Early College and Innovation Career Pathways, this chapter provides insight that may guide their decision making by comparing the two interventions.

Chapter 7: Discussion and Conclusion

This closing chapter primarily discusses how the thesis contributes to and/or engages literature, including how research questions answered fill gaps in the literature and how findings relate to findings of prior research. Secondly, the chapter covers a range of topics to be considered and discussed by readers of the thesis or any of the preceding chapters. For example, Early College and Innovation Career Pathways target Black, Latinx, and low-income students, but they are not the only groups that are underrepresented. Likewise, while Massachusetts made a human capital investment by offering the interventions, there are critiques of human capital theory regarding its intersection with race worth considering. Lastly, a synthesis of all the chapters and closing remarks are provided.

Chapter 2: Literature Review

Persistent and Pervasive Educational Inequity in the United States

Despite the widely believed notion that everyone should be entitled to the resources, opportunities, and protections that schools offer (North, 2006), there is a long history of inequity in education access, quality, and attainment based on race and socioeconomically disadvantaged status in the United States (Gamoran, 2001). In the 1800s: Native American children were coerced into attending low quality boarding schools (Loring, 2009); school administrators routinely denied Chinese American children entrance into schools based on their ethnicity (Noltemeyer et al., 2012); and numerous states enacted laws that made it illegal for Black students to be taught to read and write (Reef, 2009).

These educational inequities are not relics of the past. As late as the 1960s, most Black, Latinx, and Native American students were educated in segregated schools funded at lower rates than those serving White students and were excluded from many higher education institutions entirely (Darling-Hammond, 1998). While it is true that gaps in high school completion by race declined against the backdrop of the civil rights movement, the inequality in the percentage of young people completing college by racial groups increased (Snyder & Dillow, 2013). For example, bachelor's degree attainment rates for Black and Latino students were approximately 20 percentage points lower than for white students in 2010 (Ross et al., 2012).

Similar gaps have always existed and remain for students from socioeconomically disadvantaged backgrounds (Gamoran, 2015). Pertinent to this research project, Bailey and Dynarski found growing gaps between children from high-income and low-income families in college enrollment, persistence, and completion, when looking at 70 years of data from the U.S. Census and the National Longitudinal

Surveys of Youth (2011). Likewise, first-generation college students were found to be half as likely to obtain a degree as students whose parents attended college (Redford & Hoyer, 2017).

Decades of assessment data further demonstrate persistent inequities in American education. It was established in 1960's, that race and socioeconomically disadvantaged status were strongly associated with student performance on standardized tests (Coleman et al., 1966). 55 years later, race and socioeconomically disadvantaged status continue to have this correlation with academic performance. Hanushek et al. (2019) found that for students born between 1954 and 2001, the test performance gap between those in the ninetieth and tenth percentiles of the economic distribution remained steady at one full standard deviation for 50 years. Although, the test performance gap by race decreased from 1.3 to 0.8 standard deviations between students born in 1954 and the 1980s, the remaining gap has persisted in the latter decades.

Differences in performance on standardized tests or other cognitive measures by race and socioeconomically disadvantaged status, commonly referred to as achievement gaps in the United States, are seen at all levels of education. There is evidence that such differences appear as early as kindergarten (Fryer & Levitt, 2004), while other research shows that they remain throughout high school and college (Libassi, 2018). The literature further indicates that achievement gaps widen as students progress from primary to and through secondary school (Reardon et al., 2015), underscoring the need for interventions such as Early College and Innovation Pathways, that may have the potential to close these gaps.

There are even differences in the way racial minority and socioeconomically disadvantaged students are disciplined, relative to their White and non-disadvantaged peers. Rocque (2010) finds evidence of disproportionality in the rates at which Black and White students receive discipline referrals while Gregory and Weinstein (2008) report racial disparities in school suspensions, both favoring White

students. Consistent with the literature on racial discipline gaps, students of socioeconomically disadvantaged backgrounds are also overrepresented in adverse discipline outcomes (Brantlinger, 1991). Interestingly, discipline gaps by race are larger in more affluent areas (Gopalan, 2019). Gaps in discipline become relevant to this research when one considers that students who are excessively disciplined have a higher likelihood of dropping out of school (Raffaele Mendez, 2003) and interact with the justice system (Fabelo et al., 2011), both of which decrease the odds of enrolling in college, albeit the relationship may not be causal.

Inequity by race and socioeconomically disadvantaged status is so pervasive in American education that it surfaces in a multitude of dimensions. For example, Darling-Hammond (2000) suggests that teaching quality is the most impactful in-school factor on student outcomes. Yet, schools and districts that predominantly enroll racial minority and socioeconomically disadvantaged students have higher percentages of teachers who lack certification, are inexperienced, or do not teach a subject in which they have an educational background (Olson, 2003). Interventions that are proven to close gaps in education access, quality, and attainment by race and socioeconomically disadvantaged status are much needed in the United States.

Importance of Educational Attainment

Of all the inequity that exist in various areas in American education, the series of three papers in this thesis focus on educational attainment, namely college readiness, access, and success. While the value of a college education is in question on public forums (Ruppel Shell, 2018), it continues to be associated with a variety of positive outcomes, hence the appeal of offering Early College and Innovation Career Pathways. Even with rising costs of attending college and falling or stagnant earnings in the United States, the college wage premium remains high while reducing the

opportunity cost of going to school because the wages of those without a college degree have also been falling or stagnant (Abel & Deitz, 2014).

Using a selection-adjusted net present value methodology, Lobo and Burke-Smalley (2018) found that students with a bachelor's degree earn more than high school completers for the duration of their careers, on average. For example, when they compared the lifecycle of earnings for the 50th percentile group of high school completers and college graduates, there were positive differences upwards of $20,000 in the mean and median annual earnings for college graduates (Lobo & Burke-Smalley, 2018). Whether one believes the difference in earnings is a reflection of knowledge and skills acquired in college, or the effects of signaling—the use of a college degree as an identifier of preferrable employees by employers, irrespective to what they may have learned in college—college graduates earn substantially more than those with just a high school diploma during the course of their careers (Rose, 2013).

Petronijevic and Oreopoulos (2013) reviewed the relevant literature and found that returns of a college degree are not just financial, but also include better health, and increased community engagement, among other benefits. Disaggregating the population over the age of 25 into ordinal educational attainment levels and calculating their respective mortality rates, Hummer and Lariscy (2011) found that more educated Americans have lower yearly mortality rates than less educated ones in every age, gender, and racial group of the adult population, according to National Institutes of Health data. Some other health related associations are that college graduates have lower likelihoods of being regular smokers, being obese, or being heady drinkers (Trostel, 2015).

From a personal development perspective, college graduates have more capabilities than they would have had they not gone to college (Rose, 2013). Chickering and McCormick (1973) found that undergraduates of different backgrounds and from a range of institutions became more

autonomous, more aware, more integrated, more aesthetically sensitive, more tolerant in religious views, and less concerned about material possessions from their first to the last year in college, on average. For some, earning a college degree even has mental health benefits, such as lowering depression and raising self-esteem (Heckman et al., 2018).

Beyond the individual, there are also societal benefits of higher education. College graduates rely less on government social programs, are less likely to be incarcerated, and are more likely to be civically engaged (Cunningham, 2006). Baum and Payea (2005) found that the United States government spends at least $800 more per year on unemployment compensation, food programs, welfare, and other social programs for 30-year-old high school graduates than for college graduates of the same age, across racial and gender groups. Although correlational, it is worth mentioning that Harlow (2003) found that relative to their share of the non-incarcerated population, adults with at least some postsecondary education are underrepresented in prison, whereas individuals whose highest educational attainment is a high school diploma are overrepresented.

Drawing data from the 2008 Current Population Survey, Levin-Waldman (2013) conducted a logistical regression analysis, which estimated that U.S. citizens with high educational attainment have higher probabilities of being civically engaged. Civic engagement in their analysis is measured by the frequency with which participants discussed politics, read newspapers, attended political meetings, attended marches and rallies, showed support for candidates, and participated in civic organizations. Although covariates for their model included gender, high income occupation, high household income, marital status, and age group, among other related variables, educational attainment had the greatest impact. In totality, the benefits of educational attainment, namely earning a college degree, extend far beyond just the higher earnings.

Inequity in Educational Attainment by Economic Status and Race

While the returns of a college degree are well documented, students from socioeconomically disadvantaged families have reduced chances of attending college, persisting to later years, and completing a degree for a long list of external factors, including lack of access to high schools that offer opportunities for the advanced coursework necessary for college success (Goldrick-Rab et al., 2016). Murnane, Willett, and Papay (2014) examined educational attainment by economic groups in Massachusetts, the very setting of the thesis studies, using linear probability regressions with various educational thresholds as an outcome and controlling for relevant characteristics. They found large income-related gaps in educational attainment: For example, less than 50% of socioeconomically disadvantaged students attended college or university, compared to 75% of higher-income students. The difference is similar for second-year persistence and degree completion.

Similarly, there remains a disparity in the rates at which Black students are entering, persisting in and completing college, although there has been an increase in the share of the U.S. population accessing and graduating from college overall (Jeffrey, 2020). Using logistic regression and counterfactual substitution of coefficient values on data from the Education Longitudinal Study and the Integrated Postsecondary Education Data System, Eller and Diprete (2018) found that relative to White students, Black students experience insufficient academic preparation, inadequate guidance during the application process, and a shortage of financial resources.

There are also disparities in college readiness, access, and success for Latinx students. At 76 percent, the high school graduation rate for Latinx students lags White and Asian students who are at 87 percent and 89 percent, respectively (National Center for Education Statistics, 2016 as cited in Gándara & Mordechay, 2017). Furthermore, while 40 percent of White adults and 62 percent of Asian adults between the ages of 25 and 29 had completed at least a bachelor's degree in 2015, less

than 17 percent of Latinxs had done so (U.S. Census Bureau, 2015 as cited in Gándara & Mordechay, 2017). In addition to the same factors that negatively affect educational attainment for Black students, only 20 percent of Latinx children live with an adult who has completed at least some postsecondary education, making it even more difficult for them to successfully navigate the postsecondary system (Wildsmith et al., 2016).

Policy Interventions and Impact Evaluations in Education

In the context of public services, like public education, a policy is a government action taken in response to or in anticipation of a social problem. Given the benefits of educational attainment for the individual and society, inequity in educational attainment by race and socioeconomic status is a social problem in and of itself that warrants policy attention. It becomes an increasingly pressing social problem when considering the shifting demographics in Massachusetts and the United States, with the share of individuals identifying as racial minority increasing (MEEP, 2018). While such government actions, or policies, may come in the form of laws, regulations, procedures, administrative actions, or interventions (CDC, n.d.), this thesis concerns only the latter.

Wiseman (1979) defines a policy intervention in a designated social problem as a purposive attempt at addressing the problem to improve the situation. Policy interventions typically aim to produce certain outcomes through the delivery of some free service and categorical grants to support units of government (Bryson & Ring, 1990). In this sense, the offering of Early College and Innovation Career Pathways are policy interventions by the government of Massachusetts, in response to the social problem of inequity in educational attainment by racial and economic groups, to improve the situation. Both interventions are at no cost to students and are financed by state grants awarded to the schools that are designated. It should be noted that policy interventions and human capital investments, which will be discussed in greater detail later in this chapter, are not mutually exclusive.

There are examples of education policies that have been shown to promote equitable outcomes and yield a return on investment. One such example are policies around class-size reduction. In a randomized controlled trial, Krueger (1999) found that average performance on standardized tests increased by four percentile points after class sizes were reduced in primary school and that the effects were larger for racial minority students and those on free or reduced-price lunch. From a human capital investment perspective, Krueger (1999) calculated that the economic returns to class size reduction in his study were greater than the costs. Furthermore, Chetty et al. (2010) found that students who were randomly assigned to the smaller classes in primary school were significantly more likely to enroll in college, in a follow up to Krueger's study from 11 years earlier.

It should be noted that there are studies with mixed results around class size reduction. Jepsen and Rivkin (2009) determined that, although reduced class sizes improved mathematics and reading performance on tests, they also increased the share of teachers with neither prior experience nor full certification, which practically offset the benefits of reduced class sizes. Moreover, Sims (2009) found that the reduction of class sizes during early elementary school years resulted in class size increases during later elementary school years. Such findings do not necessarily suggest that decreasing class sizes do not yield desired outcomes, but that they may have unintended consequences if not implemented with thoughtful consideration of side effects and byproducts.

All class size reduction studies previously referenced occurred in the United States. Woessman and West (2006) estimated the effect of class size on student performance in 18 countries and found that while there are statistically significant and practically meaningful effects of smaller classes in Greece and Iceland, they could not reject the null hypothesis in Japan and Singapore. The effects were negligible in the remaining countries. They conclude that class size effects are related to the quality of the teaching force of the setting. Again, the findings do not necessarily suggest that class size

reduction is an ineffective policy intervention or a poor human capital investment, but that context matters and that interventions may play out differently in different settings.

This is covered in greater detail in each intervention's impact evaluation paper, but Early College and career and technical education (CTE), the type of intervention Innovation Career Pathways is, have been found to have positive effects on college enrollment elsewhere in the United States. Edmunds et al. (2017; 2020) found Early College participants to have attended college at 15.6-percentage point higher rates while Haxton et al. (2016) found Early College participants to have attended college at 9-percentage point higher rates than control groups, both using randomized controlled trials. Witzen (2018) found CTE participants to have attended college at 7.8 percentage point higher rates while Brodersen et al. (2021) found CTE participants to have attended college at 10 percentage point higher rates than non-participants, using propensity score matching and multivariate regression controlling for relevant covariates, respectively.

All policy interventions, including Massachusetts Early College and Innovation Career Pathways, should ideally be evaluated to determine their effectiveness. Governments and stakeholders rely on policy analysis to inform evidence-based, data driven decisions on which interventions to implement, expand, or discontinue. This line of work is commonly called impact evaluation. According to American University (n.d.), impact evaluations are studies that use rigorous methods to determine if changes in outcomes can be attributed to a policy intervention, by accounting for the counterfactual—what would have been the outcome had a subject not participated in the intervention—through the use of causal research designs that compare treated and untreated groups.

It should be noted that there are standards for rigor for impact evaluations. The Every Student Succeeds Act (ESSA), which is a federal law in the United States that focuses on state and district

decision making, encourages evidence-based policy interventions (American Institutes for Research, 2019). As part of this, ESSA established its Tiers of Evidence, a framework to help states and districts determine which interventions work in which contexts and for which students. Tier 1, Strong Evidence, stipulates that the study is a well designed and implemented experiment; Tier 2, Moderate Evidence, stipulates that the study is well designed quasi-experimental study. quasi-experiments are non-experimental causal methods, which are described in greater detail in the methods chapter of the thesis; Tier 3, Promising Evidence, stipulates that the study is a well designed and implemented correlational study, which controls for selection bias; lastly, Tier 4, Demonstrates a Rationale, stipulates that the study is a well-defined logic model based on rigorous research (American Institutes for Research, 2019).

In addition to rigorous and empirical methodology, which is covered at different but appropriate levels of detail in the methods chapter of the thesis and the methods section of each of the three papers, this work of evaluating policies should be literature corroborated and theoretically framed. Wiseman (1979) advises that the undertaking of impact evaluation should start with a description of the social setting, the relationships in which policy is to be initiated, and the larger society within which these operate, as well as ongoing social processes which reflect current policies. Cairney (2023) adds that impact evaluations should use theoretical insights to analyze and address real world problems, drawing from mainstream policy theories to explain how policymaking works or critical approaches that identify and challenge imbalance of power.

The introduction and literature review chapters of the thesis, as well as the introduction and literature review sections of each paper, define the social problem and corresponding interventions within a national and local context; outline their historical and present statuses; and discuss their social implications. The next section of this chapter, and corresponding sections in each paper, cover

an economic theory that frames the offering of the intervention, as well as a research framework that gives structure and direction to the regression models used in the impact evaluations.

Theoretical Framework

This thesis is framed by Human Capital Theory. In a seminal theoretical paper on the subject, Schutz (1961) defines human capital as the deliberate acquisition of useful skills and knowledge that yield economic value, including direct expenditures on education, earnings forgone when working age students attend school, and employees being trained on-the-job. He argues that skilled labor is not merely a reflection of innate abilities but a return on human capital investment, that individuals and governments should make. Schultz (1961) goes on to substantiate his Human Capital Theory with various arguments, including the disproportionately rapid rate at which income of the United States increased relative to the combined amount of non-human capital, including but not limited to land and man-hours worked; the rapid postwar recovery of countries that suffered severe destruction of non-human capital, such as factories, railroads, bridges, harbors, and cities; and slow growth of developing nations despite non-human capital investments made in structures, equipment, and inventories.

Applying the Schultz (1961) definition of Human Capital, Massachusetts made an investment in in human capital by offering the Early College and Innovation Career Pathway programs, so that its citizens may acquire useful knowledge and skills that will promote economic growth and individual economic value. Given the economic returns of educational attainment (Lobo & Burke-Smalley, 2018) and the outcomes of college readiness, access, and success in three papers, findings are initial measures of the return on that human capital investment by Massachusetts, the schools that offered the interventions, and the students who chose to participate. Schultz (1961) acknowledges income inequality in saying that “Negroes who operate farms, whether as tenants or as owners, earn much

less than whites on comparable farms" (p. 4), and attributes it to differences in useful knowledge and skills acquired through schooling, human capital investment. By targeting Black, Latinx, and low-income students in recruitment, Massachusetts also seeks to address the historical racial gap in human capital investment. Interactions between race and program participation included in the papers will help determine their effectiveness on that front.

In his theoretical analysis, Becker (1962) similarly defines Human Capital Investment as the embedding of resources in activities that improve the mental abilities of people—including but not limited to schooling, on-the-job training, and the acquiring of information about the economic system—that consequently influence their real income prospects. He further explains that human capital investments differ in their "relative effects on earnings and consumption, the amount of resources invested, and in the extent to which the connection between investment and return is perceived" (p. 9). Becker (1962) was sure to highlight the paradigm shift in the field of economics, where it was formerly thought that differences in economic well-being were primarily a reflection of differences in physical capital to the recognition that other factors, such as useful knowledge and skills, play a larger role in income inequality than previously believed.

As it pertains to this thesis, Becker's (1962) work compliments that of Schultz (1961) by corroborating the framing of Massachusetts' offering Early College and Innovation career Pathways as human capital investments and bolstering the argument that targeted educational interventions may potentially address income inequality. Moreover, Becker's addendum that (1962) human capital investments may differ in their relative effects and their perceived connection to the return correspond to the comparative evaluation of two interventions approach of the thesis and to the connection made between career preparation in high and educational attainment. Becker further asserts that "the typical investor in human capital is more impetuous and thus more likely to err than is the typical investor in tangible capital" (p. 10). Findings from this series of papers will perhaps help

determine if Massachusetts erred in their investments in either Early College or Innovation Career Pathways, given their respective and collective objectives.

Sweetland's (1996) review of Human Capital Theory literature spans from the independence of the United States in 1776 to the 1960's and finds that education is the primary human capital investment in research, partly because education may quantitatively be measured in costs and years. While the three studies in the thesis do not explore costs empirically, educational attainment, namely college enrollment and college second year persistence, are two of the three outcomes of interest. Sweetland (1996) further explains that the literature relating to human capital theory distinguishes among numerous types and means of education, which corresponds to the variant theories of change for the two educational interventions being investigated in this thesis, further placing this thesis in the human capital theory conversation.

To be clearer about how Human Capital Theory frames the thesis, the offering of and participation in Early College and Innovation Career Pathways, which are deliberate pursuits of knowledge and skills, are presented as human capital investments by the state of Massachusetts and the students. In terms of returns on Human Capital Investments, the World Bank's Mincer equation estimates that each additional year of education produces a private rate of return to schooling of about 5–8% per year (Patrinos, 2016). Two of the three outcomes, college enrollment and persistence to a second year in college, are indication of at least one additional year of schooling beyond high school graduation. Thus, to investigate the effects of program participation on college enrollment and persistence is analogous to gauging the returns on the interventions as human capital investments.

Research Framework

In addition to the theoretical framework, this study also applies a research framework that provides structure and direction for systematic investigation. This study is informed by Perna and Thomas'

(2006) Framework for Reducing the College Success Gap and Promoting Success for All. Based on the existing body of pertinent theoretical and methodological literature, Perna and Thomas designed this framework to evaluate policies and practices that seek to address persistent racial and socioeconomic gaps in student success. 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. College readiness is defined as aspirations or expectations and academic preparation for college; college enrollment is measured by college access and college choice; college achievement refers to performance in and completion of college; while post-college attainment denotes graduate and professional schools, employment, and income.

The four key transitions in student success from Perna and Thomas' (2006) framework map on to this research project in direct and substantive ways. Specifically, the outcomes of interest for all three studies in the thesis—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. Although of interest and eventually available, the data for college completion and post-college attainment, the fourth transition, will not be available for all cohorts in this study until at least 2028, so will be the focus of future research.

Perna and Thomas's (2006) framework further suggests that there are four layers of context to understanding student success—internal, family, school, and sociopolitical. The internal layer of context alludes to cognitive and motivational processes that shape a student's attitude and behavior, as they pertain to schooling. From the propensity score calculating regression models, as well as post-match and post-weight regression models, the included measures of prior achievement and school suspension serve as approximations to a student's internal layer. In addition to cognitive skills, student success in college is also shaped by noncognitive skills, such as motivation and self-regulation (Ruban & McCoach, 2005). Prior achievement was found to be positively associated with intrinsic

motivation and student behavioral engagement (Rodríguez et al., 2019) while school suspension was found to be associated with personal attributes relating to student antisocial behavior and rebelliousness (Sheryl et al., 2014), hence their inclusion as proxies for the internal layer.

Suspension is also associated with a variety of school level attributes, meaning that including it as a covariate also helps to account for school context, which Perna and Thomas (2006) define as the resources, academic preparation, and educational orientations of the institution a student attends. More specifically, suspension rates are associated with socioeconomic status of the school and aggregate measures of low school commitment (Sheryl et al., 2014). Two other ways that school layer of context is incorporated in the regression models are the inclusion of the prior attendance covariate and the school fixed effects feature. The prior attendance variable, Chronically Absent in Grade 8, is a binary variable which indicates whether a student missed 10% of more of school days for which they were enrolled during the school year. Dailey et al. (2020) found that a positive school climate reduces school absenteeism, so student chronic absenteeism is an approximation for school climate in the regression models. School fixed effects capture variation that may exist between schools by only comparing students to their peers within their own school.

The family layer context, which refers to experiences that family attributes can influence within and outside the home to promote various indicators of student success (Perna & Thomas, 2006), is approximated by the low-income and English learner covariates included. Per the Student Information Management (SIMS) handbook, low-income status in Massachusetts public schools 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). Both criteria speak to the family and not the student. SIMS further defines an English learner 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). Although English speaking ability is a reflection of the student, the variable as defined and measured is also a reflection of the family. According to U.S. Department of Education, Office of English Language Acquisition (2016), the very first question on the aforementioned Home Language Survey is "what is the primary language used in the home, regardless of the language spoken by the student?"

Family context is further considered by the inclusion of race as a covariate. Barring certain cases of adoption and foster parenting, students typically share a racial and ethnic background with their family. Although beyond the scope of this study, it is worth noting that a family's racial ethnic background may influence the educational experience of students and can be associated with different outcomes. For example, Robinson and Harris (2013) found that White and Black parents in the United States have distinct philosophies on and responses to inadequate student performance, which consequently affect student achievement in substantially different ways. The inclusion of race as a factor variable in the regression models ensures that students are only compared to students of the same race, while the inclusion of interaction terms would capture if the effects of program participation on college readiness, access, and success are moderated by race.

The sociopolitical layer, which refers to broader social policies and conditions that impact student choices and outcomes, is captured in the treatment, control, and outcome variables, as well as the research questions themselves—do Early College and Innovation Career Pathways participation promote equitable educational attainment in Massachusetts? This layer of context recognizes that numerous external factors—e.g., social norms, economic conditions, and public policies— influence student college choice (Perna & Thomas, 2006). In terms of economic conditions, Massachusetts was projected to be first among the 50 states, in terms of the proportion of its jobs that would require a post-secondary degree (Carnevale et al., 2010), and all the occupations that pay six figures, $100,000 or more, in the state presently require at least a bachelor's degree (Massachusetts Department of

Economic Research, 2024). Regarding social conditions, the population of Massachusetts is changing such that it can attribute all its population growth between 2000 and 2010 to the increase in its Latino population, which also has the lowest rate of college enrollment and completion among all racial groups (Massachusetts Education Equity Partnership, 2018). EC and ICP are policy interventions to address these converging trends.

The Perna and Thomas (2006) framework for understanding student success overlays onto Human Capital Theory, which pertains to a student's motivation for pursuing a college degree, in turn affecting their enrollment decision and for how long they stay, i.e. persistence. For example, African American high school students were found to be uncertain about their ability to pay the costs of attending college and about whether the economic returns of attending would exceed the costs over time (Freeman, 1997 as cited in Perna, 2006). This speaks directly to the HCT definition of the embedding of resources into academic activities that may yield an economic benefit (Schultz, 1961; Becker, 1962). Furthermore, human capital relies on educational credentials, i.e., college success and completion, to indicate to employers that the knowledge and skills have been acquired.

The Perna and Thomas (2006) framework also maps onto Bronfenbrenner's (1994) ecological theory, which posits that relationships between a student, their family, their school, and institutional patterns, such as the economy or culture, all intertwine in explaining children's progress through school. Such microsystems and macrosystems, as they're called in this ecological theory, correspond to the four Perna and Thomas (2006) contexts— internal, family, school, and sociopolitical. A connection can also be made to Sameroff's (2010) unified theory of development, which argues that an understanding of the interconnectedness of personal change, context, regulation, and representational models of development are needed to explain individual differences in life course trajectories and outcomes. Sameroff's (2010) personal change—e.g., cognition and identity

development—and context—e.g., social settings and institutions—correspond with Perna and Thomas' (2006) internal, family, school, and sociopolitical contexts.

Lastly, various aspects of the Perna and Thomas (2006) framework correspond to Coleman's (1988) Social Capital Theory. Coleman (1988) defines social capital as having access to a variety of entities, as part of one's social structures, who may facilitate certain actions that are conducive to the accomplishment of certain aims. Such aims could be college readiness, college access, or college success; the transition periods in the Perna and Thomas (2006) framework. In the context of educational attainment, such entities could be: effective teachers, who would render a student better academically prepared for college and may write more compelling letters of recommendation; informed guidance counselors, who may recommend the taking of courses more appealing to college admissions and may direct a student to the right resources; or a family member who graduated from the university where a student aspires to attend, who may be able to share insightful tips about the application and how to navigate the campus. Those entities sit at the school and family layer in the Perna and Thomas (2006) framework.

Literature Review Conclusion

There is widespread and persistent inequity at all levels of American education, where racial minority students and students from low-income families have worse outcomes than their White and non-low-income peers, including when comparing post-secondary access and success. Per this literature review, such inequity in American education spans at least 200 years, covering the period from the beginning of the 19th to the beginning of the 21st century. Moreover, systematic differences in outcomes by race and socioeconomic status are observed as early as Kindergarten and remain in the high school and college years.

Educational attainment, the highest level of education someone has completed, is of particular consequence. On average, individuals with higher levels of education, namely a college education, earn more, live healthier and longer lives, and are further along on the human development continuum. The benefits of attending college are not just for the individual, but also for society at large. College graduates are less likely to be participants of social welfare programs, are less likely to be incarcerated, and are more likely to be civically engaged.

Given the positive effects of educational attainment on a variety of outcomes of importance to individuals and society, and the shifting demographics of Massachusetts and the United States broadly, the inequity that exists in educational attainment by race and economic groups is a social problem. When a government seeks to address a social problem, they may deploy a policy intervention, which aims to produce certain desired outcomes through the delivery of some free service to the public. Early College and Innovation Career Pathways are two such policy interventions, which seek to address the social problem of inequity in educational attainment.

It is critically important to determine if such interventions have desired effect on school performance and student outcomes, or else these government efforts would be wasteful. This work is commonly referred to as impact evaluation and is defined as an analysis that is literature corroborated, empirical, methodologically rigorous, and theoretically framed. While the empirical data and the research methods are described in the methods chapter of the thesis and the methods sections of the papers, Human Capital Theory and the Framework for Reducing the College Success Gap and Promoting Success for All inform this thesis.

Human Capital Theory posits that the deliberate pursuit of knowledge and skills that yield economic value for the community and the individual via schooling is an investment by families and by governments. The findings of the three impact evaluations in the thesis are thus measures of the

return on the investment of offering and participating in the Early College and Innovation Career Pathways for Massachusetts and the student participants, respectively.

The Research Framework for Reducing the College Success Gap suggests there are four transitions in the student success journey— college readiness, college enrollment, college achievement, and post-college attainment. The former three are the three outcomes of interest in all three papers. The framework further suggests there four layers of context to understanding the four transitions— internal, family, school, and sociopolitical. All four contexts are captured in covariates for regressions used to calculate propensity scores and to estimate program effects.

The respective and comparative impact evaluations of Early College and Innovation Career Pathways, which seek to address the long and persistent inequity in the American higher education and economy, make meaningful contributions to the distinct literatures of college preparation in high school and career preparation in high school, as well as the emergent joint literature of college and career preparation. Furthermore, this thesis may potentially inform policy and practice not only in Massachusetts offer but also elsewhere.

Chapter 3: Research Methods

Temporal Precedence and Covariation

In determining whether a policy or intervention has effects on a certain outcome—such as participation in Early College or Innovation Career Pathways on educational attainment for racial minority and socioeconomically disadvantaged students—it is more convincing if research goes beyond showing association to establishing causation. That is, to not merely suggest that the two variables have a relationship, but to demonstrate that one causes the other. It is said that, to make causal claims, a researcher must meet three conditions: temporal precedence, covariation, and control for third variables (Oppewal, 2010). In other words, the cause must precede the effect, the cause must be related to the effect, and there must not be any plausible explanation for the effect other than the cause (Shadish et al., 2002).

Cause needing to precede effect is a sound logical argument, yet it is helpful to establish its role in making causal inferences in social science research. It is fair to say that causality is a process that occurs over time through some mechanism. As Miller (2000, p. 121) puts it, "one way or another, any causal explanation of some dependent occurrence must include the fact that the cause of an effect preceded the effect." In quantitative methods courses the world over, students are taught to interpret regression coefficients as a prediction of how a unit increase in the independent variable changes the values of the dependent. Temporal precedence is implicit in not only the sequence of that phrase but also in the nomenclature of independent and dependent variables. That said, temporal precedence needs to be established not just in causal but also many correlational studies that seek to explain phenomenon.

For this specific thesis project, the cause of interest is participation in the Massachusetts Early College and Innovation Career Pathways programs. The effects of interest are college readiness,

college access, and college success as approximated by MassCore completion, college enrollment, and college persistence, respectively. Because program participation begins at the earliest in grade 10 and the latest at the beginning of grade 12, while the outcome measures happen at the end of or sometime after grade 12, the criterion of temporal precedence is met. By establishing the temporal precedence of the independent variable, we also assert that the causation is unidirectional, or that the dependent variable did not cause the independent variable. It should be cautioned that temporal precedence of the independent variable over the dependent variable is not sufficient to make causal inferences. Doing so puts one at risk of committing the post hoc fallacy (Thye, 2014).

The second criterion of covariation can be measured by the measures of association that exist in statistics. More specifically, calculating covariance, correlation coefficient, and bivariate regression coefficients alongside their statistical significance can establish covariation. Covariance is the summation of products of deviations of the independent and dependent variables. Said differently, it is a measure of the joint variability between two variables that tells us how distance of values from the mean in one variable compare to distance of values from the mean in the other variable, while giving the direction of relationship.

We standardize the covariance to get the correlation coefficient and we reduce it to the scale of the dependent variable to get the regression coefficient. Depending on the variable types and their values, the appropriate significance test may then be conducted to determine if the observed covariation is random or if there is a meaningful difference. Given that the predictor and outcome for this study are binary, the appropriate significance test is the chi-square test. Covariation, however, can also be the result of a third process in which another pre-existing factor, causes changes in the relationship between the independent and dependent variables (Miller, 2000).

Therefore, in the case of determining the causal effects of Early College and Innovation Career Pathways, it is the third criterion of eliminating plausible alternative explanations for the difference in outcomes that this research seeks to meet. This is ordinarily done by demonstrating exogeneity—that participants could not manipulate their selection in the treatment or control group—and that there are no systematic differences between participants in either group (Engle et al., 1983). Failure to ensure the former, referred to as self-selection, is problematic because if the likelihood of participating in the intervention is associated with its outcomes, the results will be biased (Lavrakas, 2008). Failure to establish the latter renders the researcher unable to account for heterogeneity of effects, or the variation of effects among subgroups (Altman & Matthews, 1996).

Experimental and Non-experimental Causal Research

In quantitative social science research, it is considered optimal to rule out alternative plausible causes by conducting experiments, commonly referred to as randomized controlled trials (Hutchison & Styles, 2010). The random allocation inherently establishes exogeneity, helping to minimize bias caused by human choices. Although randomized controlled trials are often considered the "gold standard" for establishing causal evidence in education, they are not always possible because of time, costs, ethical concerns, or political considerations (Gopolan et al., 2020). As such, there has been an increase in the use of non-experimental causal designs, which attempt to establish a cause-and-effect relationship by using criteria other than randomization. The following paragraphs explain the logical underpinnings behind experimental and non-experimental causal research.

Thyer (2014) argues that the most advantageous aspect of experiments is that they give one the ability to claim, with confidence, that an independent and dependent variable have a unidirectional causal relationship. As discussed in the previous section, correlation does not imply causation. For example, ice cream sales and the number of shark attacks show correlation, due to a spurious

relationship with summer temperature. The ability of an experiment to sift causation from correlation is why it is considered the “gold standard” in social science research. Through randomization, manipulation, and controlled measurement, experimental research provides a mechanism to mitigate spurious relationships and confidently causally link an independent and dependent variable (Thyer, 2014).

According to statistician R. A. Fisher, as cited by Box (1980), randomization is the placement of research subjects such that each one has the same probability of being in either of two groups to be compared. This ensures that the two groups are equal in terms of all pre-existing factors and attributes. In other words, random assignment balances the two groups on all factors that are observed and unobserved, in theory. Manipulation simply means that one group will receive the treatment and the other will be the control group, after they’ve been assigned. Lastly, controlled measurement means that the researcher measures the dependent variable in reliable and consistent way (Box, 1980). As such, “the experimental method is the method of causal inference because it equates two or more groups on all factors, manipulates a single presumed cause, and systematically records the unique effect” (Thyer, 2014).

As mentioned earlier, experiments are not always possible because of time, costs, ethical concerns, or political considerations (Gopolan et al., 2020). Imagine telling a parent that their neighbor’s child will participate in a college preparation program like Early College, but their child was not fortunate enough to randomly be assigned to that group. Imagine the head of a school district explaining to the community that some schools are going to get a career preparation program like Innovation Career Pathways, but others are not, due to random assignments. Many research projects, including this one, employ non-experimental causal research, to be able to make causal claims without the challenges presented by experiments, albeit at the expense of statistical rigor.

A non-experimental causal study is one that estimates the effects of an intervention on participants without the use of random assignment. Like experiments, they seek to make causal claims about the effects of an independent variable on a dependent one. Such studies aim to balance pre-intervention variables between the treatment group and a selected untreated group (Harris et al., 2006). The challenge of non-experimental causal methods is that they're unable to statistically control potentially important but unobserved confounding variables, due to the lack of randomization (Shadish et al., 2002). A confounding variable is a third variable associated with the independent and dependent variable, thus causing a spurious relationship, as temperature does with ice cream sales and shark attacks.

The strength of the non-experimental causal research is that, when done rigorously, they identify an untreated group that is comparable to the treatment group on all relevant and observed variables. If the two groups are not significantly different across any of an array of attributes, it becomes plausible to attribute differences in outcome to the intervention (Miller et al., 2020). Non-experimental causal methods are particularly useful when policymakers or school administrators are unable or unwilling to have a subset of students or schools randomized to a control condition, and practical when an intervention was rolled out without evaluation in mind, as is the case with Early College and Innovation Career Pathways, the subjects of this research.

Propensity Scores

There are a series of non-experimental causal methods that can be employed from propensity scores. Statistically speaking, the propensity score is the conditional probability of being assigned a treatment given a vector of observed covariates (Rosenbaum & Rubin, 1983). It is a composite number which is derived by calculating the likelihood that each person in a population would be assigned the treatment based on available variables within the data set. Upon calculating propensity

scores, a researcher may use propensity score matching (PSM), inverse probability of treatment weighting (IPTW), stratification on the propensity score, or covariate adjustment using the propensity score (Guo & Fraser, 2015). Propensity Score Matching eliminates a greater proportion of the systematic differences in baseline characteristics, followed by Inverse Probability of Treatment weighting, relative to the other two methods (Austin, 2009), so they are used in the thesis, depending on which was the more appropriate for a given study. A broad overview of PSM and IPTW is given in this methods chapter, but detailed explanations of their appropriate applications are provided in the corresponding papers.

A key assumption in all propensity score methods is that of strongly ignorable treatment assignment, which means that treatment assignment is independent of the potential outcomes (Rosenbaum & Rubin, 1983). Thus, a common limitation across all such methods, is that an unmeasured or otherwise unincluded confounding variable may be present, leading to biased estimates of treatment effects. In the case of program participation in Early College or Innovation Career Pathways, one such confounding variable may be an exceptionally motivated and involved parent, who both encourages their child to participate in the intervention and enroll in college. Relevant diagnostics tests and limitations of each method are addressed in the corresponding papers and are excluded from this chapter, to avoid redundancy.

The prevailing approach to calculating propensity scores in education research, and social sciences broadly, is logistic regression (Guo & Fraser, 2015), with treatment assignment as the binary outcome and a set of pertinent covariates as predictors (D'Agostino, 1998). From the logistic regression model, which is described in detail in the following section, predicted probabilities for being assigned to the treatment group, referred to as propensity scores, are generated for both the treatment group and untreated group members. Given the interest in evaluating the effects of Early College and Innovation Career Pathways, respectively and comparatively, three propensity score calculating

logistic regressions were ultimately selected to identify or construct comparable untreated groups for treated groups in each of the three papers in the thesis.

The Logistic Regression

When the outcome variable for a question of interest is binary, such as whether or not a student goes to college after high school, it may be optimal to use a logistic regression in lieu of the linear regression, as the residual or error distribution of the data would violate the linear regression assumption of normality and predicted values may be less or higher than the probability range of 0 to 1. Although there are some instances where a linear probability model may still produce unbiased estimates, the logistic regression is generally more appropriate.

In a bivariate analysis, the linear model uses the least sum of squared residuals to fit a line through the data, with a rate of change, or slope, that predicts how a unit change in the independent variable affects the dependent variable. Said differently, the linear model predicts an average dependent value for every independent value, assuming linearity, normal distribution of residuals, homogeneity of variances, and independence of observations. Although linear regression is powerful and generally useful, it is best reserved for instances where the outcome variable is continuous, and the assumptions are met.

Instead of predicting the average dependent variable value that corresponds to each independent variable value, per the linear regression, the logistic regression predicts the probability of occurrence of the dependent variable for each independent variable value. Indeed, when the outcome or dependent variable is binary, its vertical axis on a scatter plot or average values of dependent variables for each independent variable value represents the probability of occurrence. As opposed to the least sum of squared residuals, logistic regression predicts estimates using the maximum likelihood estimation.

To keep the same structure and coefficient interpretation of the linear regression equation, which is fairly intuitive, the logistic regression uses log odds of the dependent variable as the outcome measure. This is because the probability of an event occurring is not linear but the log odds of an event occurring are linear, where P is the probability of having the outcome and P / (1-P) is the odds of the outcome. Somewhat similar to the linear regression, each unit increase in the independent variable corresponds with a change in the log odds of the dependent variable.

The sequence in building a model is to firstly inspect bivariate relationship between the dependent and independent variable to see if it can be adequately described by a mathematical function and secondly to determine which parameters of that function best fit the data. In the case a researcher observes a linear relationship, they would use ordinarily least squares estimation, as described. Upon observing a curvilinear relationship, or a sigmoid, a researcher would specify a logistic regression. Maximum likelihood uses an algorithmic search or convex optimization to select coefficients such that the observed values are most likely to be predicted.

Mathematically, logarithm is the inverse function to exponentiation. It asks, to what power must a base be raised to yield a given number. The calculating of odds is best understood when compared to probability, two related but different concepts. Probability is the likeliness of occurrence relative to total number of possible outcomes. There is a 1/5 (.2) probability that if I were to randomly select a finger from my right hand that it would be my thumb. Odds are the likeliness of occurrence relative to the count of nonoccurrence. There are 1/4 (.25) odds that if I were to randomly select a finger from my right hand that it would be my thumb. Arithmetically, Odds = Probability/1-Probability and Probability = Odds/1+Odds.

Multinomial Logistic Regression/Generalized Propensity Scores

Unlike the first two papers which compare Early College participants to non-participants and Innovation Career Pathways participants to non-participants, respectively, the third and last paper in the series that make up the thesis simultaneously compares three groups. Therefore, the binary logistic regression could not be used to calculate the propensity scores, as that is restricted to when the outcome variable only has two values. A multinomial logistic regression was instead used to calculate the generalized propensity scores. Multinomial logistic regression produces several regression equations, with the number of regression equations equaling one less than the number of values of the outcome/treatment variable, meaning there are several regression coefficients associated with each independent variable (Meloun & Militky, 2011). Correspondingly, the generalized propensity score is a vector representing the conditional probabilities of a subject being treated with each value of the multinomial treatment, as opposed to the single value of propensity scores when there is a binary treatment (Brown et al., 2020).

Matching/Propensity Score Matching

The first paper in the thesis uses Propensity Score Matching as the research methodology. Stuart (2010) broadly defines matching to be any method that aims to balance the distribution of covariates in the treated and untreated groups. In this thesis, matching means that each student in the treatment group is paired with a non-treated student in the population of interest with an equal or proximate propensity score. When the matching process is successful, the resulting data set will be balanced, whereas the treatment group would be matched to an untreated group that is not significantly different across observable characteristics. In this regard, matching is an attempt to mirror a randomized controlled trial, where the treated and control groups are only randomly, as opposed to systematically, different from one another on all background covariates (Stuart, 2010).

The average difference between the balanced treatment and control units from matched pairs with the same propensity scores is the average treatment effect, or ATE (Guo & Fraser, 2015).

One of the benefits of matching is that it enables a researcher to leverage the advantages of both matching and regression analysis. Stuart (2010) asserts that matching should not be seen in conflict with regression modeling but rather the two methods are complementary and are best when combined. The first paper indeed conducts regression analyses after matching. Matching methods also address areas of the covariate distribution where there is not sufficient overlap between the treatment and untreated groups (Stuart, 2010). Imbalance between treatment and control groups could otherwise be described as systematic differences, which render a researcher less able to make causal claims. As outlined in the paper which applies PSM, there is a series of choices a researcher must make in determining the specifications, including but not limited to matching ratio, matching with or without replacement, and caliper width. A caliper is a prespecified maximum distance between propensity scores of matched subjects (Guo & Fraser, 2015). Matching is thus done multiple times and the matched sample with the best balance is ultimately chosen as the final sample (Stuart, 2010).

Weighting/Inverse Probability of Treatment Weighting

The remaining two papers use inverse probability of treatment weighting as the method to reduce bias. Weighting is the creation of a synthetic sample, whereas the share of attributes represented in different groups is manipulated by the researcher to resemble each other and/or a population of interest, so that comparisons can be made. It is often the case that samples do not reflect each other or the population. For example, the share of students who are proficient in 8th grade Math is higher for the Massachusetts Early College program participants than that of Innovation Career Pathway participants and that of their school peers. In such an instance, a direct comparison of outcomes

between participants of the two programs and non-participants would yield biased estimates, because the three groups are different, with EC participants being higher achieving on average. Therefore, adjustments such as weighting may be made so that the three groups are comparable.

The weighting methodology has its roots in public opinion surveys, which have historically relied on the ability to adjust their datasets using sex, age, race and ethnicity, educational attainment, and geographic region among other variables for which data are available to correct any imbalances between the survey sample and the population (Mercer et al., 2018). The most rudimentary and commonly used form of weighting, which is useful for explanatory purposes in this chapter, is called raking. Raking entails a researcher choosing a set of variables where the population distribution is known, and iteratively adjusting the weight for each case until the sample distribution reflects the population (Mercer et al., 2018).

Inverse probability of treatment weighting is an extension of raking. After calculating the propensity score, or the probability of receiving a treatment, as described earlier in this section, weighting each case by the inverse of its probability of selection removes any bias that might result from having different kinds of people represented disproportionately (Mercer et al., 2018). Weights are calculated as 1/propensity score for the treated group and 1/(1−propensity score) for the untreated group. By including the weights in subsequent analyses, a researcher renders treatment assignment independent of the covariates included in the propensity score calculating regression (Chesnaye et al., 2021). The weighted sample may then be used in multivariate regression analyses to estimate the effect of treatment on the outcome of interest.

Note that there are four different types of weights allowed in Stata, the statistical software used—frequency weights, probability weights, analytic weights, and importance weights (StataCorp, 2017). It is the probability weights, which indicate the inverse probability of receiving treatment, that are

featured in this study. This ensures that the statistical inference takes into account the underlying number of observations in each group.

Post-Match and Post-Weight Analyses

Although comparing difference in means between the treated and untreated group and calculating statistical significance is valid way of estimating effects after matching or weighting (Guo & Fraser, 2015), a more rigorous approach is to run another series of logistic regressions on the matched and weighted samples. Although all the covariates of interest are already included in the propensity score calculating regressions and are balanced between the two groups, the post-match and post-weight logistic regressions enable us to statistically control for all the covariates included in the match, as well as other variables, such as the inclusion of school fixed effects, to give a more precise estimate of the impact of program participation. An added benefit of running a post-match and post-weight logistic regressions, and a means to answer research questions for the three papers, is the ability to include interactions, such as that between race and program participation. Indeed, Stuart (2010) asserts that matching is best when used in combination with regression adjustment.

Fixed Effects and Cluster Robust Standard Errors

The concept of statistical control is relatively rudimentary but is worth revisiting because of the extensive use of school fixed effects in the three papers of this integrated thesis. School fixed effects is controlling for school by including a series of binary variables in a regression model, indicating that a student attends a certain school. This ensures that each program participant is being compared to non-participants in their school, so that individual schools with preexisting high or low college going rates won't unduly influence the estimates of program impact. Students attend at least 40 high schools in each of the three studies, so the binary variables indicating school of attendance are

hidden in the regression tables, as their coefficients are not of interest to this study and would render the output tables three times as long.

Nielsen and Raswant (2018) assert that the choice of which covariates a researcher controls is of extreme importance in impact evaluations because the variables included in the regression model affect the significance levels and estimated effect sizes of the other variables. Incorporating school fixed effects is therefore necessary, as one can expect different schools to have different relationships with college enrollment due to variances in school culture, financial resources, teaching quality, parental involvement, and other factors. In this study, models are presented first without fixed effects and then with fixed effects. In the instances where estimates remain relatively unchanged without and with fixed effects, it means that there is little to no variation in program effects by school. When estimates change substantially with the addition of fixed effects, it means that there is meaningful variation in effects by school.

A random effects model, also known as a multilevel model, is an alternative to the fixed effects approach to addressing clustered data in education, which otherwise violates the independence of observations assumption of regressions, generally (McNeish, 2023). However, the random effects model could not be used, because it further assumes that unobserved characteristics of the school are not correlated with the independent variables in the model (Clarke et al., 2010). Even though the state defines the guiding principles for Early College and Innovation Career Pathways in detail and gives examples, schools have flexibility in interpretation and implementation (DESE & DHE, 2017). By design, this leaves room for great variation, in terms of what share of the high school are program participants, what courses and academic pathways are offered, recruitment strategies for students underrepresented in higher education, and the types and dosage of supports provided.

This means that unmeasured school level variables, such as resources, priorities, culture, climate, and parental involvement more than likely play a role in determining which and what share of the students participate. In other words, unobserved school characteristics have a relationship with student level predictor variable of program participation. Violating this assumption creates an endogeneity problem that prevents researchers from making causal interpretations when using random effects models (Antonakis et al., 2021). Therefore, it was determined that the fixed effects approach to addressing clustered data is optimal for the three papers of the integrated thesis.

In addition to the fixed effects feature, between school variation is accounted for by the use of cluster robust standard errors. When data are grouped into clusters, such as students in schools, statistical inference should be based on cluster robust standard errors (Cameron & Miller, 2015). This is because regression model errors would be independent across clusters but correlated within clusters. As such, cluster robust standard errors are used in regression models across the thesis.

Interactions

One of the statistical concepts covered and methods used in the three papers of this thesis is that of interactions, also known as moderations. In statistical terms, an interaction exists when the magnitude and/or direction of a relationship between two variables vary according to the values of a third variable (Hair et al., 2021). Said differently, the magnitude and/or direction of the relationship between two variables changes as the values of the moderator variable change. While statistical control accounts for heterogeneity in the data, the use of interactions in multivariate regression models in the thesis provides additional explanations of the variations that exist between groups. Even though that was not the case in this thesis, it should be noted that interactions can involve continuous variables.

The three papers of this thesis, which first seek to estimate the effects the participating in the Massachusetts Early College and Innovation Career Pathways on college readiness, access, and success on average, secondly seek to determine the impact on students historically underrepresented in American higher education—namely Black, Latinx, and low-income students. The former is done with multivariate regressions matching or inversely weighting on the probability of receiving the treatment, the propensity score, while the latter is done by incorporating interactions terms for program participation and being Black, Latinx, or low-income. This enables the researchers to parse out program impacts on these groups specifically, relative to reference groups, which in these cases were White and non-low-income students.

The underlying mathematics behind the interaction is the generation of a variable, which is a multiplication of the two variables believed to interact, and the inclusion of all three variables in the regression model. If the newly generated variable, the interaction term, is statistically significant, it can determine if the effects are greater or less than for a subgroup, relative to the reference group. All regression models in the thesis are logistic with results being in odds ratios, so when the interaction term yields a value greater than one, than the effects are more pronounced for the subgroup and when it yields a value less than one, the effects are less pronounced for the subgroup.

Interactions are typically hypothesized a priori by researchers (Hair et al., 2021). In this instance, interactions were both a means to answer research questions of interest and informed by the literature. Technically, a researcher may explore interactions in their data, but not all statistically significant interactions are substantively meaningful. Only interactions that answer research questions, are advised by the literature, and are found to be statistically significant are discussed in the findings and discussion sections. Those found to not be statistically significant or substantively meaningful are included in the regression output tables but are not discussed in the thesis. It should be noted that the papers only cover two-way interactions, where the moderator interacts with one

other variable to affect the outcome. Although not featured in the thesis, it is possible to analyze multiple moderator models, including three-way interactions and others (Hair et al., 2021).

It should be noted that the margins command in statistical software Stata, which was used to create the illustration of the interactions in these regression models, calculates average marginal effects (AME) unless otherwise specified, meaning that effects are calculated for each unit as they were observed and then averaged, as opposed to marginal effects at the mean (MEM) of each covariate (Perraillon, 2019). Said differently, AME, which is featured in this paper's models, estimates the partial effect of the predictor variable on the outcome variable using each observed value of covariates and then averaging all partial effects, while the alternative MEM is the difference in a predictor's effect on an outcome when all other covariates are at their mean or reference value (Williams, 2021). The choice of AME over MEM is to ensure that estimates, especially in the fixed effects models, are not unrepresentative of the sample.

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.

Data Preparation

As discussed in the data sources section, the Massachusetts Department of Elementary and Secondary Education collects a variety of data on its students, per the table below:

Data Source	**Type of Information**
Student Information Management System (SIMS)	Student demographics, attendance, behavior
MA Comprehensive Assessment System (MCAS)	Standardized test performance
National Student Clearinghouse (NSC)	College enrollment, persistence, and completion
School Safety and Discipline Report (SSDR)	Rule Infringements and Corresponding Disciplinary Actions

These data are stored disparately but can all be linked through anonymized but common student and school IDs. Before undertaking any analysis, these raw data had to be cleaned, reformatted, aggregated, sometimes pivoted, and merged to create one combined analytical data set. This section outlines the data preparation process that produces the combined analytical data set.

Various intermediate files were created and then merged to create the combined analytical data set. For all the intermediate data files created, there is a level of uniqueness, or a level at which there should not be any duplicate records. Given that some data are collected multiple times a year, and the desired level of uniqueness for the files are either once ever or once a year, there are almost always instances of duplication. When the duplicates are exact copies, only one record is kept. When the duplicates were not exact copies, the differences were investigated and decisions were made on which record would be kept. Depending on the nature of duplication, a record was kept if its value occurred the most or occurred first. In some circumstances, like when a student changed schools, values were aggregated.

In the Student Information Management System (SIMS), which is collected three times every academic year, Massachusetts Department of Elementary and Secondary Education houses time invariant and time variant demographic information. Time invariant data include date of birth, gender, and race. Date of birth is not a variable that is kept for research purposes, but instead to calculate age. Race was consolidated to a seven-value nominal variable indicating whether a student is Asian, Black, Hispanic, Multiracial, Native American, Pacific Islander, or White. Gender was converted to a binary variable indicating if a student is male. The level of uniqueness for the time invariant data file is student ID, as we can expect them to remain the same from year to year.

Time variant variables from SIMS—those we can expect to change from year to year—include proxies for economic status, disability services received, and English learner status. A binary variable for economically disadvantaged was generated to indicate whether a student's household is eligible for free or reduced-price lunch, or if they receive Transitional Aid to Needy Families benefits. And a binary variable for disability status was generated to indicate when a student meets criteria to receive one or more disability support services and accommodations. English learner status was kept as binary.

English learners are “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” (SIMS Handbook, 2021, p. 32). Also in SIMS, are fields that indicate whether a student is in Early College or Innovation Pathways. The level of uniqueness for the time variant intermediate data file is student ID and school year.

The next intermediate data files to be processed were schools and school enrollment. The schools file contains data about the school and the reporting period. School code and address were kept and a school year was generated from the reporting period. Those variables also serve as the level uniqueness. School enrollment is a closely related, but separate file that tells us where a student was enrolled during any given academic year, what their enrollment status was, and how many days they were present or absent. A school year variable was generated from the reporting period. A binary variable indicating MassCore completion was generated from the graduation status variable. Days absent was calculated by subtracting days attended from days enrolled and absence rate was calculated by dividing days absent from days enrolled. Generated variables were kept and raw variables dropped. The level of uniqueness is student ID, school ID, school year.

The Massachusetts Comprehensive Assessment System, or MCAS, as the statewide standardized test is known, is its own database. The test is administered every year in multiple grades and for multiple subjects, but for this research, only eighth grade English and Math test scores are used. Early College and Innovation Pathways are high school based programs, so eighth grade is used instead of tenth grade because they serve as an exogenous baseline. During the period where student participants would have taken their 8th grade MCAS tests, the state of Massachusetts used three different tests—Legacy MCAS, PARCC, and Next Generation MCAS. This study uses proficiency levels for consistency across years. The level of uniqueness for the file is student ID. In other words, there is one 8th grade

English score and one 8th grade math score for each student. In the case of duplicates, the highest score was kept.

DESE collaborates with the National Student Clearinghouse (NSC) to acquire data on post-secondary enrollment and completion. For every graduating high school class, Massachusetts Department of Elementary and Secondary Education submits a list of names and dates of birth to NSC, who then return a file Indicating whether a post-secondary enrollment record was found for each name and date of birth, the enrollment status of the person, and the beginning and end of the enrollment for that student during the year of interest for that student, per their name and date of birth. Furthermore, it lists the college ID and indicates whether the post-secondary institution is a two-year or four-year, whether it is public or private, and its geographic location. A binary variable indicating college attendance was generated if a record was found by NSC for any given year, and binary variables indicating if the institution attended is public, four-year, and instate were generated from the raw variables. Generated variables were kept alongside the student ID and the school year, while raw variables were dropped. An additional binary variable of persistence was generated, to indicate when college enrollment records were found for a student the year of high school graduation and the year after. The level of uniqueness for this intermediate file is student ID.

The intermediate files—time invariant and time variant demographics, high school profiles, school enrollment, baseline test scores, and college enrollment and persistence—were then merged to create one file that contains all the aforementioned components. The files are of different levels of uniqueness, but statistical software Stata allows multiple options including one to one, many to one, and one to many merges that enable the stitching of the combined data set. The level of uniqueness for the analytical data set is student ID and school year. In instances where the intermediate file had a student ID uniqueness level, the same value is shown for the student every year.

Data Reliability and Quality

Per the DESE (n.d.) Data and Accountability webpage, the Massachusetts government collects a wide range of student, teacher, and school level data multiple times a year, as part their accountability and continuous improvement processes. This enables the agency to target resources and assistance where they are most needed and improve teaching and learning in schools. These submissions are not voluntary, but legally obligated, as public schools are financed by taxpayer dollars. According to DESE's (n.d.) Overview of State Reporting document, the data are electronically collected via XML messaging using School Interoperability Framework (SIF), which is a universal standard for organizing and communicating education data.

All schools have a data administrator who is given a data handbook and error list to help with data submission. Each academic year, there are three reporting windows that surround three report dates in October, March, and June. The reporting windows open a few weeks prior to the corresponding report date, so that data administrators may review and begin to address findings from SIF error reports. Subsequently, various summary reports are produced, so that department heads may review the data for accuracy. The next step is cross validation, which ensures that each enrolled student has a valid course schedule, each course section is matched with the right teacher, and so on. The last step in the process is the district certification of the data before it is submitted to DESE. The multiple safeguards embedded in this process give us confidence in data quality and reliability.

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.

Lastly, Chronically Absent in Grade 8 and Suspended in Grade 8 were added as baseline measures. Chronically absent in Grade 8 is a binary variable indicating whether a student missed 10% or more school days in the 8th grade. For each student, the number of days they enrolled in and the number of days they attended school on an annual basis, are included in SIMS. By subtracting days attended from days enrolled, one may calculate how many days a student was absent each year. Dividing days absent by days enrolled yields the absence rate. Any student whose absence rate was equal to or greater than 0.1, or 10%, during the 8th grade year was given the value of 1 in the binary indicator Chronically Absent in Grade 8. Suspended in Grade 8 is a binary variable indicating whether a student was suspended at any time in the 8th Grade. Suspension data for all Massachusetts public schools is stored in the School Safety and Discipline Report (SSDR). SSDR not only collects information on all rule infringements that occur on school property, but also the corresponding disciplinary action taken against the student offender, including suspensions. Any student with a value greater than 0 for the days missed due to suspension during the 8th grade year was given the value of 1 in the binary indicator Suspended in Grade 8.

Data Security

This study is being conducted exclusively with secondary administrative data, that are all in a multifactor authentication guarded drive that can only be accessed via the state government issued

virtual private network. Within the data sets, name, date of birth, and address have been removed to further protect the identity of students associated with the records. Students are instead identified by a state generated ID number which is used exclusively for education administration and research purposes. As an agent of the Massachusetts Department of Elementary and Secondary Education, the researcher has governmental approval to not only view the data but has been assigned the task of using the data to conduct this analysis. The machine being used is an encrypted PC issued by the state of Massachusetts government for the purpose of this research.

Only the researcher has access to the data during the project, which will remain in the Massachusetts Department of Elementary and Secondary Education secure drive and will not be held beyond the project. The research outputs are going to be aggregate results for treatment and comparison groups, so there will not be any personally identifiable information in the dissertation, publications, presentations, or reports. Lastly, the Massachusetts Department of Elementary and Secondary Education's Office of Planning and Research (OPR) requires that academic performance data for which the underlying number of students is 10 or fewer be suppressed. For non-academic data, OPR requires suppression if the underlying number of students is 6 or fewer (Massachusetts Department of Elementary and Secondary Education, 2024).

Chapter 4: Effects of Early College on Educational Attainment for All in Massachusetts

Abstract

Evaluations of Early College, a type of intervention that enables simultaneous enrollment in secondary and post-secondary courses in the United States, consistently find positive effects on educational attainment across racial and socioeconomic groups. Unlike Early College initiatives in other states, Massachusetts launched Early College in Fall 2018, enabling a within-school as well as a whole-school intervention, in which each participating school may enroll some or all of its students in Early College, with guiding principles of equitable access, guided academic pathways, student support, and connection to career. This study uses propensity score matching to evaluate the impact of participating in Massachusetts Early College on students' educational attainment. Positive effects found on college enrollment, with statistically significant positive interactions between the treatment and being socioeconomically disadvantaged, suggest the intervention may help promote equitable access to higher education in Massachusetts. Massachusetts is a local-control state, where public school governance is legally delegated to district and school boards located in the communities they serve, as opposed to the state government, making it more difficult to have state-wide interventions. The flexibility of Massachusetts Early College renders it more easily replicated in local-control states, than the whole school models previously studied.

Introduction

Although contemporary education systems in the United States often claim to be founded on the notion that all people are educable and deserve an opportunity to learn (Domina et al., 2017), there is a long history of inequity in education access, quality, and attainment based on race and socioeconomic status in the US (Gamoran, 2015). These educational inequities are not relics of the past but remain. For example, bachelor's degree attainment rates for Black and Latinx adults in the US are 14 and 21 percentage points lower than the rates for White adults, respectively (U.S. Census

Bureau, 2023). Likewise, 14 percent of students from low socioeconomic backgrounds and 29 percent of students from middle socioeconomic backgrounds attained a bachelor's degree within 8 years of high school completion, compared to 60 percent of high socioeconomic background students (National Center for Education Statistics, 2015). Furthermore, first-generation college students were found to be half as likely to obtain a degree as students whose parents attended college (Redford & Hoyer, 2017). These inequities persist not only temporally but also geographically, as they are seen throughout the country, including the setting of this study, Massachusetts.

Massachusetts ranks at or among the top US states, when comparing primary, secondary, and tertiary education outcomes, on average. Looking at the results from the National Assessment of Educational Progress (NAEP)—the largest nationally representative and continuing assessment of student performance in core subjects (National Center for Education Statistics, 2018)—Massachusetts ranked first, second or third in 4th and 8th grade reading and math scores in 2022, the most recent year in which those data were collected (The Nation's Report Card, 2023). Likewise, Massachusetts has higher shares of residents over the age of 25 who have associate degrees or higher, and who have bachelor's degrees or higher, than any other US state (U.S. Census Bureau, 2021).

However, when the data is disaggregated, great variations are apparent in achievement and attainment by race and socioeconomic status. In Massachusetts, Black and Latinx students averaged 21 and 23 points lower than White students, respectively, on the 2022 8th grade NAEP reading tests, while students who were eligible for the National School Lunch Program averaged 26 points lower than students who were not eligible (National Center for Education Statistics, 2022). Furthermore, only 31 percent of Black students and 36 percent of Latinx students meet college-readiness benchmarks in reading and math compared to 65 percent of White students in Massachusetts (The College Board, 2022). At the college level, inequity persists in Massachusetts, and there is variation in

college readiness, access, and success by race (Massachusetts Department of Higher Education, 2016); the Latinx/White Gap in college enrollment (-21 percentage points) is nearly twice that of the national average (-11 percentage points). Performance gaps between White students and Black and Latinx students in post-secondary math and reading in Massachusetts are also higher than the national average. Six years after enrolling at a public college or university, less than 33 percent of Black and Latinx students have earned a degree (Massachusetts Department of Higher Education, 2016).

Higher educational attainment has been consistently found to predict higher earnings, better health, and civic engagement, among other positive outcomes (Petronijevic & Oreopoulos, 2013; Lobo & Burke-Smalley, 2018; Hummer & Lariscy, 2011; Kubota et al., 2017; Levin-Waldman, 2013). As state demographics shift, with the share of the population that are Black or Latinx increasing (Massachusetts Education Equity Partnership, 2018), promoting educational attainment for all is an increasingly urgent matter for Massachusetts, so that it may remain a leading state educationally and economically. In response, the Massachusetts Department of Elementary and Secondary Education (DESE) and the Massachusetts Department of Higher Education (DHE) launched Early College in Autumn 2018 to promote equitable educational attainment.

This study seeks to investigate the effectiveness of the Early College program in promoting educational attainment for all in the state of Massachusetts. More specifically, the research questions are:

1. What is the effect of participating in Early College 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 Early College on students' likelihood of enrolling in college within 6 months of on-time secondary school completion?
3. What is the effect of participating in Early College on students' likelihood of persisting to a second year in college, after having enrolled within 6 months of on-time secondary school completion?
4. Do these effects vary by racial and economic background?

Although effects of Early College participation on earning a college degree is of high interest, the data will not be available in time for this study, so this will be investigated in future research.

Literature Review

Effects of Early College on College Access and Success

With the persistent and pervasive disparities in educational attainment by economic status and race in the United States, school districts, state education agencies, and charter management networks continue to explore policies and practices that may close the gaps. Early College is one such intervention. Although descriptive and qualitative studies have been conducted on Early College in other states, much of the impact evaluation of Early College is limited to two series of evaluations by the American Institutes for Research (AIR) and the University of North Carolina's SERVE Center, discussed below.

AIR conducted a longitudinal randomized controlled trial to evaluate the impacts of Early College with a sample of 2,458 students from 10 schools, in five states, that used lotteries in their admissions processes. By comparing the outcomes across the groups offered and not offered enrollment, they estimated the effects of program participation over the course of 3 studies. Regarding college readiness, Berger et al. (2013) found that Early College participants were 5 percentage points more likely to graduate high school. In terms of college access, Haxton et al. (2016) found that being

admitted to an Early College high school made a 9-percentage point positive difference in college enrollment, and this effect did not differ significantly by demographic characteristics including racial and socioeconomic background. For college success, Song and Zeiser (2019) found that 6 years after expected high school graduation, Early College participants were more likely than their non-Early College counterparts to earn a certificate, associate degree or a bachelor's degree by 11.9 percent.

Using data from 12 Early College high schools in the state of North Carolina, The SERVE Center likewise conducted a longitudinal randomized controlled trial by comparing outcomes for lottery applicants who were offered enrollment with the outcomes for lottery applicants who were not offered enrollment and attended high school elsewhere. For the first SERVE center study, Edmunds et al. (2017) found that six years after enrolling in the Early College program in grade 9, Early College students enrolled in college at a rate 15.6 percentage points higher than students in the control group. Program participation made slightly less of a positive difference for students underrepresented in higher education (14.3 percent). In a follow-up study, Edmunds et al. (2020) found that 6 years after grade 12 -- when students generally graduate high school -- 44.3 percent of the Early College participants, compared to 33 percent of the control group, earned a post-secondary credential or degree.

Consistent with experimental literature, a non-experimental study also suggests that Early College impacts students of all racial backgrounds positively. Britton et al. (2022) used survival analysis to measure the relationship between demographic factors and college persistence of Early College participants, while controlling for academic and behavioral risk factors. They found that participating Black and Latinx students are as likely as White students to persist in college, when baseline achievement and attendance are controlled. Thus, we argue that participating in the Early College intervention has the potential to promote equity in educational attainment, if there is a higher

concentration of students underrepresented in higher education enrolled, relative to the rest of the state, as is the case in Massachusetts.

Theory of Change

College course taking in high school, a prominent feature of the Massachusetts Early College program, is indeed a way to promote educational attainment. Shields et al. (2021) found that earning college credits in high school has a large, positive, statistically significant effect on the probability of graduating from high school, immediately enrolling in college, and avoiding enrollment in remedial courses during the first year of college in Massachusetts' neighboring state of Rhode Island. Altogether, the literature suggests that cutting costs for families, better preparing students through rigorous courses, helping them gain momentum via credit accumulation, giving students favorable perception in the admissions process, and exposing students to norms and expectations early are the mechanisms by which taking college courses in high school, such as through the Early College program, promotes post-secondary enrollment, persistence, and completion.

Even after entry into an institution of higher learning, high costs prevent college students from completing their degrees. An estimated 1.6 million bachelor's degrees were not earned among college-qualified high school graduates with socioeconomically disadvantaged backgrounds in the 1990's due to costs (Advisory Committee on Student Financial Assistance, 2006). It is within reason then for those who wish to promote college enrollment and completion for said students to cut the costs. Among many others, one way to do that is to offer college credit-bearing courses at no additional costs to families when students are in high school. The Center for College Affordability and Productivity (2010) found that the total cost of a college education could potentially be reduced by up to 12.5% by offering a program like Early College.

Moreover, students exposed to rigorous curricula during their secondary schooling are better prepared to succeed at post-secondary institutions, due to the increased effort demanded (Shireman, 2004). Shireman (2004) further explains that "in the high schools that serve low-income and minority youth, there often is little attention to rigorous, standards-based instruction" (p. 3). Using data from the National Education Longitudinal Study, which randomly sampled nearly 25,000 students from about 1,000 nationally representative schools, Akerhielm et al. (1998) found the relationship between taking advanced courses and pursuing higher education to be greater for students of low-income backgrounds. From that same survey, Stearns et al. (2010) found that Black and Latinx students benefit most from taking more rigorous academic courses, relative to other racial groups. Culver et al. (2019) found that students who take rigorous courses—which they define as courses that promote a higher-order understanding of concepts and skills, as opposed to just more work—are more likely to think critically, value skills and ideas from the discipline, and appreciate the challenge of the course content. Culver et al. (2019) further assert that in-class rigor especially benefits the critical thinking skills of students underrepresented in higher education. Course rigor is thus the principal theory of change.

Barnett (2016) draws from various empirical papers to conclude that college level courses taken in high school are particularly effective at promoting college enrollment and completion, as they serve as preparation for postsecondary success. For example, Karp et al. (2008) ran OLS and logistic regressions, controlling for observable preexisting characteristics, to conclude that students who dually enroll in high school and college courses are more likely to graduate from high school, attend college, and persist. Using the National Education Longitudinal Study, An (2013) found dual enrollment participation to increase the probability of attaining any postsecondary degree and a bachelor's degree by 8 percentage points and 7 percentage points, respectively. Credit accumulation in high school is valuable in and of itself. Adelman's (2006) series of logistic regressions found that

there is a minimum number of credits earned during the first term and first year below which completion becomes less likely. In other words, college credit accumulation in high school gives students momentum to get to and through college (Leinbach & Jenkins, 2008).

Furthermore, Klopfenstein and Thomas (2009) found from their literature review that advanced course taking in secondary school, including college level courses, is perceived by college admissions officers as an indicator of student motivation. Consequently, colleges use advanced course enrollment and performance as a proxy for college readiness, viewing said students favorably in the admissions process (Kretchmar & Farmer, 2013). The last mechanism by which taking college courses in high school promotes post-secondary enrollment, persistence, and completion is by exposing students to the cultural aspects of college prior to their enrollment. Per Smith and Wertlieb (2005), introducing students to norms and expectations that they will encounter in postsecondary institutions facilitates their transition from high school.

Theoretical Framework

This study is framed by Human Capital Theory, which posits that any deliberate acquisition of useful skills and knowledge that yields economic value, including direct expenditures on education, is an investment (Schutz, 1961; Becker, 1962). Given the economic returns of educational attainment (Lobo & Burke-Smalley, 2018) and the effects of Early College on educational attainment (Edmunds et al., 2017; Haxton et al., 2016) this paper argues that Massachusetts made a human capital investment by offering the Early College, so that its citizens may acquire useful knowledge and skills that will produce an economic return. Determining the effects of Early College on college readiness, access, and success is analogous to a return-on-investment analysis. Schultz (1961) further attributes differences in earnings by race to differences in human capital investment by racial groups. By targeting Black and Latinx students in recruitment for Early College, Massachusetts also seeks to

address this supposed racial gap in human capital investment. Interactions between race and program participation included in the paper will help determine their effectiveness on that front.

Additionally, 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-matching regression models that estimate effects of program participation correspond to Perna and Thomas' (2006) layers of context.

Intervention Description

The increasing use of the term Early College in American education in the last twenty years or so can be traced back and attributed to the 2002 Bill and Melinda Gates Early College High School Initiative, which aimed to promote college access for students historically underrepresented in higher education by enabling them to earn a high school diploma while simultaneously building credits toward a post-secondary credential (Berger et al., 2010). High schools in the United States have offered dual enrollment, or the opportunity to simultaneously take college courses, for many decades, but these opportunities were typically reserved for academically advanced or gifted students (Berger et al., 2010).

Given the above-noted inequities in an otherwise high performing state, Massachusetts launched its Early College initiative in 2018 to promote equitable access to higher education. Unlike Early College in other states, Massachusetts Early College can involve participation from only some students in participating schools, or the whole school. Additionally, schools offering the program are asked to present a plan for outreach and recruitment specifically for racial minority and socioeconomically disadvantaged students (DESE & DHE, 2017). Furthermore, programs must demonstrate that students are not excluded based on prior academic performance, that students will be onboarded to ensure they ready for the coursework, and that students will be provided ongoing support to help them succeed in the courses they take (DESE & DHE, 2017). These features distinguish Massachusetts Early College from other Early College interventions evaluated in the existing literature.

Participating schools must partner with a local higher education institution (henceforth referred to as "college") to offer college-level courses. Per the Early College designation criteria, which determine which high school and college partnerships get to offer Early College, participating in Massachusetts Early College means that a student has the option to enroll in at least 12 credits by high school graduation, starting as early as 9th grade (DESE & DHE, 2017). 12 credits are approximately four college-level courses (typically 3 credits), and one tenth (1/10) of the typical 120-credit requirement to graduate with a bachelor's degree in the United States. These 12 credits must all be taken in a pathway, meaning that the 4 courses must feed into a subject-specific concentration, and should ideally be sequential so that the student is progressing toward a degree at the partner institution of higher education (DESE & DHE, 2017). Furthermore, courses must be transferable to public college or university in the state.

Courses are offered during the school day to minimize the logistical burden on students and their families. Furthermore, the high school and college partners must collaborate to schedule college courses such that they present negligible to no interference with students' high school experience.

Courses may be offered at the high school or at the college. In instances where a course is offered at the college, transportation must be provided for students and their departure and arrival must fit within their high school schedule. In all instances, instructors must be qualified to teach college courses (DESE & DHE, 2017). In addition to taking 12 college credits toward a degree, student participants receive academic advising from an Early College counselor at the high school. This is a critical component of the initiative, as program participants are likely to be those underrepresented in higher education, including first generation collegegoers, and as such are less likely to receive similar guidance at home (DESE & DHE, 2017).

Lastly, the high school and college partnerships that offer Early College must have in place adequate student support. This may include "on-ramping", which involves provision of preparatory courses in advance as well as scaffolding services (e.g. tutoring) to ensure that students have an opportunity to fully participate and benefit from Early College (DESE & DHE, 2017). The designation criteria provided by the state, which serve as the intervention description for this study, leave room for variation across schools and thus introduces some uncertainty. It would be useful to be able to categorize and measure aspects of implementation across participating schools, such as details of college advising student support offerings, but data on these aspects are not readily available and so are beyond the scope of this study's secondary analysis.

It should be noted that variation across schools in their implementation in terms of what proportion of students participate, what courses and academic pathways are offered, what recruitment strategies are used, types and dosage of supports provided, and profiles of the college or university partners—complicate the evaluation of the initiative as a whole but were put in place by design: "Flexibility will allow for learning during the first years of this designation process. While each element of the designation criteria was developed with intention and purpose, we understand that

parts of this process will evolve, and it is likely that we will revisit and revise the criteria" (DESE & DHE, 2017, p. 6).

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

Early College 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 must demonstrate evidence of building "strong and efficient pathways for student groups who may have been traditionally underserved in higher education" (DESE & DHE, 2017, p. 7). More specifically, schools had to present an effective plan for outreach and recruitment of students who are historically underrepresented in higher education, including students of color and socioeconomically disadvantaged students (DESE & DHE, 2017) to receive designation. To meet those ends, the schools are further asked to provide "tuition-free participation, open enrollment without regard to prior academic performance, student supports to promote success, multiple entry points for students, and student supports to prepare students for entry into the program" (DESE & DHE, 2017, p. 9). If they operate within those guidelines, schools can select students however else they think best and retain their designation. Furthermore, there is "no minimum initial cohort size requirement" (DESE, 2017, p. 7), so a school may enroll their entire student body in the program or very few students. For example, 40 Massachusetts high schools offered EC to 12th graders in 2022. In terms of count of 12th grade EC enrollment in the 40 schools, the range was from 1 student to 226 students, with a mean of 49 students. In terms of share of the school enrolled in EC, the range was from 1.5% to 100% of the 12th graders in the school, when rounded, with a mean of 21%.

It should be noted that there were two interventions launched as part of the Massachusetts High Quality College and Career Pathway programs in 2018, Early College and Innovation Career Pathways. During the years of the study, the two interventions are mostly offered at different schools, but there is some overlap, which results in 243 Innovation Career Pathways students attending schools that also offer Early College. Those 243 students were excluded from the sample. Therefore, the treated students used in this study are the 5,196 Early College participants in grade 12 from the 2018-19 through the 2021-22 school years. The untreated comparison students are drawn from the 28,153 remaining 12th grade students who attend a school that offers Early College but do not participate in the program during that same time (Table 1), minus the 243 who participate in Innovation Career Pathways. 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. From the matching process used in this study, described in greater detail in the upcoming methods section, 84 percent of the treatment observations were kept, while 16 percent were pruned, due to not having a sufficiently approximate match in terms of maximum distance from their propensity score in standard deviations. This means that the final sample included 4,373 Early College participants and 4,373 untreated comparison students, totaling 8,746 students.

Program Participation

There were 44 unique high schools in the state of Massachusetts that offered the Early College program to 12th graders at any point during the 2018-19 to the 2021-22 academic years. There were 18 schools that offered the program in 2018-19, the first year in the study, which increased to 42 by 2021-22, the last year in the study, due to additional programs being designated each year and a couple ceasing to offer the program. There were 27 high schools participating in 2019-20 and 31 in 2020-21. There were 367 Early College participants in the 12th grade in 2018-19, making up 7 percent of 12th graders at those schools. In 2019-20, there were 1,154 Early College participants in the 12th

grade, and they made up 15.6 percent of 12th graders in the Early College offering schools. In 2020-21, there were 1,704 Early College participants in the 12th grade, with a school participation rate of 18.5 percent. Lastly, there were 1,971 Early College participants in the 12th grade in 2021-22, with a participation rate of 17.2 percent. On aggregate, participants made up 15.6 percent of 12th graders in their schools during those 4 years (Table 1).

Table 1. Early College Participation in 12th Grade

	Student Group			
School Year	Early College	Rest of School	Rest of State	Total
2019	367	4899	66637	71903
2020	1154	6249	64128	71531
2021	1704	7500	63358	72562
2022	1971	9505	60031	71507
Total	5196	28153	254154	287503

Early College is typically offered at schools with higher rates of Black, Latinx, and socioeconomically disadvantaged students than the state. There are a small number of schools where this is not the case, but they focus on serving those groups. Mutually exclusively, 59 percent of 5,196 grade 12 Early College participants were Black or Latinx from the 2018-19 to 2021-22 academic years, while 57 percent of their 28,153 school peers, and 24 percent of their 254,154 state peers identified similarly. 49% of 12th grade Early College participants were from socioeconomically disadvantaged families, compared to 56 percent of the rest of their schools, and 28 percent of the rest of the state. Demographically, participation in the program within schools offering Early College seems broadly representative of those schools (Table 2).

Table 2. Participation of Underrepresented Students in EC

	Percent Black	Percent Latinx	Percent Low Income
Early College	16%	43%	49%
Rest of School	11%	46%	56%
Rest of State	9%	15%	28%

However, Early College participants are more likely to be proficient or advanced in English and Math than their school peers (Table 3). Looking at the 8th grade standardized test scores for the 12th graders from the 2018-19 to the 2021-22 academic years, 44 percent of Early College participants were proficient or advanced in Math, compared to 28 percent of their school peers and 47 percent of their state peers. 53 percent of Early College participants were proficient or advanced in English Language Arts (ELA), compared to 37 percent of their school peers and 60 percent of their state peers. In terms of baseline achievement, participation in the program within schools is more reflective of the state than of the schools.

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
Early College	32%	43%	12%	10%
Rest of School	21%	31%	7%	6%
Rest of State	31%	45%	16%	15%

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.

Lastly, Chronically Absent in Grade 8 and Suspended in Grade 8 were added as baseline measures. Chronically absent in Grade 8 is a binary variable indicating whether a student missed 10% or more school days in the 8th grade. For each student, the number of days they enrolled in and the number of days they attended school on an annual basis, are included in SIMS. By subtracting days attended from days enrolled, one may calculate how many days a student was absent each year. Dividing days absent by days enrolled yields the absence rate. Any student whose absence rate was equal to or greater than 0.1, or 10%, during the 8th grade year was given the value of 1 in the binary indicator Chronically Absent in Grade 8. Suspended in Grade 8 is a binary variable indicating whether a student was suspended at any time in the 8th Grade. Suspension data for all Massachusetts public schools is stored in the School Safety and Discipline Report (SSDR). SSDR not only collects information on all rule infringements that occur on school property, but also the corresponding disciplinary action taken against the student offender, including suspensions. Any student with a value greater than 0 for the days missed due to suspension during the 8th grade year was given the value of 1 in the binary indicator Suspended in Grade 8.

Methods

This paper gauges the effects of the Early College program on participants using propensity score matching. The propensity score is the conditional probability of being assigned a treatment given a vector of observed covariates (Rosenbaum & Rubin, 1983). Matching means that each member of the treatment group is then paired with a non-treated person in the population with an equal or proximate propensity score. When the matching process is successful, the resulting data set will be balanced, whereas the treatment group would be matched to a comparison group that is similar on observable characteristics. The average difference between the balanced treatment and control units from matched pairs with the same propensity scores is an estimate of the average treatment effect on the treated, or ATT (Guo & Fraser, 2015).

This research project chooses to match for several different reasons. Because regression analyses can be conducted post-match, matching enables one to leverage the advantages of both matching and regression analysis. Stuart (2010) asserts that matching should not be seen in conflict with regression modeling, rather the two methods are complementary and are best when combined. This study does indeed conduct regression analyses after matching. More importantly, matching methods address areas of the covariate distribution where there is not sufficient overlap between the treatment and control groups (Stuart, 2010). Imbalance between treatment and control groups could otherwise be described as systematic differences, which render a researcher less able to make causal claims. Indeed, Littnerova et al. (2013) argue that the benefit of propensity score matching over multivariable adjustment is "the separation of confounding factors adjustment and analysis of the treatment effect steps" (p. 384).

It should be noted that the propensity score calculation introduced by Rosenbaum and Rubin (1983) may employ various analytic approaches. Upon calculating propensity scores, a researcher may use propensity score matching, stratification on the propensity score, inverse probability of treatment weighting, and covariate adjustment using the propensity score (Guo & Fraser, 2015). Because matching eliminates a greater proportion of the systematic differences in baseline characteristics between the treatment and comparison groups than the three other methods (Austin, 2011) and the Rosenbaum Bounds Sensitivity Analysis, discussed later in the paper (Table 6), determined that the matching model used is not highly sensitive to an unobserved confounder (DiPrete & Gangl, 2004), matching was preferred.

The prevailing approach to calculating propensity scores in education research, and social sciences broadly, is logistic regression (Guo & Fraser, 2015), with treatment assignment as the binary outcome and a set of pertinent covariates as predictors (D'Agostino, 1998). From the logistic regression model, predicted probabilities for being assigned to the treatment group, referred to as propensity scores,

are generated for both the treatment group and potential comparison group members. The step following the calculation of propensity scores is to match treated participants to non-treated ones of a similar propensity score, as an approximation of comparability. After the logistic regression—which had Early College participation as the outcome variable—and the subsequent matching process, a sample including Early College students and their corresponding untreated match was generated.

This study matches using nearest neighbor with a caliper, as opposed to other approaches, such as Mahalanobis metric matching and optimal matching. Nearest neighbor is understood as pairing each treatment participant to a control participant with the nearest propensity score (Stone & Tang, 2013). When the nearest neighbor is far, the treated may be matched with a control that is quite different, in terms of propensity score. To overcome shortcomings of erroneously choosing a distant match, a researcher may impose a prespecified maximum distance between propensity scores, known as a caliper (Guo & Fraser, 2015). Although Rosenbaum and Rubin (1983) recommend a caliper that is .25 standard deviations of the logit of the propensity score, the reduced one of .2 standard deviations was selected, to minimize the mean square error of the resultant estimated treatment effect (Austin, 2011).

Nearest neighbor matching with a caliper is particularly favorable for this study because it "permits subsequent multivariate analysis of almost any kind that allows researchers to evaluate causal effects as they do with randomized experiments" (Guo & Frazer, 2015, p. 148). More specifically, a researcher may "perform multivariate analyses and undertake covariate adjustments for matched sample as is done in randomized experiments," (Guo & Frazer, 2015, p. 153) to estimate average treatment effects. It should also be noted that this study matches one-to-one, as opposed to many-to-one. That is one comparison student per program participant. One of the benefits of one-to-one matching is that it enables a researcher to estimate the effect of treatment by directly comparing outcomes between treated and untreated subjects in the matched sample. Furthermore, Austin

(2010, p. 1094) conducted 1,000 simulations and found that "bias increased as *M* increased with *M*:1 matching." In other words, increasing the number of untreated subjects matched to each treated subject increases the bias in the estimated treatment effect. Additionally, one-to-one matching allows for the sensitivity test conducted and discussed in the robustness checks section (Table 6).

It should also be noted that although the matching ensures the treatment and comparison students are similar across covariates on average in the entire sample, it leaves room for variation between pairs. Consequently, a matched treatment and comparison pair of students with similar propensity scores may differ on multiple characteristics. Because of this, a researcher may consider stratifying the match by variables believed to need exact matching, such as test score proficiency levels and school year in this study. In our case, this results in 64 different groups, considering 4 school years, and 4 proficiency levels, for 2 subjects. Having this many groups presents two critical challenges. Firstly, Guo and Frazer (2015) conclude their text by explaining that a common pitfall in propensity score matching is "failure to justify and present the model predicting propensity scores" (p. 383). Stratifying in the manner described, would result in 64 separate regressions to calculate propensity scores, many of which do not have enough power and do not statistically significantly predict program participation, due to the smaller samples. Secondly, stratifying complicates the interpretation of the result of sensitivity analysis, which is most helpful when the effect of the unknown confounder is compared to covariates in the model predicting program participation. With both considerations, matching was done without stratification. Odds ratios for the propensity score calculating logistic regression can be seen in Table 4.

Table 4. Propensity Score Calculating Logistic Regression

	Logistic Regression Odds Ratios	Standard Error
Black	2.63***	(0.15)
Other Race	1.37***	(0.08)
Latinx	1.83***	(0.08)
Economically. Disadvantaged/Low Income	0.91*	(0.03)
Male	0.54***	(0.02)
Disability	0.39***	(0.03)
English Learner	0.64***	(0.07)
Chronically Absent in G8	0.60***	(0.04)
Suspended in G8	0.62***	(0.05)
Missing ELA Test	1.82***	(0.30)
Needing Improvement/Partially Meeting Expectations in ELA	1.34***	(0.11)
Proficient/Meeting Expectations in ELA	1.67***	(0.14)
Advanced/Exceeding Expectations in ELA	1.73***	(0.18)
Missing Math Test	1.51*	(0.28)
Needing Improvement/Partially Meeting Expectations in Math	1.25***	(0.08)
Proficient/Meeting Expectations in Math	1.77***	(0.13)
Advanced/Exceeding Expectations in Math	2.28***	(0.20)
School Year=2019	0.40***	(0.03)
School Year=2021	1.45***	(0.07)
School Year=2022	1.32***	(0.07)
Observations	25819	

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

When matching on propensity scores, the concern is whether covariate balance between the treated and untreated is achieved after the application of propensity scores. As such, a good propensity score calculating logistic regression is not necessarily one that best predicts treatment assignment (Shiba & Kawahara, 2021). In other words, reporting measures of model fit that assess the predictive performance of a propensity model is of limited value (Westreich et al., 2011).

Matching Within the Early College Network

Ideally, Early College participants would be matched with comparable students within their own school. However, the share of students participating in the program varied by school, such that some schools have less than 5 percent of their 12th graders participating while others have more than 50 percent of their 12th grade students participating. In the schools with higher shares of students participating, there would not be enough non-participating students with whom to match. Thus, program participants were matched with students within the network of schools that offer Early

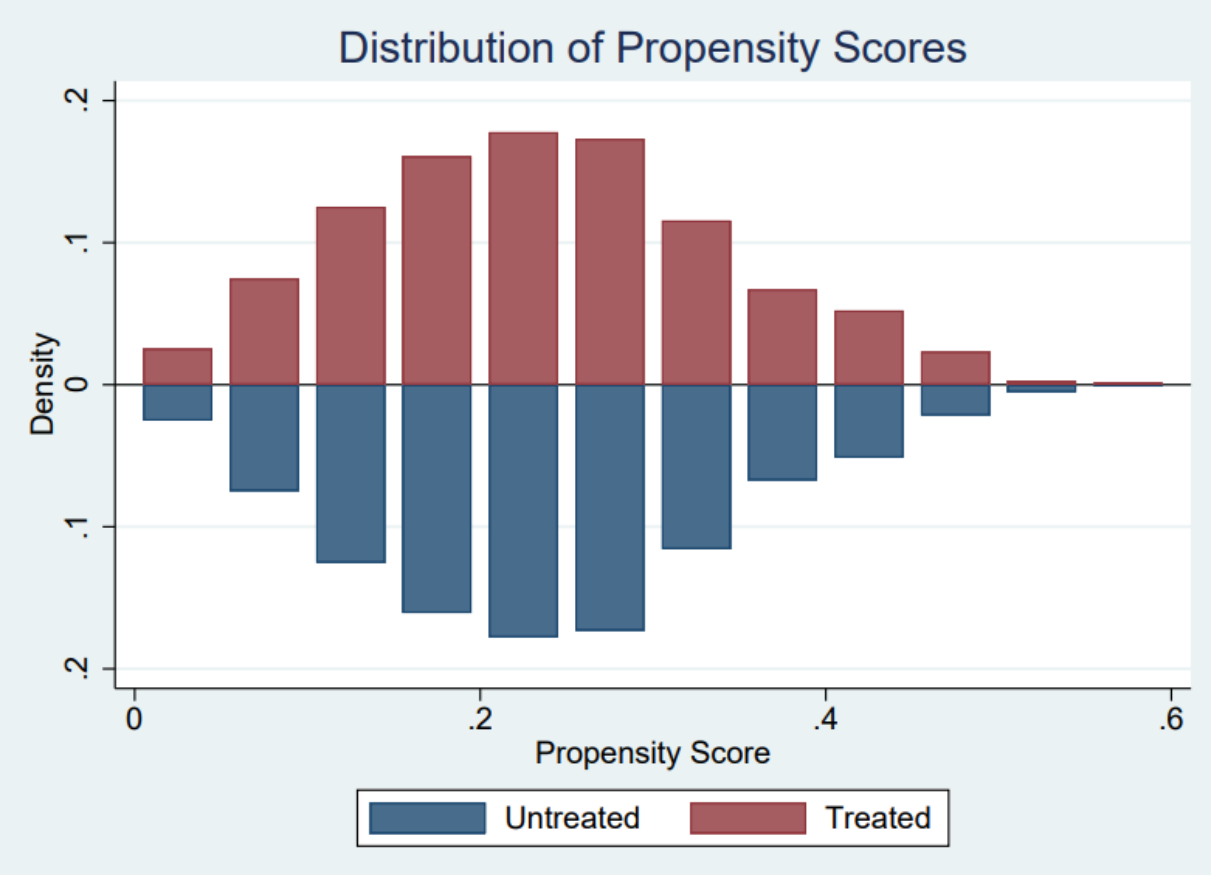
College. Given that schools self-selected to apply, drawing only from the Early College designated schools, as opposed to the rest of the state, alleviates concerns around the possibility that participating schools and non-participating schools are systematically different, which may lead to the erroneous conclusion that school effects are Early College program effects. School fixed effects are included in the post-match regression analysis to address variation that may exist between the Early College-offering schools.

Diagnostic Tests

Balance between Treatment and Comparison Groups

After calculating propensity scores, one must confirm that there is common support, or investigate whether there is overlap in the range of propensity scores across treatment and comparison groups (Garrido et al., 2014). Garrido et al. (2014) further assert that inferences about the effect of an intervention cannot be made for treated observations for whom there are no comparison observations with similar propensity scores. Common support may be assessed by examining a graph of propensity score distribution across treatment and comparison groups. As shown in Figure 1, there is nearly an identical distribution as well as overlapping of propensity scores in the treated and comparison groups.

Figure 1. Distribution of Propensity Score across Treatment and Comparison Groups



Furthermore, a balance table was constructed and shows that there are no statistically significant differences, in terms of the rates at which different attributes are represented, between the treatment and comparison group (Table 5). At an 84 percent match rate, 4,373 of the 5,196 Early College participants that were in grade 12 from the 2018-19 to the 2021-22 academic years were matched with 4,373 students from Early College offering schools. Note that the two reference groups from the regressions—White for race and Not Meeting Expectations for test level—are omitted.

Table 5. Post-match Early College Balance Table

Variable	Treated	Comparison	t-statistic	p-value
Black	15%	14%	0.49	0.626
Other Race	13%	14%	-0.28	0.778
Latinx	43%	42%	0.26	0.795
Female	64%	63%	0.4	0.689
Economically. Disadvantaged/Low Income	48%	48%	-0.11	0.915
English Learner	3%	3%	1.29	0.196
Disability	4%	4%	0.48	0.635
Missing ELA Test	1%	1%	1.28	0.202
Needing Improvement/Partially Meeting Expectations in ELA	30%	30%	-0.07	0.944
Proficient/Meeting Expectations in ELA	51%	52%	-0.53	0.593
Advanced/Exceeding Expectations in ELA	12%	11%	0.13	0.893
Missing Math Test	1%	1%	0.58	0.562
Needing Improvement/Partially Meeting Expectations in Math	37%	37%	0.18	0.859
Proficient/Meeting Expectations in Math	38%	39%	-0.29	0.775
Advanced/Exceeding Expectations in Math	15%	15%	-0.21	0.832
Chronically Absent in G8	7%	7%	0.13	0.897
Suspended in G8	4%	4%	1.06	0.287
Total Students	4,373	4,373	—	—

Sensitivity Analysis

A common strategy for addressing hidden bias from unobserved characteristics that may affect treatment assignment as well as the outcome is 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). One may determine the strength an unmeasured influence must have in order to render the estimated treatment effect inconclusive by looking at the Rosenbaum bounds on treatment effects at different levels of gamma (DiPrete & Gangl, 2004). According to the Rosenbaum bounds test on this propensity score match, as displayed in Table 6, the critical level of gamma at which we would have to question our conclusion of a positive effect is between 1.55 and 1.6, when sigma becomes greater than .05. In other words, it would require a hidden bias of gamma between 1.55 and 1.6 to render spurious the conclusion of a positive effect of program participation on college enrollment.

Table 6. Rosenbaum Bounds for Delta

Gamma	Sig +
1.25	2.00E-10
1.3	2.80E-08
1.35	1.70E-06
1.4	0.000049
1.45	0.000769
1.5	0.006827
1.55	0.036843
1.6	0.128635
1.65	0.309372
1.7	0.547173
1.75	0.763264

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. 1.55 is higher than all but 7 of the 20 covariates in the propensity score calculating model— including Black, Latinx, Proficient in ELA, Advanced in ELA, Proficient in Math, and Advanced in Math (See Table 4, on page 90). Given that EC specifically targets Black and Latinx students in recruitment, per the equitable access guiding principle in the designation criteria (DESE & DHE, 2017), and the observed pattern of EC enrolling higher achieving students, as described in the Program Participation section of this paper, it is expected that these variables would have the highest odd ratios in the model predicting program participation. Sitting in the range of 1.55 to 1.6 odds ratio, the unobservable confounder would have to change the odds of participating in the program as much as variables expected to strongly predict program participation. Thus, the researchers interpret the results to suggest that this match is not particularly sensitive to omitted variables. The seventh covariate that has an odds ratio higher than or equal to 1.55 is Missing ELA Test Score. Less than one percent of 12th graders are missing ELA test scores in the state of Massachusetts during the years of this study, so the odds ratio of 1.7 for this particular covariate is not strongly considered.

Matched vs. Unmatched Records

Under the .2 caliper specification chosen by the researcher, 84 percent of the treatment observations were kept, while 16 percent were pruned. In the context of propensity score matching, pruning can be described as a negotiation between imprecise matching and incomplete matching (Sainani, 2012). More precise matches can mean a smaller sample and a larger sample can mean less precise matching, i.e. a trade-off between internal and external validity. As shown in Table 7, the two largest statistically significant differences in the matched and pruned records are the higher rates at which the pruned records are English learners, needing improvement in ELA, and advanced in math, at 27, 14, and 13 percentage point differences, respectively. Henry et al. (2016) find English proficiency to have a statistically significant positive relationship with mathematics scores, so it is sensible that English learners who need improvement in ELA and score highly in math are scarce and thus difficult to match. This potentially presents a limitation on the external validity of this research, such that its findings have limited applicability to English Learners who need improvement in ELA but score highly in Math. Other differences are either much smaller or not statistically significant.

Table 7. Matched vs. Unmatched Early College Treatment Records

Variable	Matched	Pruned	t-statistic	p-value
Black	15%	22%	-5.34	0
Other Race	13%	8%	3.92	0
Latinx	43%	43%	-0.47	0.636
Female	64%	65%	-0.38	0.703
Economically. Disadvantaged/Low Income	48%	55%	-3.64	0
English Learner	3%	30%	-29.22	0
Disability	4%	2%	2.95	0.003
Missing ELA Test	1%	8%	-2.84	0.005
Needing Improvement/Partially Meeting Expectations in ELA	30%	44%	-1.5	0.133
Proficient/Meeting Expectations in ELA	51%	44%	0.69	0.491
Advanced/Exceeding Expectations in ELA	12%	4%	1.17	0.241
Missing Math Test	1%	0%	0.48	0.631
Needing Improvement/Partially Meeting Expectations in Math	37%	32%	0.54	0.59
Proficient/Meeting Expectations in Math	38%	28%	1.06	0.29
Advanced/Exceeding Expectations in Math	15%	28%	-1.89	0.058
Chronically Absent in G8	7%	8%	-0.48	0.63
Suspended in G8	4%	2%	0.96	0.339
Total Students	4,373	823	__	__

Results/Findings

Effects of EC on College Readiness

Post-match regression models estimate that EC participation has a positive effect on college readiness, as approximated by MassCore completion (Table 8). The first model, which is a logistic regression including all the covariates in the match, estimates that EC participants have 1.93 times the odds of being college ready, relative to their comparison group. The second regression model which adds the school fixed effects feature, estimates that EC participants have 1.34 times the odds of being college ready, relative to the comparison group. The big difference in the first and second model suggests that there is great variation in impact by school. This is possibly because MassCore is a recommended, but not a mandated program of study by the state, although the MassCore Curriculum is a feature of the Early College program. Some schools do not require it for high school graduation. The third model adds interaction terms, to explore whether race or income serve as a moderator for the effects of program participation on college readiness. No significant interactions were found between treatment and race or income status in this model.

Table 8. Effects on MassCore Completion/College Readiness

	Treatment with Covariates	(SE)	Treatment with Covariates and School Fixed-Effects	(SE)	Treatment with Covariates, School Fixed-Effects, and Interactions	(SE)
EC	1.93**	(0.47)	1.34*	(0.20)	1.27	(0.25)
Black	0.74	(0.20)	0.89	(0.11)	0.98	(0.19)
Other	0.39***	(0.11)	0.96	(0.14)	0.93	(0.17)
Latinx	0.66	(0.17)	0.66***	(0.06)	0.64*	(0.11)
Low-Income	0.81*	(0.07)	0.73***	(0.05)	0.70***	(0.06)
Male	0.90	(0.08)	0.79*	(0.09)	0.78*	(0.09)
Disability	0.76	(0.11)	0.62*	(0.12)	0.62*	(0.12)
English Learner	0.91	(0.23)	0.82	(0.26)	0.82	(0.26)
Chronically Absent in G8	0.57***	(0.08)	0.48***	(0.06)	0.49***	(0.06)
Suspended in G8	0.74	(0.17)	0.68	(0.15)	0.68	(0.15)
Missing ELA Test	0.84	(0.21)	0.77	(0.28)	0.78	(0.28)
Partially Meeting ELA	1.03	(0.11)	1.25	(0.24)	1.25	(0.24)
Meeting ELA	1.29*	(0.17)	1.31	(0.26)	1.31	(0.26)
Exceeding ELA	1.55*	(0.32)	1.50	(0.49)	1.51	(0.49)
Missing Math Test	0.96	(0.33)	1.06	(0.37)	1.06	(0.37)
Partially Meeting Math	1.20	(0.15)	1.46*	(0.24)	1.46*	(0.24)
Meeting Math	1.10	(0.27)	2.07***	(0.38)	2.08***	(0.38)
Exceeding Math	0.88	(0.28)	2.33**	(0.62)	2.33**	(0.62)
School Year=2019	1.76	(0.65)	1.11	(0.29)	1.12	(0.29)
School Year=2021	0.99	(0.20)	0.85	(0.25)	0.85	(0.25)
School Year=2022	1.00	(0.21)	1.02	(0.29)	1.02	(0.29)
EC # Black					0.78	(0.22)
EC # Other					1.06	(0.21)
EC # Latinx					1.06	(0.25)
EC # Low-Income					1.10	(0.20)
Constant	3.31***	(0.96)	159.82***	(59.46)	187.90***	(68.26)
Observations	8746		7874		7874	

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

Effects of EC on College Access

Early College is likewise estimated to have positive effects on college enrollment, by various regression models (Table 9). Per the post-match logistic regression containing all covariates from the match, EC participants have 1.69 times the odds of enrolling in college the year after completing high school, relative to the comparison group. Including school fixed effects in the second model increased the estimate to 2.01 times the odds of enrolling in college for EC participants, relative to the comparison group, meaning that variation in impact by school may mask an even greater impact. The third regression model features an interaction between being a participant and being low-

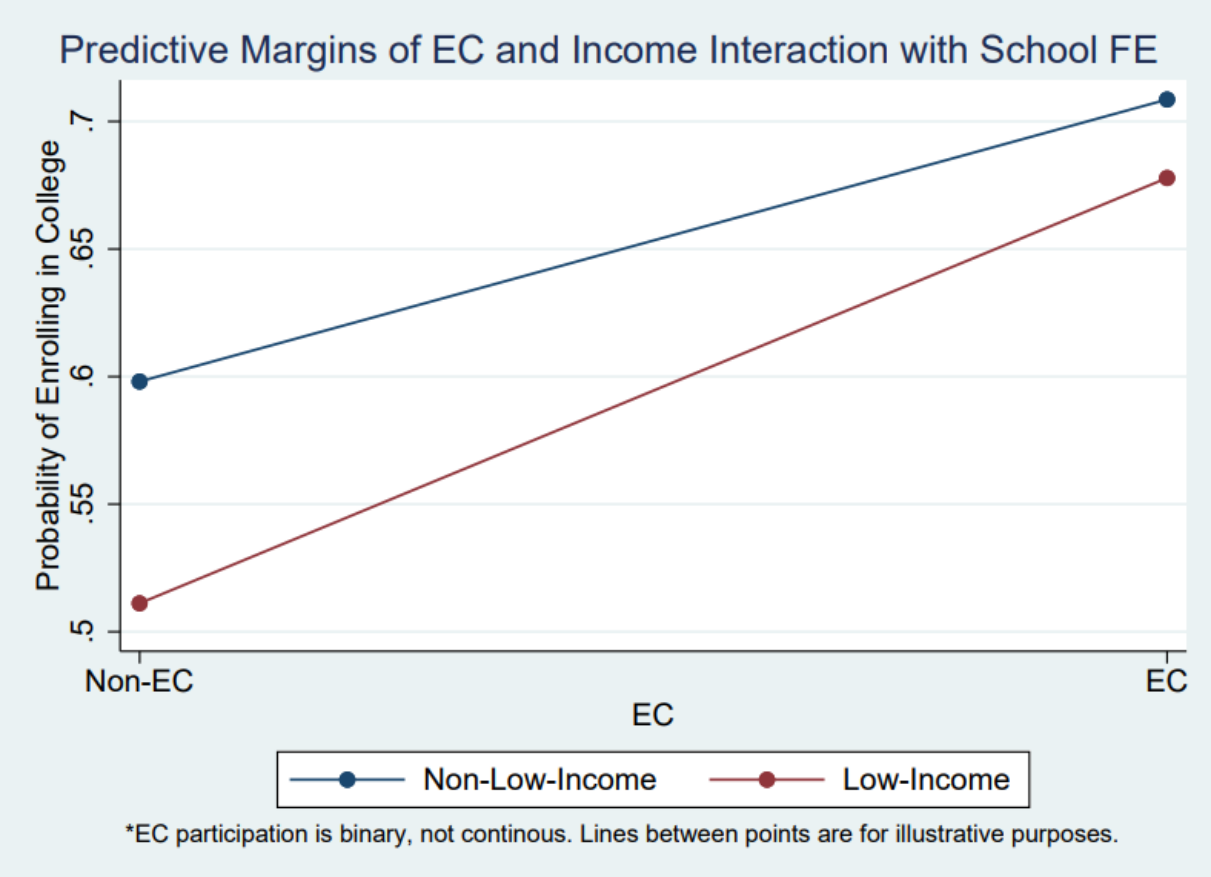
income, which remained significant with school fixed effects. It estimates an impact of increasing the odds of enrolling in college by 1.94 times for non-low-income participants, and a further 1.28 higher odds for students from a socioeconomically disadvantaged background. This means that although Early College participation increases the odds of enrolling in college for all students on average, the increased odds are greater for low-income students. This interaction is graphed in probability units in Figure 2. There were no significant interactions between program participation and race values of Black or Latinx, per the same regression model.

Table 9. Effects on College Enrollment/College Access

	Treatment with Covariates	(SE)	Treatment with Covariates and School Fixed Effects	(SE)	Treatment with Covariates, School Fixed Effects, and Interactions	(SE)
EC	1.69***	(0.14)	2.01***	(0.14)	1.94***	(0.25)
Black	1.01	(0.12)	1.15	(0.12)	1.30*	(0.17)
Other	0.94	(0.10)	0.90	(0.07)	1.05	(0.09)
Latinx	0.53***	(0.05)	0.57***	(0.04)	0.58***	(0.05)
Low-Income	0.70***	(0.05)	0.74***	(0.04)	0.66***	(0.05)
Male	0.70***	(0.05)	0.71***	(0.05)	0.71***	(0.05)
Disability	0.71**	(0.08)	0.66***	(0.07)	0.66***	(0.07)
English Learner	0.65**	(0.10)	0.64**	(0.10)	0.64**	(0.10)
Chronically Absent in G8	0.54***	(0.05)	0.59***	(0.05)	0.59***	(0.05)
Suspended in G8	0.56***	(0.09)	0.56***	(0.09)	0.56***	(0.09)
Missing ELA Test	0.93	(0.19)	0.87	(0.17)	0.87	(0.17)
Partially Meeting ELA	0.95	(0.10)	0.93	(0.10)	0.93	(0.10)
Meeting ELA	1.19	(0.13)	1.15	(0.13)	1.15	(0.13)
Exceeding ELA	1.37*	(0.18)	1.29	(0.18)	1.29	(0.18)
Missing Math Test	1.67	(0.46)	1.75	(0.55)	1.76	(0.55)
Partially Meeting Math	1.49***	(0.18)	1.41**	(0.18)	1.41**	(0.18)
Meeting Math	2.16***	(0.29)	1.96***	(0.28)	1.96***	(0.28)
Exceeding Math	3.55***	(0.54)	3.01***	(0.49)	3.01***	(0.49)
School Year=2019	1.49**	(0.23)	1.77***	(0.23)	1.76***	(0.22)
School Year=2021	0.94	(0.07)	0.92	(0.07)	0.91	(0.07)
School Year=2022	0.92	(0.09)	0.81*	(0.08)	0.81*	(0.08)
EC # Black					0.75	(0.16)
EC # Other					0.73*	(0.10)
EC # Latinx					0.97	(0.13)
EC # Low-Income					1.28*	(0.13)
Constant	1.28	(0.21)	0.78	(0.16)	0.82	(0.18)
Observations	8746		8737		8737	

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

Figure 2. Early College and Low-income Interaction for College Enrollment (School Fixed Effects)



Effects of EC on College Success

With a smaller sample, due to needing an additional year of data to calculate, Early College made an estimated positive difference on second-year persistence (Table 10). Looking at the post-match regression with the covariates, EC participants had 1.7 times the odds of persisting to a second year in college, relative to the comparison students. Including school fixed effects in the second regression model increased the estimated impact to 2.01 times the odds of persisting to a second year in college for EC participants, relative to the comparison group. Like the impact on college enrollment, this means that variation in impact by school may mask a greater effect size for EC participation. The third model adds interactions between program participation and being Black, Latinx, or low-income.

There were no statistically significant interactions between program participation and race or income status in the post-match regression with school fixed effects.

Table 10. Effects on Second-year Persistence/College Success

	Treatment with Covariates	(SE)	Treatment with Covariates and School Fixed-Effects Model	(SE)	Treatment with Covariates, School Fixed-Effects Model, and Interactions	(SE)
EC	1.70***	(0.17)	2.01***	(0.15)	1.70***	(0.24)
Black	1.09	(0.18)	1.23	(0.16)	1.27	(0.22)
Other	0.93	(0.12)	0.91	(0.12)	0.91	(0.16)
Latinx	0.46***	(0.05)	0.48***	(0.04)	0.41***	(0.05)
Low-Income	0.76***	(0.06)	0.81***	(0.05)	0.76**	(0.08)
Male	0.64***	(0.03)	0.64***	(0.04)	0.64***	(0.04)
Disability	0.61*	(0.12)	0.60**	(0.12)	0.60**	(0.12)
English Learner	0.70	(0.15)	0.70	(0.16)	0.71	(0.16)
Chronically Absent in G8	0.44***	(0.06)	0.47***	(0.06)	0.47***	(0.06)
Suspended in G8	0.53**	(0.11)	0.54**	(0.12)	0.54**	(0.12)
Missing ELA Test	1.44	(0.33)	1.44	(0.33)	1.45	(0.33)
Partially Meeting ELA	1.17	(0.14)	1.14	(0.16)	1.14	(0.16)
Meeting ELA	1.54***	(0.20)	1.50**	(0.23)	1.50**	(0.23)
Exceeding ELA	2.10***	(0.33)	2.01***	(0.37)	2.02***	(0.36)
Missing Math Test	2.02*	(0.55)	1.99*	(0.63)	1.99*	(0.62)
Partially Meeting Math	1.66**	(0.29)	1.53*	(0.29)	1.52*	(0.29)
Meeting Math	2.58***	(0.46)	2.30***	(0.47)	2.30***	(0.47)
Exceeding Math	4.29***	(0.78)	3.54***	(0.81)	3.53***	(0.81)
School Year=2019	1.28	(0.21)	1.47**	(0.21)	1.48**	(0.22)
School Year=2021	1.07	(0.10)	1.01	(0.09)	1.01	(0.09)
EC # Black					0.91	(0.27)
EC # Other					1.00	(0.22)
EC # Latinx					1.34	(0.24)
EC # Low-Income					1.13	(0.18)
Constant	0.50**	(0.11)	0.32***	(0.08)	0.39**	(0.13)
Observations	5416		5410		5410	

Exponentiated coefficients; Standard errors in parentheses

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

Robustness Checks

As a robustness check, the researchers 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 covariates remained the same and school fixed effects were also featured in the models. As shown in Table 11,

this approach estimates that Early College Participants do not have statistically significant higher odds of being college ready but have 1.89 higher odds of enrolling in college and 1.71 higher odds of persisting to a second year in college, relative to non-participants in their schools, excluding those who participate in Innovation Career Pathways. Notably, the 1.89 higher odds estimated effect on college enrollment and the 1.71 higher odds estimated effect on college persistence from this school fixed effects model using continuous test scores are similar in direction and magnitude to the 2.01 odds estimated effects on college enrollment and persistence from the fixed effect models in Table 9 (on page 98) and Table 10 (on page 100), which use performances levels.

Table 11. Effects Using Continuous Test Scores from 2020-21 and 2021-22 (School Fixed Effects)

	Effects on College Readiness	(SE)	Effects on College Access	(SE)	Effects on College Success	(SE)
EC	1.19	(0.20)	1.89***	(0.15)	1.71***	(0.16)
Black	1.02	(0.17)	1.21	(0.13)	1.23	(0.18)
Other	0.90	(0.19)	0.85	(0.11)	0.66*	(0.13)
Latinx	0.66**	(0.08)	0.64***	(0.05)	0.55***	(0.05)
Low-Income	0.76*	(0.09)	0.76***	(0.05)	0.78*	(0.09)
Male	0.75*	(0.09)	0.71***	(0.06)	0.64***	(0.05)
Disability	0.60*	(0.13)	0.80	(0.12)	0.67	(0.16)
English Learner	0.92	(0.29)	0.77	(0.16)	0.81	(0.33)
Chronically Absent in G8	0.51**	(0.11)	0.57***	(0.09)	0.54**	(0.11)
Suspended in G8	0.66*	(0.12)	0.54***	(0.09)	0.45**	(0.11)
Next Gen ELA Test	1.01**	(0.00)	1.01**	(0.00)	1.01***	(0.00)
Next Gen Math Test	1.01	(0.00)	1.01***	(0.00)	1.02***	(0.00)
School Year=2022	1.34	(0.32)	0.90	(0.06)	1.00	(.)
Constant	0.08	(0.20)	0.00***	(0.00)	0.00***	(0.00)
Observations	5068		6050		2726	

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

As an additional robustness check for these logistic regression models, one may regress the same variables as linear probability models. In expectation, relationships between the dependent variable and the independent variables should remain similar across logistic and linear probability models (Papke & Wooldridge, 1996). Including all the years in the data, linear probability models estimated that Early College Participants do not have a statistically significant higher probability of being college ready, but have 14% higher probability of enrolling in college, and 8% higher probability of persisting

to a second year in college, relative to non-participants in their schools, excluding those who participate in Innovation Career Pathways (Table 12). All models—logistic or linear probability, continuous test scores or factor test performance levels—estimate that Early College participation has a positive effect on college enrollment and persistence.

Table 12. Estimated Effects Using Linear Probability Models (School Fixed Effects)

	Effects on College Readiness	(SE)	Effects on College Access	(SE)	Effects on College Success	(SE)
EC	0.03	(0.01)	0.14***	(0.01)	0.08***	(0.01)
Black	-0.01	(0.01)	0.03	(0.02)	0.03	(0.02)
Other	-0.01	(0.02)	-0.02	(0.01)	-0.01	(0.01)
Latinx	-0.04**	(0.01)	-0.11***	(0.01)	-0.09***	(0.01)
Low-Income	-0.03**	(0.01)	-0.06***	(0.01)	-0.03**	(0.01)
Male	-0.02	(0.01)	-0.07***	(0.01)	-0.06***	(0.01)
Disability	-0.05*	(0.02)	-0.08***	(0.02)	-0.04*	(0.02)
English Learner	-0.02	(0.04)	-0.09**	(0.03)	-0.05*	(0.02)
Chronically Absent in G8	-0.08***	(0.01)	-0.11***	(0.02)	-0.07***	(0.01)
Suspended in G8	-0.04	(0.03)	-0.13***	(0.03)	-0.05*	(0.03)
Missing ELA Test	-0.02	(0.04)	-0.03	(0.04)	-0.00	(0.03)
Partially Meeting ELA	0.02	(0.02)	-0.01	(0.02)	-0.03	(0.01)
Meeting ELA	0.03	(0.02)	0.04	(0.02)	0.00	(0.02)
Exceeding ELA	0.03	(0.02)	0.05	(0.03)	0.05**	(0.02)
Missing Math Test	0.00	(0.03)	0.12	(0.06)	0.14*	(0.05)
Partially Meeting Math	0.04*	(0.02)	0.08**	(0.03)	0.08**	(0.02)
Meeting Math	0.07***	(0.02)	0.15***	(0.03)	0.13***	(0.02)
Exceeding Math	0.08**	(0.02)	0.22***	(0.03)	0.22***	(0.03)
School Year=2019	0.01	(0.02)	0.11***	(0.02)	0.05	(0.03)
School Year=2021	-0.01	(0.03)	-0.02	(0.02)	-0.01	(0.02)
School Year=2022	0.00	(0.02)	-0.04*	(0.02)	-0.51***	(0.02)
Constant	-0.02	(0.04)	0.44***	(0.04)	0.44***	(0.03)
Observations	8746		8746		8746	

Standard errors in parentheses

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

Discussion

The findings of this paper add to the broader discussion on Early College. As previously mentioned, Edmunds et al. (2017) indicated that an area for further research is the investigation of the efficacy of Early College strategies within traditional comprehensive high schools. This study does indeed respond to that call, by evaluating the impact of Massachusetts Early College, which is mostly a program within a school model, with an average of 21% of 12th grade students at any designated

school participating and only one school having 100% of its students participate. The 2.01 odds ratio from the post-match multivariate logistic regression with school fixed effects that estimates the impact of EC participation on college enrollment translates to a 14-percentage point positive difference when using a linear probability model. At a 14-percentage point positive impact estimate on college enrollment, the findings of this paper are consistent in direction and magnitude with the 15.6-percentage point positive impact estimate found by Edmunds et al. (2017; 2020), as part of their longitudinal randomized controlled trial in North Carolina.

Albeit to a lesser extent, the 14-percentage point positive impact estimate is also relatively consistent with Haxton et al. (2016), who found Early College to have a 9-percentage point positive impact estimate on college enrollment from a longitudinal randomized controlled trial. Thus, this propensity score matching non-experimental causal study—in addition to the experimental studies of Edmunds et al. (2017; 2020), Berger et al. (2013), and Haxton et al. (2016)—provides further evidence that Early College promotes educational attainment. While the estimated effects are positive and consistent with the experimental literature, the mechanism by which Massachusetts Early College is promoting college readiness, access, and success is not evaluated, as part of this study. We posit that while the implementation of Massachusetts Early College as a policy decision has had positive effects on average, further studies should be conducted, to identify best practices to inform the improvement of existing Early College programs and the expansion of the intervention.

Beyond the effectiveness of the program on average, this paper particularly argues that Early College is an intervention to promote more equitable educational attainment. In models estimating effects on college access, including one with school fixed effects, there is an interaction between program participation and having a socioeconomically disadvantaged background, which result in increased odds of said students enrolling in college. In a society where socioeconomically disadvantaged students are underrepresented in their attendance at colleges and universities, relative to their share

of the population, this intervention may be a sensible way to address this inequity in Massachusetts, and potentially beyond.

Although the within-school feature is what distinguishes Massachusetts Early College from the whole school Early College models in other states, a point of discussion is the variation in the count and share of 12th graders who participate in EC at each EC-offering school. With one school having as few as 1.5% of 12th graders participating and another having 100% of 12th graders participating, 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 Early College as well for 5% of the cohort as it does 100 %? In light of these questions, further research – and the Massachusetts DESE and DHE – might usefully consider issues around implementation and program quality for schools. It should be noted that the number of students across the commonwealth enrolled in Early College during the years of the study is relatively low. Per Table 1, although there were 5,196 12th grade students participating in Early College between 2018-19 and 2021-22, they made up just under 2% of 12th graders in the state of Massachusetts.

Massachusetts is a local-control state, where public school governance is legally delegated to district and school boards located in the communities they serve, as opposed to the state government, making it more difficult to have state-wide interventions. Therefore, this impact evaluation should be of particular interest to the northeastern states where local-control is prominent. The flexibility of Massachusetts Early College renders it more easily replicated in such states, than the whole school models of southern or western states, where state-directed control is the norm.

Although the discussion emphasizes college enrollment, there are two additional outcomes investigated in this study—college readiness and college success. It should be noted that regression coefficients from the college readiness models may be about the relationship between EC and the

measure of college readiness used in the study, as opposed to college readiness itself, which is unknown. College readiness is approximated by MassCore completion, which is the taking and completion of certain courses that align with college and workforce expectations. There is a world in which a student may have completed MassCore but is not college ready, and vice versa. Likewise, college success is approximated by second-year persistence, which is an intermediary measure of the ultimate measure of college success, earning a degree. Nevertheless, this study finds that Early College participants have higher odds of enrolling in college the year after graduating high school and persisting to a second year in college than non-participants with similar observable characteristics and baseline achievement.

With the framing of offering Early College 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 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 enrolled in college and persisted to second year as a result of participating in this intervention, this theoretical return on investment may be 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.

It would be remiss for a researcher using propensity score matching not to acknowledge its limitations. There are three standout limitations of this analysis—imbalance on unobserved characteristics, pruning, and uncertainty that it is the intervention and not something else at the school causing the differences in outcomes—all of which have been variously addressed above. Methods that seek to mitigate bias by controlling for confounding variables, such as propensity score matching, do well in balancing observed baseline covariates between groups, but they do not necessarily balance unmeasured characteristics and confounders (Nuttall & Houle, 2008). In other words, propensity score matching is limited in that unmeasured or otherwise unincluded confounding variables—e.g. a highly motivated parent—may be present, leading to biased estimators of treatment effects. This is addressed with a sensitivity analysis.

Additionally, researchers who use propensity score matching for policy analysis and program evaluation must often negotiate a trade-off between imprecise matching and incomplete matching (Sainani, 2012). Propensity scores can also be understood as a measure of the distance between two participants in a sample or population, which are used to determine whether an individual is a good match for another (Huber et al., 2017). As discussed, a researcher decides the caliper, or minimum distance between treatment and control participants to be matched. The shorter the distance, the more precise the match, but the less likely that a match will be found—incomplete matching. The longer the distance, the less precise the match, but the higher likeliness of finding a match—imprecise matching.

The consequence of incomplete matching is that treatment participants for whom a sufficiently close control participant could not be found are dropped. Why would a researcher move forward with an incomplete match? Dropping records, referred to as pruning in the literature, by eliminating poorly matched treatment participants, ensures balanced propensity score distributions (Ripollone, 2018). The downside to pruning, however, is that it progressively leads to a lack of generalizability of

findings. Conversely, while increasing the minimum distance between treatment and control participants to be matched safeguards against pruning and gives researchers a large sample, imprecise matching may lead to residual confounding. This paper addresses pruning by comparing the kept and the pruned records.

Lastly, it should be noted that there is limited ability to estimate the effect of program participation on MassCore completion, the approximation for college readiness used in this study, when incorporating fixed effects. This is because many schools in Massachusetts have all their high school graduates completing MassCore, although it is suggested and not a required program of study from the state. When fixed effects are included in a logistic regression model with a binary-dependent variable, groups or clusters with no variation in the dependent variable are dropped because the fixed effects perfectly predict the outcome (Beck, 2020). This in turn substantially reduces the sample size, and is perhaps why the estimated effects on MassCore completion are not statistically significant in many of the models.

Conclusion

This study finds Early College to be both generally effective, with odds of enrolling in college that are 2.01 times higher for program participants relative to non-participants, and to promote equity by particularly benefitting low-income participants via interactions. Other impact evaluations of Early College have similarly found this type of intervention to be effective. The within-school option of Massachusetts Early College—as opposed to entirely whole-school programs—distinguishes the Massachusetts program from otherwise similar programs that have been studied elsewhere, giving states that are considering Early College, especially those with local-control, another model to consider. Edmunds et al. (2017) indeed suggest that implementation of Early College within

traditional comprehensive high schools need to be evaluated to determine whether it works in these settings.

There remain areas to be further researched. Although the effects are positive on average, there is great variation in their magnitude across the schools, evidenced by school foxed effects models. Because the guiding principles and designation criteria are flexible, it is not clear what is the driver behind the efficacy of Early College. This paper is therefore limited in its ability to highlight which and what dosage of the components of the Massachusetts Early College intervention works best. Furthermore, as of the writing of this paper, the college completion rate, which is typically measured five to six years after students enter college, is not yet available for evaluation, but further analysis is planned to focus on this outcome.

Chapter 5: Do Innovative Career Pathways Promote Equitable Access to Higher Education?

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, Helmet 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 1,886 Early College students attending schools that also offer Innovation Career Pathways. Those 1,886 students were excluded from this study. Therefore, the treatment students used in this study are the 1,359 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 26,055 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 1,886 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 26 ICP participants in the 12th grade in 2018-19, making up 1.4 percent of 12th graders at those schools. In 2019-20, there were 318 ICP participants in the 12th grade, and they made up 4.8 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 4.3 percent. Lastly, there were 575 ICP participants in the 12th grade in 2021-22, with a participation rate of 6.5 percent. On aggregate, participants made up 5 percent of 12th graders in their schools 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	26	1804	70073	71903
2020	318	6299	64914	71531
2021	440	9683	62439	72562
2022	575	8269	62663	71507
Total	1359	26055	260089	287503

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, as shown in Table 2, 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 (Table 3). Looking at the 8th grade standardized test scores for the 12th graders from the 2018-19 to the 2021-22 academic years, 41% of ICP participants were proficient or advanced in Math, compared to 35% of the rest of their peers at the ICP offering schools, and 47% of their remaining state peers, mutually exclusively. At 49% and 45%, respectively, ICP participants

were proficient or advanced in ELA at a rate comparable to the rest of their peers at the ICP offering schools. 59% 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%	9%	8%
Rest of School	27%	37%	8%	8%
Rest of State	31%	45%	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.

Lastly, Chronically Absent in Grade 8 and Suspended in Grade 8 were added as baseline measures. Chronically absent in Grade 8 is a binary variable indicating whether a student missed 10% or more school days in the 8th grade. For each student, the number of days they enrolled in and the number of days they attended school on an annual basis, are included in SIMS. By subtracting days attended from days enrolled, one may calculate how many days a student was absent each year. Dividing days absent by days enrolled yields the absence rate. Any student whose absence rate was equal to or

greater than 0.1, or 10%, during the 8th grade year was given the value of 1 in the binary indicator Chronically Absent in Grade 8. Suspended in Grade 8 is a binary variable indicating whether a student was suspended at any time in the 8th Grade. Suspension data for all Massachusetts public schools is stored in the School Safety and Discipline Report (SSDR). SSDR not only collects information on all rule infringements that occur on school property, but also the corresponding disciplinary action taken against the student offender, including suspensions. Any student with a value greater than 0 for the days missed due to suspension during the 8th grade year was given the value of 1 in the binary indicator Suspended in Grade 8.

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, 2009), 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):

Table 4. Propensity Score Calculating Logistic Regression

	Logistic Regression Odds Ratios	(SE)
Black	1.23*	(0.12)
Other Race	1.43***	(0.14)
Latinx	1.31**	(0.11)
Economically. Disadvantaged/Low Income	1.13	(0.08)
Male	0.83**	(0.05)
Disability	0.63***	(0.08)
English Learner	1.14	(0.17)
Chronically Absent in G8	0.81	(0.09)
Suspended in G8	0.83	(0.11)
Missing ELA Test	1.56	(0.40)
Needing Improvement/Partially Meeting Expectations in ELA	0.87	(0.10)
Proficient/Meeting Expectations in ELA	0.89	(0.12)
Advanced/Exceeding Expectations in ELA	0.83	(0.14)
Missing Math Test	0.23*	(0.17)
Needing Improvement/Partially Meeting Expectations in Math	1.25*	(0.14)
Proficient/Meeting Expectations in Math	1.44**	(0.18)
Advanced/Exceeding Expectations in Math	1.60**	(0.25)
School Year=2019	0.30***	(0.06)
School Year=2021	0.92	(0.08)
School Year=2022	1.31**	(0.11)
Observations	21196	

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, on page 130), which means the confounder is likely able to 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	0.089467
1.1	0.362265
1.2	0.709568
1.3	0.916988
1.4	0.984546
1.5	0.998016
1.6	0.999814
1.7	0.999987
1.8	0.999999
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 = .03453139
Iteration 1:	criterion = .03542409
Iteration 2:	criterion = .03594585
Iteration 3:	criterion = .03744733
Iteration 4:	criterion = .03788978
Iteration 5:	criterion = .03809142
Iteration 6:	criterion = .03818701
Iteration 7:	criterion = .03827437
Iteration 8:	criterion = .03832683
Iteration 9:	criterion = .03836701
Iteration 10:	criterion = .03838504
Iteration 11:	criterion = .03838981
Iteration 12:	criterion = .03839156
Iteration 13:	criterion = .03839359
Iteration 14:	criterion = .03839497
Iteration 15:	criterion = .03839567
Iteration 16:	criterion = .03839603
Iteration 17:	criterion = .03839614
Iteration 18:	criterion = .0383962
Overidentification test for covariate balance	
H0: Covariates are balanced:	
chi2(21) = 25.0442	
Prob > chi2 = 0.2453	

To further 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. 19 out of 20 calculated standardized differences between the treated and untreated are closer to 0 in the weighted sample than in the unweighted sample and 19 out of 20 calculated variance ratios are closer to 1 in the weighted sample than in the unweighted sample (Table 7). Furthermore, all the

weighted standardized differences are 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	0.031	0.009	1.068	1.020
Other Race	0.089	-0.024	1.270	0.932
Latinx	0.049	-0.032	1.068	0.955
Economically. Disadvantaged/Low Income	0.071	-0.017	1.031	0.991
Male	-0.106	0.011	0.996	0.999
Disability	-0.166	0.020	0.646	1.044
English Learner	0.028	-0.005	1.120	0.978
Chronically Absent in G8	-0.064	0.036	0.828	1.101
Suspended in G8	-0.069	0.006	0.773	1.020
Missing ELA Test	0.065	-0.016	1.788	0.847
Needing Improvement/Partially Meeting Expectations in ELA	-0.030	0.010	0.979	1.007
Proficient/Meeting Expectations in ELA	0.031	-0.008	1.007	0.998
Advanced/Exceeding Expectations in ELA	-0.009	-0.006	0.975	0.982
Missing Math Test	-0.123	-0.002	0.144	0.982
Needing Improvement/Partially Meeting Expectations in Math	0.007	-0.014	1.003	0.995
Proficient/Meeting Expectations in Math	0.078	0.001	1.055	1.000
Advanced/Exceeding Expectations in Math	0.021	0.011	1.057	1.028
School Year 2019	-0.242	-0.006	0.309	0.981
School Year 2021	-0.079	0.020	0.948	1.012
School Year 2022	0.188	-0.006	1.106	0.996

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 sample is 18,794 while the difference is the post weight synthetic sample is 68, 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	21,196	21,196
Number of Treated observations	1,201	10,632
Number of non-treated observations	19,995	10,564

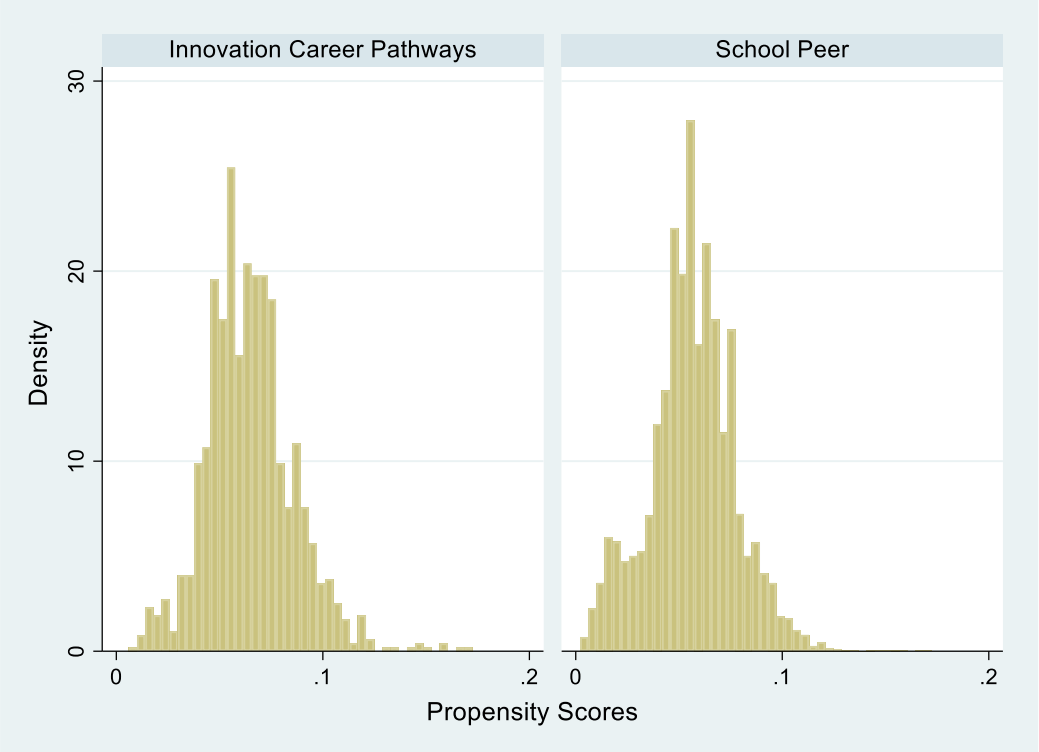
A critically important plausibility assumption of IPTW is that of positivity. The positivity assumption posits that the conditional probability of receiving a given treatment cannot be 0 or 1 for any combination of covariate values within a dataset (Zhu et al., 2021). Austin and Suart (2015) similarly assert that a difficulty that can arise when using IPTW is that treated subjects with low propensity scores can result in very large weights and that control subjects with a high propensity score can result in very low weights. Most applicably, the lack of variability in treatment assignments may threaten the identifiability of causal effects (Zhu et al., 2021) while extreme weights can increase the variability of the estimated treatment effect (Austin & Stuart, 2015).

Said in plainer language, when there are sufficiently large differences in characteristics between treated and untreated groups, such that some subjects end up with a very high or low probability of being exposed, taking the inverse of the propensity score may subsequently lead to extreme weight values, which in turn inflates the variance and confidence intervals of the impact estimate (Chesnaye et al., 2022). There are a couple of actionable steps that a researcher may take regarding this concern. Firstly, the plausibility of the positivity assumption can be explored from the distribution of the propensity score; and secondly, weight truncation or trimming can limit the contribution of large weights to the analysis, to ensure the validity of the estimation (Bettega et al., 2024).

Indeed, Lee et al. (2011) argue that although misspecified logistic regression propensity score models may yield increased bias and standard errors, weight trimming following logistic regression improves the accuracy and precision of final parameter estimates. It is the standard practice to trim or truncate weights at the 1st and 99th percentiles (Chesnaye et al., 2022; Austin & Stuart, 2015; Naimi et al.,

2014). Below are histogram distributions of propensity scores for Innovation Career Pathways treated and untreated subjects (Figure 1), with similar variability in treatment assignment, and IPTW regression results from trimmed weights, with estimates nearly identical to the untrimmed weights regressions, can be seen in Appendix A.

Figure 1. Distribution of Propensity Scores



Results/Findings

Effects of ICP on College Readiness

Weighted regression models with school fixed effects 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, without school fixed effects, estimates that ICP participants do not have statistically significant higher odds of being college ready than non-participants. The second model is the weighted multivariate

logistic regression from model one with school fixed effects, which estimates that ICP participants have 1.57 times the odds of being college ready than non-participants. The effect size from model one to two is essentially the same, but the change in significance suggests that the school fixed effects feature are accounting for unobserved heterogeneity across schools. The third model incorporates interactions between program participation and race, and program participation and family income status. There are no statistically significant interactions between program participation and being Black, Latinx, or low-income, when estimating effects on college readiness with school fixed effects. This means that Innovation Career Pathways participation increases the odds of completing MassCore for all students on average, without evidence that the relationship is different for Black, Latinx, and 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.

Table 9. Effects on MassCore Completion/College Readiness

	Treatment with Covariates	(SE)	Treatment with Covariates and School Fixed Effects	(SE)	Treatment with Covariates, School Fixed Effects, and Interactions	(SE)
ICP	1.56	(0.66)	1.57*	(0.32)	1.73*	(0.46)
Black	0.31*	(0.15)	0.87	(0.14)	0.95	(0.13)
Other	0.47	(0.20)	0.73*	(0.10)	1.06	(0.10)
Latinx	0.72	(0.23)	0.85	(0.12)	0.88	(0.08)
Low-Income	0.67**	(0.10)	0.67***	(0.08)	0.63***	(0.07)
Male	0.73	(0.12)	0.74**	(0.09)	0.73**	(0.08)
Disability	0.57*	(0.13)	0.44**	(0.14)	0.44**	(0.14)
English Learner	1.24	(0.37)	0.74	(0.16)	0.74	(0.16)
Chronically Absent in G8	0.62**	(0.09)	0.55**	(0.11)	0.55**	(0.10)
Suspended in G8	1.27	(0.26)	0.73	(0.13)	0.73	(0.12)
Missing ELA Test	0.59*	(0.16)	1.24	(0.27)	1.27	(0.28)
Partially Meeting ELA	1.75**	(0.37)	2.04***	(0.40)	2.03***	(0.40)
Meeting ELA	2.12*	(0.64)	2.72***	(0.57)	2.69***	(0.58)
Exceeding ELA	1.66	(0.67)	2.77**	(0.90)	2.80**	(0.95)
Missing Math Test	4.34***	(1.83)	1.42	(0.38)	1.41	(0.38)
Partially Meeting Math	1.13	(0.12)	1.31	(0.18)	1.31*	(0.18)
Meeting Math	1.46**	(0.19)	1.99***	(0.31)	2.03***	(0.31)
Exceeding Math	1.01	(0.30)	1.22	(0.42)	1.23	(0.43)
School Year=2019	0.97	(0.45)	0.39*	(0.17)	0.39*	(0.17)
School Year=2021	1.73	(0.58)	2.84	(1.67)	2.75	(1.63)
School Year=2022	2.14*	(0.83)	3.65*	(1.99)	3.61*	(1.96)
ICP # Black					0.78	(0.22)
ICP # Other					0.36***	(0.11)
ICP # Latinx					0.93	(0.29)
ICP # Low-Income					1.16	(0.39)
Constant	2.12	(0.96)	1.63	(0.52)	1.64	(0.53)
Observations	21196		20475		20475	

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

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. Including school fixed effects in the second model increased the estimate to 1.46 times the odds of enrolling in college for ICP participants, relative to non-participants, suggesting that variation in effects by school may mask an even greater impact. In the third model, an interaction between being a participant and being low-income was

observed, which remained significant with school fixed effects. It estimates an impact of increasing the odds of enrolling in college by 1.36 times for non-low-income participants, and a further 1.31 higher odds for students from low-income families. This means that although Early College participation increases the odds of enrolling in college for all students on average, the increased odds are greater for low-income students. This interaction is graphed in probability units in Figure 2. From that same model, there were no significant interactions between program participation and race values of Black or Latinx.

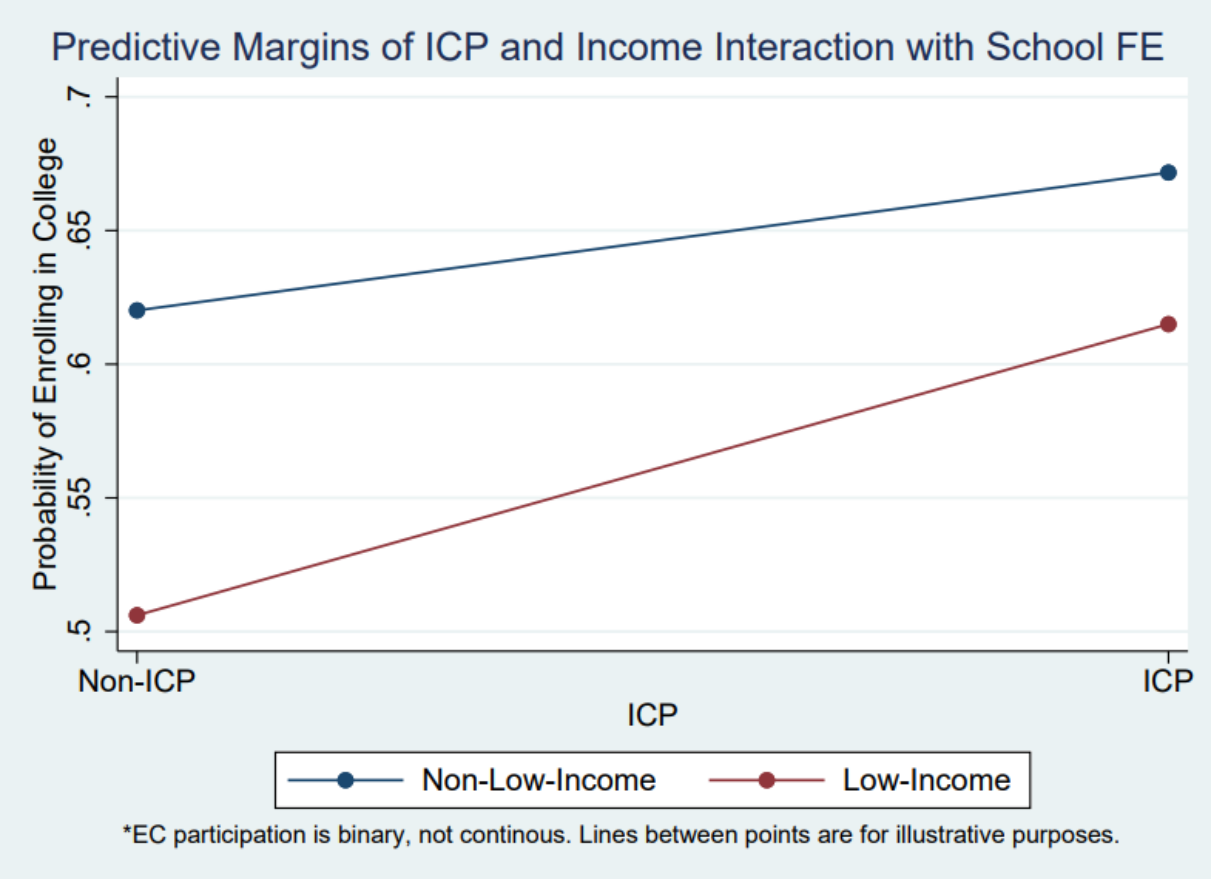
Table 10. Effects on College Enrollment/College Access

	Treatment with Covariates	(SE)	Treatment with Covariates and School Fixed Effects	(SE)	Treatment with Covariates, School Fixed Effects, and Interactions	(SE)
ICP	1.34***	(0.09)	1.46***	(0.14)	1.36**	(0.13)
Black	1.10	(0.15)	1.40*	(0.19)	1.40***	(0.13)
Other	0.85	(0.17)	0.92	(0.15)	1.03	(0.09)
Latinx	0.58***	(0.04)	0.70***	(0.06)	0.72***	(0.07)
Low-Income	0.59***	(0.05)	0.64***	(0.04)	0.56***	(0.03)
Male	0.66***	(0.05)	0.63***	(0.05)	0.63***	(0.05)
Disability	0.75	(0.17)	0.77	(0.18)	0.77	(0.18)
English Learner	0.62**	(0.11)	0.62**	(0.10)	0.62**	(0.10)
Chronically Absent in G8	0.58***	(0.07)	0.57***	(0.08)	0.57***	(0.07)
Suspended in G8	0.46**	(0.12)	0.45**	(0.12)	0.45**	(0.12)
Missing ELA Test	1.72*	(0.42)	1.84*	(0.52)	1.85*	(0.52)
Partially Meeting ELA	1.82***	(0.29)	1.79***	(0.29)	1.80***	(0.30)
Meeting ELA	2.80***	(0.49)	2.81***	(0.46)	2.82***	(0.47)
Exceeding ELA	4.42***	(1.30)	4.54***	(1.33)	4.55***	(1.33)
Missing Math Test	5.30*	(3.59)	4.71*	(3.07)	4.62*	(2.94)
Partially Meeting Math	1.21	(0.15)	1.19	(0.15)	1.20	(0.15)
Meeting Math	1.99***	(0.30)	1.87***	(0.28)	1.89***	(0.28)
Exceeding Math	2.74***	(0.52)	2.63***	(0.54)	2.65***	(0.53)
School Year=2019	1.28	(0.33)	1.31	(0.43)	1.32	(0.43)
School Year=2021	1.46***	(0.15)	1.44***	(0.15)	1.44***	(0.14)
School Year=2022	1.20	(0.14)	1.14	(0.14)	1.14	(0.14)
ICP # Black					1.01	(0.23)
ICP # Other					0.78	(0.25)
ICP # Latinx					0.96	(0.16)
ICP # Low-Income					1.31*	(0.17)
Constant	0.71	(0.14)	0.68*	(0.11)	0.69*	(0.11)
Observations	21196		21196		21196	

Exponentiated coefficients; Standard errors in parentheses

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

Figure 2. ICP and Low-income Interaction for College Enrollment (School Fixed Effects)



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 1.38 times the odds of persisting to a second year in college, relative to non-participating students. Incorporating school fixed effects to the post-weight regression model yields an estimate of 1.34 times the odds of persisting to a second year in college for ICP participants, relative to non-participants. Because school fixed effects do not substantially change the estimate, there is no evidence of variation by school. Lastly, per the third model, there are no statistically

significant interactions between being Black, Latinx, or low-income and participating in ICP when estimating effects on college persistence.

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

	Treatment with Covariates	(SE)	Treatment with Covariates and School Fixed Effects Model	(SE)	Treatment with Covariates, School Fixed Effects Model, and Interactions	(SE)
ICP	1.38***	(0.10)	1.34*	(0.19)	1.18	(0.15)
Black	1.20	(0.19)	1.51*	(0.24)	1.30*	(0.15)
Other	0.81	(0.20)	0.89	(0.17)	0.97	(0.10)
Latinx	0.52***	(0.07)	0.63**	(0.09)	0.60***	(0.06)
Low-Income	0.60***	(0.05)	0.66***	(0.05)	0.56***	(0.04)
Male	0.58***	(0.07)	0.57***	(0.06)	0.57***	(0.06)
Disability	0.72	(0.16)	0.72	(0.16)	0.72	(0.17)
English Learner	0.73	(0.21)	0.74	(0.21)	0.74	(0.21)
Chronically Absent in G8	0.62*	(0.13)	0.62*	(0.14)	0.63*	(0.14)
Suspended in G8	0.39**	(0.12)	0.38**	(0.12)	0.38**	(0.12)
Missing ELA Test	1.30	(0.36)	1.25	(0.35)	1.25	(0.35)
Partially Meeting ELA	2.38***	(0.55)	2.24***	(0.49)	2.26***	(0.51)
Meeting ELA	3.79***	(1.08)	3.59***	(0.94)	3.57***	(0.96)
Exceeding ELA	7.04***	(2.51)	6.76***	(2.34)	6.61***	(2.34)
Missing Math Test	6.92*	(5.35)	6.67*	(5.01)	6.60**	(4.73)
Partially Meeting Math	1.29	(0.28)	1.33	(0.30)	1.35	(0.31)
Meeting Math	2.05***	(0.43)	2.01**	(0.45)	2.04***	(0.44)
Exceeding Math	3.09***	(0.81)	3.08***	(0.88)	3.16***	(0.89)
School Year=2019	1.16	(0.21)	1.24	(0.28)	1.28	(0.30)
School Year=2021	1.48***	(0.12)	1.45***	(0.11)	1.45***	(0.11)
ICP # Black					1.40	(0.40)
ICP # Other					0.82	(0.26)
ICP # Latinx					1.11	(0.30)
ICP # Low-Income					1.39	(0.24)
Constant	0.32***	(0.11)	0.34***	(0.10)	0.35***	(0.10)
Observations	14164		14164		14164	

Exponentiated coefficients; Standard errors in parentheses

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

Robustness Checks

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 do not have statistically significant higher odds of being college ready but have 1.53 higher odds of enrolling in college, and 1.51 higher odds of persisting to a second year in college, relative to non-participants in their schools, excluding those who participate in Early College. Notably, the 1.53 odds estimated effect on college enrollment from this main effect model using continuous test scores is similar in magnitude to the 1.46 odds estimated effect from the weighted school fixed effects model in Table 10 (on page 138), which uses test performances levels.

Table 12. Effects Using Continuous Test Scores from 2020-21 and 2021-22 (School Fixed Effects)

	Effects on College Readiness	(SE)	Effects on College Access	(SE)	Effects on College Success	(SE)
ICP	1.29	(0.45)	1.53***	(0.20)	1.51**	(0.24)
Black	1.16	(0.19)	1.62***	(0.22)	2.00*	(0.54)
Other	1.27	(0.16)	1.07	(0.16)	1.27	(0.26)
Latinx	0.86	(0.10)	0.80*	(0.07)	0.79	(0.11)
Low-Income	0.53***	(0.09)	0.63***	(0.05)	0.61***	(0.06)
Male	0.68**	(0.10)	0.71**	(0.08)	0.73*	(0.10)
Disability	0.31***	(0.09)	0.79	(0.20)	0.77	(0.21)
English Learner	0.63	(0.16)	0.82	(0.16)	1.09	(0.34)
Chronically Absent in G8	0.44***	(0.07)	0.48***	(0.07)	0.28***	(0.06)
Suspended in G8	0.59**	(0.10)	0.35**	(0.11)	0.26***	(0.07)
Next Gen ELA Test	1.02***	(0.00)	1.01***	(0.00)	1.02***	(0.01)
Next Gen Math Test	1.01*	(0.00)	1.02***	(0.00)	1.02***	(0.00)
School Year=2022	1.09	(0.16)	0.79*	(0.08)	1.00	(.)
Constant	0.00***	(0.00)	0.00***	(0.00)	0.00***	(0.00)
Observations	13798		14163		7247	

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

As an additional robustness check for these logistic regression models, one may regress the same variables as linear probability models. In expectation, relationships between the dependent variable and the independent variables should remain similar across logistic and linear probability models (Papke & Wooldridge, 1996). Including all the years in the data, linear probability models estimated that ICP participants do not have a statistically significant higher probability of being college ready or persisting in college, but have 7% higher probability of enrolling in college, relative to non-participants in their schools, excluding those who participate in Early College (Table 13). All models—

logistic or linear probability, continuous test scores or factor test performance levels—estimate that ICP participation has a positive effect on college enrollment.

Table 13. Estimated Effects Using Linear Probability Models (School Fixed Effects)

	Effects on College Readiness	(SE)	Effects on College Access	(SE)	Effects on College Success	(SE)
ICP	0.03	(0.02)	0.07***	(0.02)	0.03	(0.02)
Black	-0.02	(0.01)	0.06*	(0.03)	0.04	(0.02)
Other	-0.02	(0.01)	-0.01	(0.03)	-0.02	(0.02)
Latinx	-0.02	(0.02)	-0.08***	(0.02)	-0.07***	(0.02)
Low-Income	-0.04***	(0.01)	-0.09***	(0.01)	-0.05***	(0.01)
Male	-0.03**	(0.01)	-0.09***	(0.01)	-0.08***	(0.01)
Disability	-0.07	(0.04)	-0.06	(0.05)	-0.05*	(0.02)
English Learner	-0.01	(0.02)	-0.08**	(0.03)	-0.05	(0.03)
Chronically Absent in G8	-0.04*	(0.02)	-0.11***	(0.02)	-0.04	(0.03)
Suspended in G8	-0.01	(0.02)	-0.16**	(0.05)	-0.12*	(0.05)
Missing ELA Test	0.01	(0.03)	0.11*	(0.05)	-0.04	(0.04)
Partially Meeting ELA	0.08**	(0.02)	0.12***	(0.03)	0.02	(0.02)
Meeting ELA	0.10***	(0.03)	0.22***	(0.03)	0.08**	(0.03)
Exceeding ELA	0.10**	(0.04)	0.27***	(0.05)	0.16**	(0.05)
Missing Math Test	0.08*	(0.04)	0.28*	(0.10)	0.27	(0.14)
Partially Meeting Math	0.04*	(0.02)	0.04	(0.03)	0.05	(0.03)
Meeting Math	0.07**	(0.02)	0.13***	(0.03)	0.11**	(0.03)
Exceeding Math	0.04	(0.03)	0.18***	(0.04)	0.23***	(0.04)
School Year=2019	-0.09	(0.05)	0.04	(0.06)	0.03	(0.04)
School Year=2021	0.08	(0.05)	0.06**	(0.02)	0.04*	(0.02)
School Year=2022	0.10*	(0.04)	0.02	(0.02)	-0.47***	(0.03)
Constant	0.71***	(0.04)	0.43***	(0.03)	0.44***	(0.04)
Observations	21196		21196		21196	

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, with school fixed effects, translate to a 7-percentage point increase in college enrollment, relative to non-participants when using a linear probability model. This is smaller than the 10-percentage point impact found by Brodersen et al. (2021) but very close to the 7.8 percentage point positive difference found by Witzen (2018).

Beyond the effectiveness of the program on average, this paper particularly argues that ICP is an intervention to promote more equitable educational attainment. In models estimating effects on college access, including one with school fixed effects, there is an interaction between program participation and having a socioeconomically disadvantaged background, which result in increased odds of said students enrolling in college. In a society where socioeconomically disadvantaged students are underrepresented in their attendance at colleges and universities, relative to their share of the population, this intervention may be a sensible way to address this inequity in Massachusetts, and potentially beyond.

It should be noted that the relationship between ICP and college readiness observed in this study 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 in college suggests that these students 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. 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.

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). As illustrated in Figure 1, histogram distributions of propensity scores for Innovation Career Pathways treated and untreated subjects have similar variability in the likelihood of receiving the treatment assignment, and IPTW regression results from trimmed weights, with estimates nearly identical to the untrimmed weights regressions, are shown in Appendix A.

Furthermore, while the effects of ICP on college enrollment 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.

Lastly, it should be noted that there is limited ability to estimate the effect of program participation on MassCore completion, the approximation for college readiness used in this study, when incorporating fixed effects. This is because many schools in Massachusetts have all their high school

graduates completing MassCore, although it is suggested and not a required program of study from the state. When fixed effects are included in a logistic regression model with a binary-dependent variable, groups or clusters with no variation in the dependent variable are dropped because the fixed effects perfectly predict the outcome (Beck, 2020). This in turn substantially reduces the sample size, and is perhaps why the estimated effects on MassCore completion are not statistically significant in many of the models.

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, especially those from low-income backgrounds, have higher odds of enrolling in college, and thus argue that more targeted recruitment of underrepresented 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.

Chapter 6: Comparative Effects of Early College and Innovation Career Pathways

Abstract

Literature suggests that promoting equitable educational attainment may be one of the effective ways to address the historical inequities in American society, due to its positive association with an array of desirable outcomes. College preparation and career preparation in high school have both been shown to have positive effects on college enrollment, persistence, and completion, respectively. In Fall 2018, Massachusetts launched Early College and Innovation Career Pathways—a college preparation intervention and a career preparation intervention, respectively—to promote educational attainment and career success for all. This study uses generalized propensity score (GPS) inverse probability of treatment weighting (IPTW) to gauge the comparative effects of participating in either program on college readiness, access, and success. Given that an emergent share of the literature and the United States government define college and career readiness collectively, findings and discussions of this paper explore variations in outcomes by intervention and by racial and socio-economic groups to inform policy and practice towards promoting educational attainment for all in Massachusetts high schools.

Introduction

Although Massachusetts is the national leader in educational attainment in terms of the share of adults aged 25 or older with an associate or bachelor's degree (U.S. Census Bureau, 2021), there are persistent disproportionalities in the rates at which Black, Latinx, and economically disadvantaged students are getting degrees, relative to their representation in the population (DHE, 2016). Likewise, there is income inequality in Massachusetts, such that employees of color earn 73 cents for each dollar their White counterparts earn (Cristantiello, 2023). Such inequities have negative consequences not only for individuals and their families, but also for the economy of the state, as

Massachusetts demographics are shifting, with the share of the population that identify as Black or Latinx increasing (MEEP, 2018).

In response, the Massachusetts Department of Elementary and Secondary Education (DESE) and the Massachusetts Department of Higher Education (DHE) launched Early College (EC) and Innovation Career Pathways (ICP), to provide students historically underrepresented in higher education a supportive and rigorous academic experience and career development relevant to their interests, so that they may graduate secondary school with a well-designed post-secondary plan (DESE & DHE, 2017; DESE, 2020). Per the EC Designation Criteria (DESE & DHE, 2017), EC seeks to promote post-secondary school enrollment by allowing secondary school students to experience and complete post-secondary courses on a pathway and gain exposure to a variety of career opportunities. Furthermore, by providing the courses at no cost to students, EC would reduce the time and expense of earning a post-secondary credential while increasing the likelihood of completion.

Per the IP Designation Criteria (DESE, 2020), IPs are structures within secondary schools that connect student learning to an in-demand industry sector—e.g., information technology, engineering, healthcare—in the regional and state economy. More specifically, schools leverage partnerships with local career centers and employers to provide students career awareness and work-based learning activities. The students also participate in a series of courses, which are often post-secondary level, and experiences relevant to achieving industry recognized credentials (DESE, 2020).

Although EC and ICP are addressing different issues—educational inequity and income inequality—literature shows that college preparation and career preparation in high school both promote educational attainment (Mueller & Gozali-Lee, 2013). While Lucien, Lindorff, and Strand (2024; 2024b) did conduct impact evaluations of Early College and Innovation Career Pathways, respectively, the estimates from those two studies should not be directly compared, as they were

derived from different subsets of the sample and thus do not represent the same populations (Garrido et al., 2021). Furthermore, the estimates were calculated using different methods—Propensity Score Matching (PSM) and Inverse Probability of Treatment Weighting (IPTW)—which can yield different results (Pirracchio et al., 2012), albeit in very particular circumstances, potentially further complicating comparisons.

Likewise, college preparation in high school and career preparation in high school have their distinct literatures, although there is an emergent joint college and career readiness literature. This warrants a third study, which includes recipients of both treatments and untreated subjects in one sample, using the same research methodology, and speaking to the collective college and career readiness literature. Therefore, this study uses generalized propensity score (GPS) inverse probability of treatment weighting (IPTW) to gauge the comparative effects of Early College and Innovation Career Pathways participation on college readiness, access, and success for racial minority and socioeconomically disadvantaged students, by asking the following research questions:

- What are the respective effects of EC and ICP participation on a student's likelihood of being college ready, as approximated by completing MassCore (a recommended program of study that aligns high school coursework with college and workforce expectations)?
- What are the respective effects of EC and IP participation on a student's likelihood of enrolling in college within six months of high school completion?
- What are the respective effects of EC and IP participation on a student's likelihood of persisting from year 1 to year 2 in college, after having enrolled within six months of high school completion?
- How do these comparative effects vary by racial and socioeconomic groups?

Literature Review

Although college readiness and career readiness are separate topics, there is an emergent share of the literature that does not disentangle college preparation and career preparation but is instead about college and career preparation, collectively. That is because many researchers are now increasingly approaching this work with the idea that the tasks of preparing students for college and preparing them for a career are analogous (Gaertner et al., 2014). This is not an unfounded position. While there is some variation in the definitions of college and career readiness, thirty-three states share the same joint definition—knowledge and skills that enable high school graduates to enroll in postsecondary coursework without remediation and succeed in both college and the workforce (Mishkind, 2014). This is consistent with the outlook of the U.S. Department of Education, which said that preparing every student to effectively transition to adulthood and become college and career ready is an important goal of America's educational system (Xing et al., 2019).

Indeed, there is evidence suggesting that the preparation required for higher education and the workforce are similar. With the aim of developing high school graduation standards in Indiana, Kentucky, Massachusetts, Nevada, and Texas, the American Diploma Partnership (ADP, 2004) convened panels of employers from diverse industries and academics from various disciplines to cross-examine workplace tasks and postsecondary assignments and found convergence around core knowledge and skills that high school graduates will need in high-performance workplaces and in credit-bearing college courses. Using statistical concordance to compare student performance on test questions that measure workforce readiness and test questions that measure college readiness, American College Testing (ACT, 2006) determined that, high school graduates need comparable proficiency in reading and mathematics whether they were planning to pursue a college degree or join a workforce training program.

Perhaps the most empirically substantiated argument for the congruence between college and career readiness presented in this paper is how college completion and earnings, irrespective of post-secondary education, are mutually positively affected by higher level course taking in high school. Using nonlinear probit models controlling for demographics, family attributes, school variables, and baseline achievement, Rose and Betts (2001) found that the more advanced math courses taken by students during high school, the higher their probability of graduating from college. Subsequently, they used linear multivariate models controlling educational attainment, in addition to the aforementioned covariates, and found that a decade later, the more advanced math courses taken by students during high school, the higher their annual earnings were on average, whether or not they went to college. This example is math specific, but likely speaks to a broader reality.

In addition to findings that college and career preparation respectively have positive effects on educational attainment on average (Edmunds et al., 2020; Song & Zeiser, 2019; Brodersen et al., 2021; Dougherty et al., 2019), there's literature further suggesting that they both specifically have positive effects on educational attainment for students historically underrepresented in American higher education. Using weighted hierarchical logistic models on a nationally representative sample, ACT (2013) found that college course taking in high school, a prominent feature of college preparation programs, may be a vehicle to reduce gaps in persistence and degree completion among racial and socioeconomic groups. Allen's (2010) comprehensive literature review on the subject similarly concludes that taking college courses while in high school directly impacts the college readiness of underrepresented racial groups. Moreover, Conley's (2010) qualitative investigation found that individuals from socioeconomically disadvantaged backgrounds—those raised outside of a college-bound cultural or social capital network—rely more heavily on their high schools to provide access to higher education.

Cave and Quint (1990) conducted an experimental study in which 1,574 high school students were randomly assigned to either Career Beginnings, a career preparation program that targets urban high school 11th graders from low-income families, or a control group. They found that Career Beginnings participants had a college enrollment rate that was 4.7 percentage points higher than that of the control group, the year after high school graduation. Kemple (2004) leveraged the oversubscription induced random assignment of applicants to Career Academies, a career preparation program that was 85 percent Black or Latinx, to evaluate the intervention. He found that Career Academies are viable pathways to a range of post-secondary education opportunities and improve labor market prospects without compromising college preparation for the 1,458 participants, relative to their control group. Although the studies are relatively dated, the U.S. Department of Education (2023) presently advises high schools to provide students opportunities to explore career interests, a prominent feature of career preparation, as a strategy for increasing diversity and opportunity in higher education.

Although this paper does not argue for one or the other, it should be noted that the unification and separation of college and career preparation is a topic of debate in the United States, with some believing the two are sufficiently differentiated paths while others arguing the contrary. The Association for Career and Technical Education (2018) agrees that a rigorous level of academic proficiency in core subjects is essential for any post-high school path in the 21st century. However, they argue that career readiness further implies the application of said academic skills and content knowledge. Additionally, Casner-Lotto and Barrington (2006) point out that soft skills—such as professionalism, collaboration, and oral communication—distinguish career readiness from other forms of preparation. Conversely, Conley (2012) acknowledges that college and career readiness are not exactly the same but argues that given the considerable overlap between the knowledge and

skills associated with college success and workforce development, and that practically all students aspire to join the workforce eventually, it is not useful to separate students into two distinct groups.

Literature suggests that college and career preparation in high school have the potential to address the pervasive inequity in educational attainment by race and socioeconomically disadvantaged status in American education. This comparative evaluation of the Massachusetts Early College and Innovation Career Pathways programs, which distinctly prioritize the enrollment of students historically underrepresented in American higher education, is an opportunity to make a contribution to both the literature on college and career readiness as well as on that of educational equity.

Theory of Change

The literature provides various mechanisms by which college preparation as well as career preparation programs in American high schools promote college readiness, access, and success. Perhaps one would expect that from a college preparation program, such as Early College, given that its aims are explicitly connected to and reflective of those outcomes. Nevertheless, the mechanisms include but are not limited to: reducing the otherwise high costs of college or university attendance (The Center for College Affordability and Productivity, 2010); better preparing students for college courses through higher level and rigorous course taking in high school (Culver et al., 2019); enabling students to gain momentum toward completion via credit accumulation before starting (Leinbach & Jenkins, 2008); and favorable perception by college admissions officers (Kretchmar & Farmer, 2013).

It is with career preparation where the connectedness and conduciveness to college readiness, access, and success is more implicit. The literature proposes: students may discover that their desired job or profession requires a college degree via career exploration components of a CTE program (Hughes et al., 2001); the pedagogical emphasis on applied learning in CTE programs can stimulate students who might have otherwise disengaged with academic study (Advisory Committee

for the National Assessment of Vocational Education, 2003); there may be improvements in non-cognitive intermediary outcomes such as improved attendance in the early high school years (Helmet et al., 2017); and students receive more personal, academic, and social support (Visher & Stern, 2015); all of which are mechanisms by which career preparation in high school may promote college enrollment and completion.

There is some overlap in the arguments presented for why college preparation and career preparation are conducive to college readiness, access, and success. For example, CTE programs connect students to employers (DeLuca, 2006) and the majority of American employers offer tuition reimbursement as an employee benefit (Glover, 2017). This is effectively the reducing total costs of attendance argument. Edmunds et al. (2022) suggest that it is the increasingly common practice of offering Dual Enrollment—simultaneous taking of high school and college courses by students—in CTE programs that drives the relationship between CTE participation and college enrollment. This feature of CTE programs, depending on the dosage and how pervasive, may render it indistinguishable from a college preparation program like Early College.

Theoretical Framework

This study is framed by Human Capital Theory. Schultz (1961) defines a human capital investment as any deliberate acquisition of useful competencies that add economic value, while Becker (1962) defines it as the embedding of resources in activities that render individuals more proficient in economically valuable knowledge or skills. Moreover, Sweetland (1996) explains that human capital theory distinguishes among numerous types and means of education and Becker (1962) suggests that human capital investments may differ in their relative effects. Therefore, this paper not only assesses the return of Early College and Innovation Career Pathways as human capital investments—via their effects on educational attainment, which has a positive relationship with earnings (Lobo & Burke-

Smalley, 2018)—but it further speaks to the Human Capital Literature by estimating their effects comparatively. Schultz (1961) further attributes differences in earnings by race to differences in human capital investment by racial groups. By targeting Black and Latinx students in recruitment for both interventions, Massachusetts also seeks to address this supposed racial gap in human capital investment. Interactions between race and program participation explored in this paper will help determine their effectiveness on that front.

This study is also 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

Early College

Massachusetts launched its Early College initiative in 2018 to promote equitable access to higher education. Unlike Early College in other states, Massachusetts Early College can involve participation from only some students in participating schools, or the whole school. Additionally, schools offering the program are asked to present a plan for outreach and recruitment specifically for racial minority

and socioeconomically disadvantaged students (DESE & DHE, 2017). Furthermore, programs must demonstrate that students are not excluded based on prior academic performance, that students will be onboarded to ensure they ready for the coursework, and that students will be provided ongoing support to help them succeed in the courses they take (DESE & DHE, 2017). These features distinguish Massachusetts Early College from other Early College interventions evaluated in the existing literature.

Participating schools must partner with a local higher education institution (henceforth referred to as "college") to offer college-level courses. Per the Early College designation criteria, which determine which high school and college partnerships get to offer Early College, participating in Massachusetts Early College means that a student has the option to enroll in at least 12 credits by high school graduation, starting as early as 9th grade (DESE & DHE, 2017). 12 credits are approximately four college-level courses (typically 3 credits), and one tenth (1/10) of the typical 120-credit requirement to graduate with a bachelor's degree in the United States. These 12 credits must all be taken in a pathway, meaning that the 4 courses must feed into a subject-specific concentration, and should ideally be sequential so that the student is progressing toward a degree at the partner institution of higher education (DESE & DHE, 2017). Furthermore, courses must be transferable to public college or university in the state.

Courses are offered during the school day to minimize the logistical burden on students and their families. Furthermore, the high school and college partners must collaborate to schedule college courses such that they present negligible to no interference with students' high school experience. Courses may be offered at the high school or at the college. In instances where a course is offered at the college, transportation must be provided for students and their departure and arrival must fit within their high school schedule. In all instances, instructors must be qualified to teach college courses (DESE & DHE, 2017). In addition to taking 12 college credits toward a degree, student

participants receive academic advising from an Early College counselor at the high school. This is a critical component of the initiative, as program participants are likely to be those underrepresented in higher education, including first generation collegegoers, and as such are less likely to receive similar guidance at home (DESE & DHE, 2017).

Lastly, the high school and college partnerships that offer Early College must have in place adequate student support. This may include "on-ramping", which involves provision of preparatory courses in advance as well as scaffolding services (e.g. tutoring) to ensure that students have an opportunity to fully participate and benefit from Early College (DESE & DHE, 2017). The designation criteria provided by the state, which serve as the intervention description for this study, leave room for variation across schools and thus introduces some uncertainty. It would be useful to be able to categorize and measure aspects of implementation across participating schools, such as details of college advising student support offerings, but data on these aspects are not readily available and so are beyond the scope of this study's secondary analysis.

It should be noted that variation across schools in their implementation in terms of what proportion of students participate, what courses and academic pathways are offered, what recruitment strategies are used, types and dosage of supports provided, and profiles of the college or university partners—complicate the evaluation of the initiative as a whole but were put in place by design: "Flexibility will allow for learning during the first years of this designation process. While each element of the designation criteria was developed with intention and purpose, we understand that parts of this process will evolve, and it is likely that we will revisit and revise the criteria" (DESE & DHE, 2017, p. 6).

Innovation Career Pathways

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, 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).

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

Both Early College and Innovation Career Pathways are school level designations, meaning that the commonwealth of Massachusetts determines which schools may offer students who are interested these interventions. Within a designated school, any number of students ranging from one student to the entire school may participate in either program that is offered, but no student may participate in both, although schools can offer both. During the years of the study, the two interventions are mostly offered at different schools with minimal overlap. For this study, students at all schools that offered either Early College or Innovation Career Pathways, or both, are included. While it would have been helpful, research wise, to only keep the schools that offer both—to alleviate potential concerns about systematic differences between schools that offer either EC or ICP and systematic differences between schools that offer both and those that offer just one—the overlap is so minimal that only 243 Innovation Career Pathways students attended schools that also offer Early College between 2019 and 2022, the four years included in this study (18% of total IP students during that

time). There was a total of 71 high schools that offered either EC or ICP—44 EC offering schools and 43 ICP offering schools, with 16 offering both—and they enrolled 50,766 students, including program participants and non-participants. As can be seen in Table 1, For the 4 years included in this study, EC 12th grade participation is nearly 4 times that of ICP, with the biggest difference in 2019, the first year for both interventions. Note that program participation increased in two ways during the years of the study—more schools offered each intervention each year and the share of students participating within each school increased, on average. Lastly, it should be noted that at a combined 13%, EC and ICP participants make up a relatively small share of 12th graders in their schools during the years in this study.

Table 1. Early College and Innovation Career Pathways Participation in 12th Grade

	Early College Participants	Innovation Career Pathways Participants	Non-participating students	Grade 12 Enrollment at IP and EC schools
2019	367	26	6089	6482
2020	1154	318	10383	11855
2021	1704	440	12974	15118
2022	1971	575	14765	17311
Total	5196	1359	44211	50766

Program Participation

EC and ICP enrollment by racial and economic groups are not only different from one another but also differ in opposite directions from the untreated group, on average, in this sampling methodology. More specifically, while EC and ICP students are similarly likely to be Black, EC students are 8 percentages point more likely to be Latinx than nonparticipants while ICP students 11 percentage points less likely. Described differently, EC students are 19 percentage points more likely to be Latinx than ICP students, in this sample. EC students are similarly likely to be low-income than the nonparticipants, but 6 percentage points more likely to be low-income than ICP students, as shown in Table 2. These differences are an indication that adjustments are needed to achieve covariate balance to estimate the comparative effects of the two interventions. It should be noted

that the schools designated for EC and the schools designated for ICP differ demographically, which results in them systematically enrolling different students, even though Black, Latinx, and low-income students are not underrepresented in either program, relative to their school peers. In their evaluations of the two interventions, Lucien, Lindorff, and Strand (2024; 2024b) found that Black, Latinx, and low-income participation in both EC and ICP are reflective of the offering schools' enrollment demographics, on average. The underrepresentation of racial minority and low-income students seen in ICP here is a function of the sampling methodology, which combines enrollment of all schools that offer either or both EC and ICP from 2019 to 2022. In other words, while EC and ICP participants are reflective of their respective schools demographically, the combined enrollment of both sets of schools yields a sample in which racial minority students are similarly or overrepresented in EC while underrepresented in ICP. The rationale for the sampling is explained in the preceding section.

Table 2. Participation of Underrepresented Students in EC and IP

	Percent Black	Percent Latinx	Percent Low-Income
EC Participants	16%	43%	49%
ICP Participants	15%	24%	43%
Non-participating School Peers	13%	35%	48%

EC and ICP enrollments are more similar when looking at baseline achievement compared to demographics, especially relative to baseline achievement of non-participants, but are still different from one another. With 4 and 3 percentage point positive differences, Early College 12th grade Participants are slightly more likely to have been proficient or advanced in both their 8th grade ELA and 8th Grade Math scores than ICP participants, respectively, as shown in Table 3. Both EC and ICP participants are more likely to be proficient or advanced in ELA and math than non-participants in the sample, with Early College having the positive differences of 11 and 12 percentage points while

ICP participants have positive differences of 7 and 9 percentage points, relative to non-participants in ELA and math, respectively.

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
EC Participants	32%	43%	12%	10%
ICP Participants	32%	41%	9%	8%
Non-participating School Peers	24%	35%	8%	7%

Largely due to the differences in the demographic profiles of the schools that offer the two interventions, EC and ICP enrollment are systematically different from one another and from the untreated group in this sample, across covariates that are of importance to this study. Adjustments, such as the inverse probability of treatment weighting (IPTW) based on the generalized propensity score (GPS) described in the methodology section, are what enable us to make causal claims about average differences in outcomes for students who do participate in either intervention, relative to students who do not participate in either intervention, at the schools that offer either or both.

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.

Lastly, Chronically Absent in Grade 8 and Suspended in Grade 8 were added as baseline measures. Chronically absent in Grade 8 is a binary variable indicating whether a student missed 10% or more school days in the 8th grade. For each student, the number of days they enrolled in and the number of days they attended school on an annual basis, are included in SIMS. By subtracting days attended from days enrolled, one may calculate how many days a student was absent each year. Dividing days absent by days enrolled yields the absence rate. Any student whose absence rate was equal to or greater than 0.1, or 10%, during the 8th grade year was given the value of 1 in the binary indicator Chronically Absent in Grade 8. Suspended in Grade 8 is a binary variable indicating whether a student was suspended at any time in the 8th Grade. Suspension data for all Massachusetts public schools is stored in the School Safety and Discipline Report (SSDR). SSDR not only collects information on all rule infringements that occur on school property, but also the corresponding disciplinary action taken against the student offender, including suspensions. Any student with a value greater than 0 for the days missed due to suspension during the 8th grade year was given the value of 1 in the binary indicator Suspended in Grade 8.

Methods

This study estimates the comparative effects of Early College and Innovation Career Pathways on their respective participants via generalized propensity score (GPS) inverse probability of treatment weighting (IPTW). Rosenbaum and Rubin (1983) define the propensity score as the conditional probability of being assigned a treatment given observed covariates. It is the estimated probability that each person in a study population would be assigned the treatment based on available and relevant variables. The propensity score calculation introduced by Rosenbaum and Rubin (1983) and the analytic approaches that employ it—matching, weighting, subclassifying, covariate adjusting—were intended for binary treatments—instances where there is one treated and one untreated group (Imai & van Dyk, 2003).

This study, however, has two treated groups and one untreated group, requiring an extension of Rosenbaum and Rubin's (1983) propensity scores. Generalized propensity scores may be used to extend the applicability of propensity score methods by allowing for multinomial treatments (Imbens, 2000). As opposed to the single value of propensity scores when there is a binary treatment, the generalized propensity score is a vector representing the conditional probabilities of a subject being treated with each value of the multinomial treatment (Brown et al., 2020). In the case where the values of the treatment are non-binary and qualitatively distinct, a researcher may use a multinomial logistic regression to calculate the generalized propensity score (Guo & Fraser, 2015).

An outcome analysis can be conducted by employing the inverse of one propensity score from the vector generalized propensity scores as a sampling weight (Imbens, 2000). Guo and Fraser (2015) confirm that "even though each participant has multiple propensity scores obtained from the multinomial logit model, only one such score is used and defined in the propensity score weighting analysis" (p. 314). Incorporating the inverse probability of receiving the treatment as a sampling weight 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 (Guo & Fraser, 2015). 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).

While matching eliminates a greater proportion of the systematic differences in baseline characteristics than the other propensity score methods when the treatment is binary (Austin, 2011), followed by inverse probability of treatment weighting, it is not optimal to match when there are multiple treatments. Three-way matching often leads to many subjects being excluded because appropriate matches are unavailable, especially when there are unequally sized treatment groups (Yoshida et al., 2017), as is the case in this study where there are about four times more EC

participants than there are ICP participants. Even when that is not the case, there is high potential to form dissimilar triplets (Lopez & Gutman, 2017) and there is no known standard for caliper widths for three-way matching (Yoshida et al., 2017). A caliper is a prespecified maximum distance between propensity scores of matched subjects (Guo & Fraser, 2015). It should also be noted that the complexity of the match increases exponentially with three groups. "A three-group match with 5000 patients per group would have 125 billion possible combinations" (Rassen et al., 2013, p. 402).

Diagnostic Tests

To begin the analysis, generalized propensity scores were calculated, using a multinomial logistic regression, with treatment as a multinomial factor outcome variable and a set of relevant covariates as predictors. Below is the output for the propensity score calculating multinomial logistic regression, which compares odds of participation in either intervention for various attributes (Table 4):

Table 4. Propensity Score Calculating Logistic Regression

	EC Treatment	(SE)	ICP Treatment	(SE)
Black	2.712***	(0.148)	1.258*	(0.117)
Other	2.161***	(0.119)	1.115	(0.109)
Latinx	3.147***	(0.135)	0.820*	(0.0663)
Low Income	1.086*	(0.0396)	0.994	(0.0664)
Male	0.577***	(0.0200)	0.816***	(0.0493)
English Learner	0.653***	(0.0672)	1.225	(0.182)
Disability	0.431***	(0.0349)	0.588***	(0.0696)
Chronically Absent in G8	0.646***	(0.0428)	0.760*	(0.0855)
Suspended in G8	0.664***	(0.0551)	0.830	(0.113)
Missing Test Score (ELA)	1.897***	(0.301)	1.360	(0.341)
Partially Meeting Expectations (ELA)	1.357***	(0.105)	0.865	(0.101)
Proficient/Meeting Expectations (ELA)	1.674***	(0.138)	0.915	(0.117)
Advanced/Exceeding Expectations (ELA)	1.741***	(0.175)	0.887	(0.151)
Missing Test Score (Math)	1.592*	(0.288)	0.232*	(0.166)
Partially Meeting Expectations (Math)	1.200**	(0.0787)	1.226	(0.135)
Proficient/Meeting Expectations (Math)	1.660***	(0.119)	1.340*	(0.168)
Advanced/Exceeding Expectations (Math)	2.332***	(0.196)	1.424*	(0.220)
School Year =2019	0.544***	(0.0374)	0.161***	(0.0337)
School Year =2021	1.463***	(0.0714)	1.057	(0.0903)
School Year =2022	1.460***	(0.0695)	1.190*	(0.0972)
Observations	40991	-	40991	-

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.

Since the aim of inverse probability of treatment weighting is to create a weighted sample in which the distribution of covariates is the same between treated and untreated subjects, pre-weighted and post-weighted standardized mean differences across covariates are used to gauge balance (Austin & Stuart, 2015). Unlike statistical significance tests, the standardized mean difference does not incorporate sample size, enabling its use to compare balance in measured variables between treated and untreated subjects in the same sample when different weights are assigned to the same subjects. It also offers the added function of comparing the relative balance across variables, because it is calculated on the standard deviation scale (Austin & Stuart, 2015). In addition to comparing 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. Below are the standardized differences and variance ratios between EC participants and the untreated group, and between ICP participants and the untreated group, respectively (Table 5):

Table 5. Standardized differences and Variance Ratios

	Standardized Differences		Variance Ratios	
	Raw	Weighted	Raw	Weighted
Early College				
Black	0.090	0.005	1.218	1.012
Other Race	0.113	-0.002	1.319	0.995
Latinx	0.239	-0.030	1.142	0.976
Economically. Disadvantaged/Low Income	0.077	0.006	1.012	1.001
Male	-0.323	-0.001	0.924	1.000
Disability	-0.355	0.004	0.336	1.009
English Learner	-0.139	0.069	0.530	1.281
Chronically Absent in G8	-0.161	0.030	0.620	1.079
Suspended in G8	-0.157	0.016	0.543	1.054
Missing ELA Test	0.018	0.014	1.172	1.134
Needing Improvement/Partially Meeting Expectations in ELA	-0.083	0.019	0.938	1.013
Proficient/Meeting Expectations in ELA	0.157	-0.014	1.019	0.997
Advanced/Exceeding Expectations in ELA	0.101	-0.007	1.314	0.980
Missing Math Test	-0.017	0.006	0.846	1.061
Needing Improvement/Partially Meeting Expectations in Math	-0.072	0.010	0.968	1.004
Proficient/Meeting Expectations in Math	0.170	0.001	1.120	1.000
Advanced/Exceeding Expectations in Math	0.145	-0.029	1.403	0.926
School Year=2019	-0.188	0.029	0.599	1.068
School Year=2021	0.061	-0.003	1.052	0.998
School Year=2022	0.081	-0.001	1.048	1.000
Innovation Career Pathways				
Black	0.080	0.003	1.194	1.008
Other Race	0.056	-0.021	1.158	0.944
Latinx	-0.173	-0.045	0.838	0.964
Economically. Disadvantaged/Low Income	-0.056	-0.053	0.984	0.985
Male	-0.117	0.000	0.996	1.000
Disability	-0.214	0.011	0.584	1.023
English Learner	-0.010	-0.019	0.962	0.928
Chronically Absent in G8	-0.114	0.010	0.726	1.025
Suspended in G8	-0.102	-0.045	0.694	0.854
Missing ELA Test	0.044	-0.025	1.446	0.783
Needing Improvement/Partially Meeting Expectations in ELA	-0.037	-0.020	0.974	0.985
Proficient/Meeting Expectations in ELA	0.054	-0.000	1.013	1.000
Advanced/Exceeding Expectations in ELA	0.017	0.028	1.052	1.083
Missing Math Test	-0.116	-0.003	0.156	0.974
Needing Improvement/Partially Meeting Expectations in Math	0.015	-0.041	1.006	0.982
Proficient/Meeting Expectations in Math	0.119	0.037	1.091	1.029
Advanced/Exceeding Expectations in Math	0.026	0.021	1.070	1.056
School Year=2019	-0.420	-0.031	0.182	0.928
School Year=2021	0.055	0.013	1.048	1.011
School Year=2022	0.154	0.016	1.080	1.010

When comparing Early College participants to untreated subjects, as shown in Table 5, almost all weighted standardized differences are nearly 0, and almost all weighted variance ratios are nearly 1. In the minority of instances when a reader may interpret a number to not be nearly 0 for standardized differences or not be nearly 1 for variance ratios, such as the 1.281 weighted variance

ratio for English Learners, they are typically closer to 0 and 1 in the weighted data than the pre-weighted data and fall within bounds of what's deemed acceptable in the propensity score literature. Austin (2009) suggests that an absolute standardized difference of less than 0.1 is an indication that covariates are balanced between groups. All the weighted standardized differences between EC and the untreated are below 0.1. Stuart (2010) argues that regression adjustments yielding variance ratios between 0.5 and 2 are trustworthy. All weighted covariance ratios between EC and the untreated, including the 1.281 for English Learners, fall within that range. In other words, even when not perfectly balanced, the data are better balanced weighted than pre-weighted and are sufficiently balanced for causal claims across 100% of the variables when comparing Early College to the untreated group.

When comparing Innovation Career Pathways participants to the untreated, weighted data is better balanced than pre-weighted data across 85% of the included variables. This may not be across 100% of variables, as is the case for EC, but in the minority of cases when pre-weighted data is better balanced, it is by a relatively small margin, and both the pre-weighted and weighted standardized differences and variance ratios are nearly 0 and 1. Most importantly, all the weighted standardized differences between ICP and the untreated are below 0.1, as recommended by Austin (2009), and all weighted covariance ratios between ICP and the untreated, fall within .5 and 2, as recommended by Stuart (2010), meaning there is sufficient balance between the treated group and the untreated, to make causal claims.

Weighting not only causes balance across relevant variables, as shown in Table 5, but also in observation counts between treated and non-treated groups. The difference in frequencies of treated and untreated observed in the pre-weighted sample is virtually eradicated in the post weight synthetic sample, where the treated and untreated records are nearly equally represented. Looking

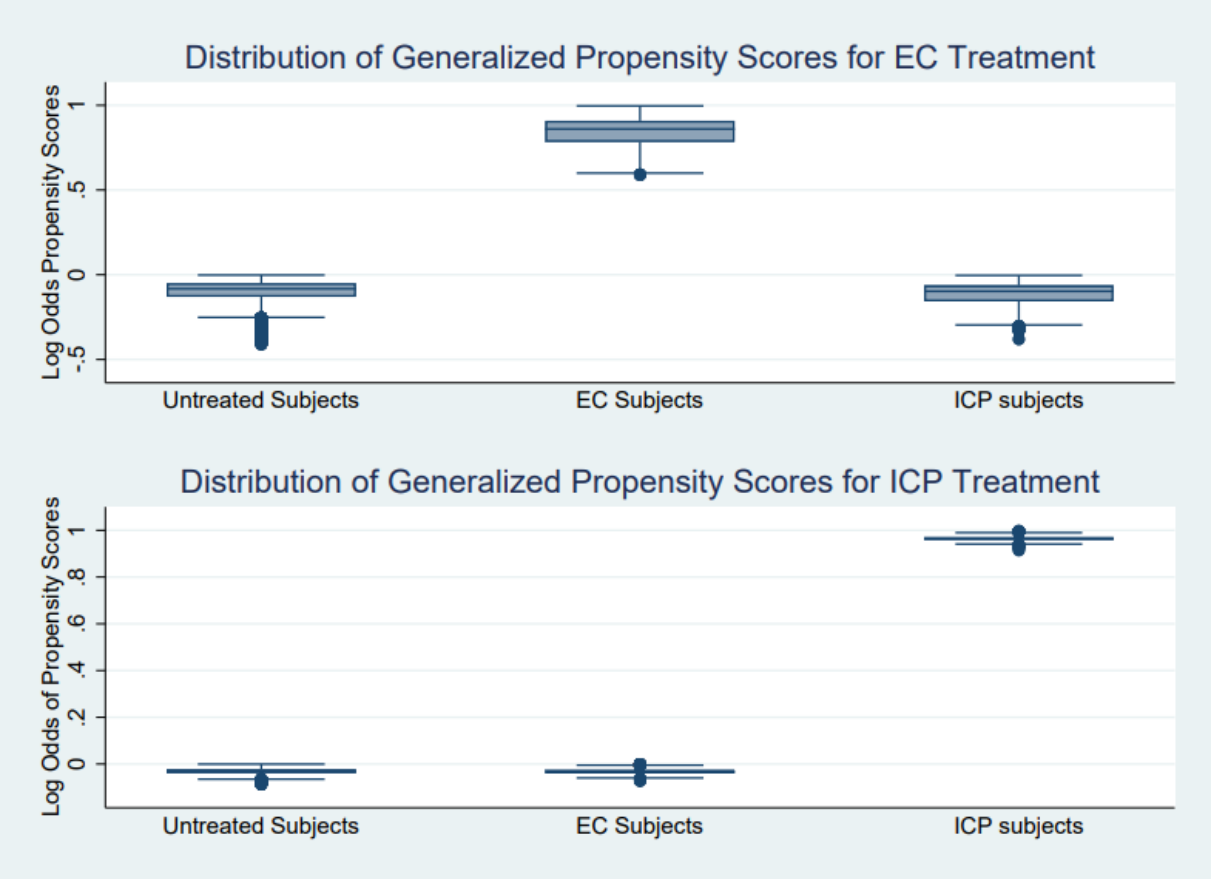
at the observation balance summary (Table 6), the weighted data is such that the ratio of non-treated to treated observations is approximately 1:1:1.

Table 6. Observation Balance Summary

Observation Counts	Raw	Weighted
Number of total observations	40,991	40,991
Number of EC observations	4,381	13,821
Number of ICP observations	1,201	13,540
Number of non-treated observations	35,409	13,630

Although the principal aim of IPTW is to achieve balanced covariates between treated and untreated groups (Shiba & Kawahara, 2021), McCaffrey et al. (2013) suggest that a researcher may also assess overlap of propensity scores as an additional check, when there are multiple treatments. This could be done by comparing the distributions of the estimated propensity scores across the treatments with separate box plots for subjects receiving each type of treatment (McCaffrey et al., 2013). As shown in Figure 1, there isn't any overlap between EC and ICP participants in their likelihood of being assigned one another's interventions. However, McCaffrey et al. (2013) also explain that there are no specific rules for what constitutes sufficient overlap and that separation in the propensity score box plots does not imply that weighting cannot balance pretreatment variables. There are instances when tuning a model to achieve greater balance in the covariates with weights results in greater separation of the propensity score box plots (McCaffrey et al., 2013), so the researchers are not concerned.

Figure 1. Overlap of Propensity Scores Box Plots



Results/Findings

Comparative Effects of EC and IP on College Readiness

The first multivariate regression model inversely weighted by the generalized propensity scores finds that EC participants have statistically significant higher odds of being college ready than non-participants while participating in ICP does not yield such increased odds (Table 7). However, after adding school fixed effects in the second model, we find the opposite, with ICP participants having 1.8 times the odds of being college ready relative to non-participants and EC participants showing no statistically significant difference. The school fixed effects means that ICP and EC participants are exclusively being compared to students in the same schools as them. The second model thus suggests that there were unobserved heterogeneity across schools unaccounted for in the first

model, and that the significant effect that EC had on college readiness in the first model is primarily driven by school effects. There were no statistically significant interactions between program participation and being Black, Latinx, or low-income for either EC or ICP in the third model.

Table 7. Effects on MassCore Completion/College Readiness

	Treatment with Covariates	(SE)	Treatment with Covariates and School Fixed Effects	(SE)	Treatment with Covariates, School Fixed Effects, and Interactions	(SE)
EC	1.79*	(0.50)	1.20	(0.18)	1.37	(0.30)
ICP	1.75	(0.81)	1.80**	(0.38)	1.80*	(0.48)
Black	0.47**	(0.12)	0.97	(0.08)	1.00	(0.09)
Other	0.44**	(0.12)	1.01	(0.08)	1.06	(0.11)
Latinx	0.66	(0.16)	0.86*	(0.07)	0.87	(0.07)
Low-Income	0.75***	(0.06)	0.70***	(0.04)	0.69***	(0.04)
Male	0.86**	(0.04)	0.74***	(0.05)	0.74***	(0.05)
English Learner	0.95	(0.16)	0.94	(0.12)	0.94	(0.12)
Disability	0.78*	(0.08)	0.53***	(0.05)	0.53***	(0.05)
Chronically Absent in G8	0.60***	(0.05)	0.53***	(0.03)	0.53***	(0.03)
Suspended in G8	0.70***	(0.08)	0.63***	(0.04)	0.63***	(0.04)
Missing ELA Test	0.74*	(0.10)	0.84	(0.10)	0.83	(0.10)
Partially Meeting ELA	1.18**	(0.08)	1.31**	(0.12)	1.31**	(0.12)
Meeting ELA	1.39**	(0.16)	1.67***	(0.18)	1.67***	(0.18)
Exceeding ELA	1.53*	(0.33)	2.13***	(0.31)	2.13***	(0.31)
Missing Math Test	1.30	(0.37)	1.30	(0.21)	1.30	(0.21)
Partially Meeting Math	1.28***	(0.08)	1.55***	(0.12)	1.55***	(0.12)
Meeting Math	1.41**	(0.17)	2.20***	(0.23)	2.20***	(0.23)
Exceeding Math	1.20	(0.23)	2.49***	(0.36)	2.50***	(0.37)
School Year=2019	1.57	(0.42)	1.11	(0.20)	1.11	(0.19)
School Year=2021	1.50**	(0.21)	1.55	(0.37)	1.55	(0.37)
School Year=2022	1.59**	(0.24)	1.85**	(0.44)	1.84*	(0.44)
EC # Black					0.68	(0.14)
EC # Other					0.70**	(0.09)
EC # Latinx					0.83	(0.13)
ICP # Black					0.87	(0.22)
ICP # Other					0.47	(0.20)
ICP # Latinx					1.10	(0.33)
EC # Low-Income					1.09	(0.17)
ICP # Low-Income					1.24	(0.36)
Constant	2.33***	(0.52)	2.76***	(0.51)	2.76***	(0.52)
Observations	40991		39804		39804	

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

Comparative Effects of EC and ICP on College Access

Multivariate logistic regression models inversely weighted by the generalized propensity scores find that both Early College and Innovation Career Pathways have a positive effects on college enrollment

within 6 months of graduating high school (Table 8). More specifically, EC participants have 1.6 times the odds and ICP participants 1.46 times the odds of enrolling in college within 6 months of high school graduation, compared to students who attend schools that offer either or both interventions but participate in neither, per the first model in Table 8. When incorporating school fixed effects while looking effects on immediate college enrollment, per the second model, the odds ratios for ICP do not change meaningfully while they increase from 1.6 to 1.97 higher odds for EC participants, meaning that there is considerable variation in impact by school for EC.

In the third model in Table 8, which includes interactions between program participation and being Black, Latinx, or low-income, the odds ratio for college enrollment for EC participants increased to 2.07, with an odds ratio of 1.38 for the interaction between program participation and low-income and an odds ratio of .75 for the interaction between program participation and being Latinx. This means that although Early college participation increases the odds of enrolling in college for all students on average, the increased odds are greater for low-income students while the effects may be less pronounced for Latinx students. These interactions are illustrated in Figures 2 and 3, respectively. As can be seen in that same model, there are no statistically significant interactions between ICP participation and race or income group, when looking at immediate college enrollment.

Table 8. Effects on College Access

	Treatment with Covariates	(SE)	Treatment with Covariates and School Fixed Effects	(SE)	Treatment with Covariates, School Fixed Effects, and Interactions	(SE)
EC	1.60***	(0.12)	1.97***	(0.13)	2.07***	(0.22)
ICP	1.46***	(0.16)	1.47***	(0.12)	1.51***	(0.16)
Black	1.15	(0.10)	1.41***	(0.10)	1.46***	(0.11)
Other	0.93	(0.08)	1.01	(0.07)	1.06	(0.07)
Latinx	0.60***	(0.04)	0.73***	(0.03)	0.75***	(0.04)
Low-Income	0.60***	(0.02)	0.65***	(0.02)	0.63***	(0.02)
Male	0.58***	(0.02)	0.58***	(0.02)	0.58***	(0.02)
English Learner	0.74**	(0.07)	0.78*	(0.08)	0.77*	(0.08)
Disability	0.65***	(0.04)	0.65***	(0.04)	0.65***	(0.04)
Chronically Absent in G8	0.54***	(0.02)	0.57***	(0.02)	0.57***	(0.02)
Suspended in G8	0.53***	(0.03)	0.53***	(0.03)	0.53***	(0.03)
Missing ELA Test	1.08	(0.14)	1.08	(0.14)	1.07	(0.14)
Partially Meeting ELA	1.37***	(0.07)	1.37***	(0.07)	1.37***	(0.07)
Meeting ELA	2.02***	(0.13)	2.00***	(0.13)	2.00***	(0.13)
Exceeding ELA	2.79***	(0.24)	2.70***	(0.22)	2.69***	(0.22)
Missing Math Test	1.81***	(0.27)	1.85***	(0.24)	1.85***	(0.24)
Partially Meeting Math	1.30***	(0.06)	1.28***	(0.05)	1.28***	(0.05)
Meeting Math	2.13***	(0.11)	2.04***	(0.10)	2.05***	(0.10)
Exceeding Math	3.17***	(0.21)	2.98***	(0.20)	3.00***	(0.20)
School Year=2019	1.45***	(0.09)	1.72***	(0.10)	1.72***	(0.10)
School Year=2021	1.27***	(0.06)	1.22***	(0.05)	1.22***	(0.05)
School Year=2022	1.12*	(0.06)	1.06	(0.05)	1.06	(0.05)
EC # Black					0.69*	(0.12)
EC # Other					0.70**	(0.08)
EC # Latinx					0.75**	(0.08)
ICP # Black					0.99	(0.19)
ICP # Other					0.76	(0.26)
ICP # Latinx					0.93	(0.11)
EC # Low-Income					1.38***	(0.12)
ICP # Low-Income					1.06	(0.11)
Constant	0.87	(0.07)	0.98	(0.06)	0.98	(0.07)
Observations	40991		40974		40974	

Exponentiated coefficients; Standard errors in parentheses

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

Figure 2. Early College and Income Interaction for College Access

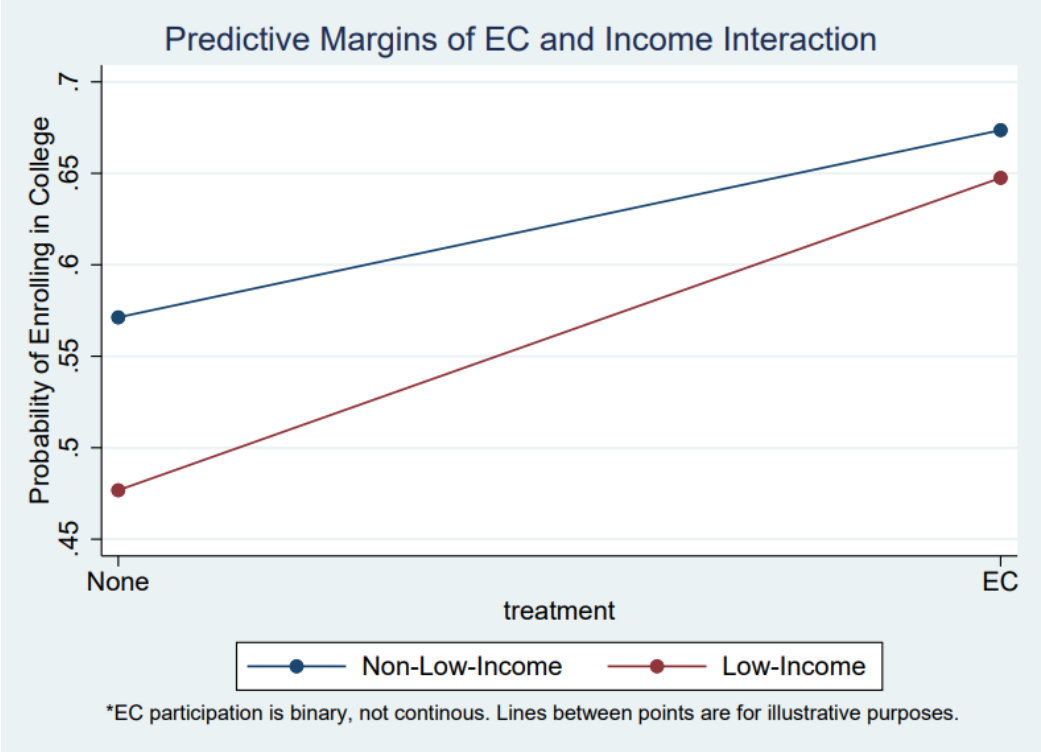
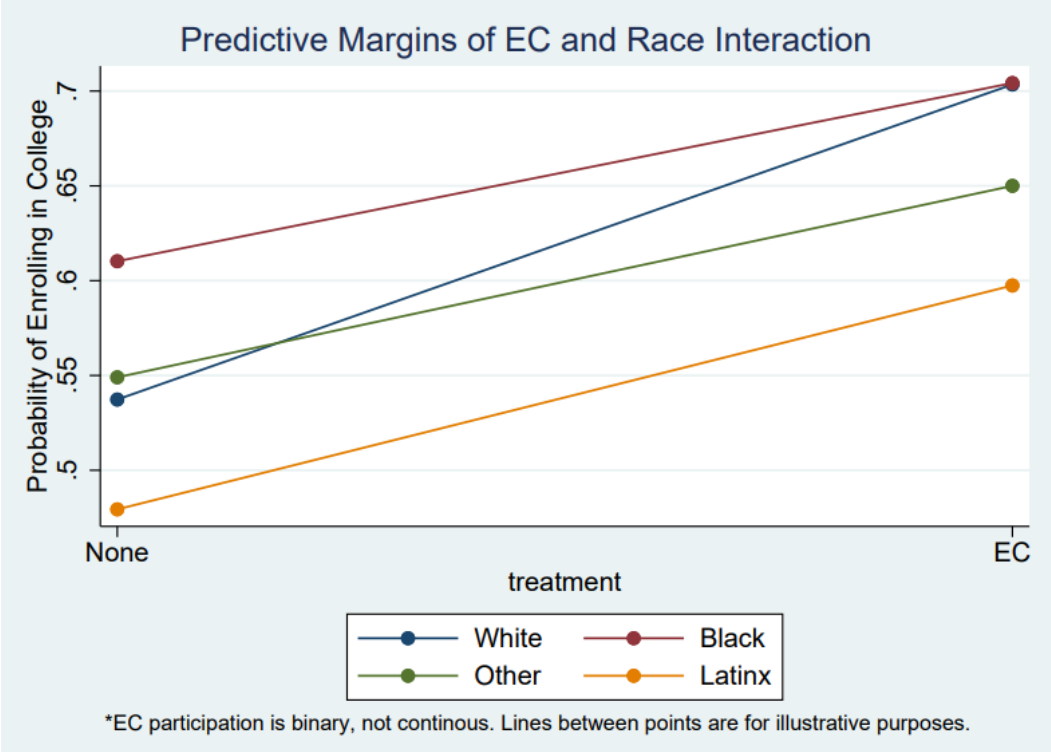


Figure 3. Early College and Race Interaction for College Access



Comparative Effects of EC and ICP on College Success

Lastly, a multivariate regression model inversely weighted by the generalized propensity scores finds that Early College and Innovation Career Pathways have a similar positive effect on students persisting to a second year in college, at 1.52 higher odds each, relative to students who participate in neither at schools that offer either one (Table 9). Incorporating school fixed effects while looking at effects on college persistence in the second model, the odds ratios for ICP decrease from 1.52 to 1.47, while they increase from 1.52 to 1.99 higher odds for EC participants, indicating that the impact of Early College varies more by school than that of Innovation Career Pathways. While no statistically significant interactions between race and program participation for either intervention were found, with school fixed effects, there is an interaction between income group and Early College, which brings the odds ratio for EC down to 1.77 from 1.99, but with an odds ratio of 1.37 for the interaction between program participation and being low-income. This means that although Early college participation increases the odds of persisting in college for all students on average, the increased odds are greater for low-income students. This interaction is illustrated in Figure 4. There are no statistically significant interactions between ICP and any of the underrepresented groups of interest.

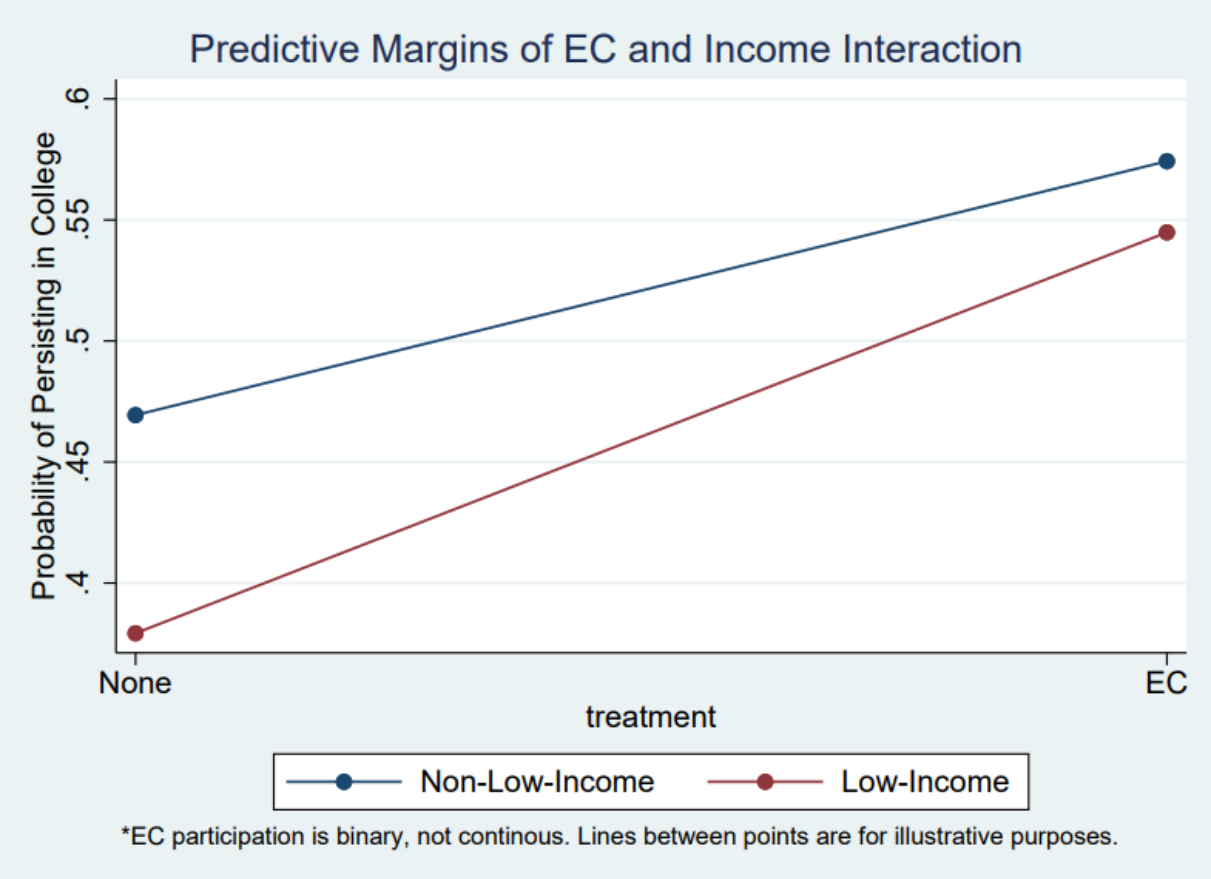
Table 9. Effects on College Success

	Treatment with Covariates	(SE)	Treatment with Covariates and School Fixed Effects	(SE)	Treatment with Covariates, School Fixed Effects, and Interactions	(SE)
EC	1.52***	(0.15)	1.99***	(0.15)	1.77***	(0.26)
ICP	1.52***	(0.12)	1.47**	(0.18)	1.34*	(0.16)
Black	1.04	(0.11)	1.32**	(0.13)	1.32**	(0.14)
Other	0.82*	(0.08)	0.95	(0.08)	0.96	(0.08)
Latinx	0.47***	(0.03)	0.61***	(0.03)	0.61***	(0.04)
Low-Income	0.59***	(0.03)	0.65***	(0.03)	0.62***	(0.03)
Male	0.54***	(0.02)	0.54***	(0.02)	0.54***	(0.02)
English Learner	0.85	(0.08)	0.89	(0.10)	0.89	(0.10)
Disability	0.63***	(0.04)	0.63***	(0.05)	0.63***	(0.05)
Chronically Absent in G8	0.49***	(0.02)	0.51***	(0.03)	0.52***	(0.03)
Suspended in G8	0.49***	(0.03)	0.50***	(0.03)	0.50***	(0.03)
Missing ELA Test	1.26	(0.22)	1.27	(0.23)	1.26	(0.22)
Partially Meeting ELA	1.60***	(0.11)	1.58***	(0.11)	1.57***	(0.11)
Meeting ELA	2.43***	(0.20)	2.38***	(0.20)	2.37***	(0.20)
Exceeding ELA	3.82***	(0.37)	3.61***	(0.36)	3.59***	(0.37)
Missing Math Test	2.17***	(0.33)	2.31***	(0.32)	2.32***	(0.31)
Partially Meeting Math	1.36***	(0.06)	1.35***	(0.07)	1.34***	(0.07)
Meeting Math	2.22***	(0.14)	2.16***	(0.16)	2.16***	(0.16)
Exceeding Math	3.50***	(0.28)	3.37***	(0.32)	3.37***	(0.32)
School Year=2019	1.30***	(0.08)	1.54***	(0.10)	1.54***	(0.10)
School Year=2021	1.34***	(0.07)	1.28***	(0.06)	1.28***	(0.06)
EC # Black					0.90	(0.22)
EC # Other					0.98	(0.17)
EC # Latinx					0.97	(0.15)
ICP # Black					1.38	(0.26)
ICP # Other					0.82	(0.23)
ICP # Latinx					1.10	(0.16)
EC # Low-Income					1.37**	(0.16)
ICP # Low-Income					1.19	(0.15)
Constant	0.46***	(0.05)	0.54***	(0.05)	0.54***	(0.05)
Observations	26688		26688		26688	

Exponentiated coefficients; Standard errors in parentheses

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

Figure 4. Early College and Income Interaction for College Success



Robustness Checks

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 10, this approach estimates that neither EC nor ICP participants have statistically significant higher odds of being college ready. However, EC participants have 1.84 higher odds of enrolling in college and 1.61 higher odds of persisting in college, while ICP students have 1.51 higher odds of enrolling in college, and 1.68 higher odds of persisting to a second year in college, relative to students who don't participate in either intervention

at EC and ICP offering schools. The 1.84 and 1.51 higher odds estimated effects of EC and ICP on college enrollment from this school fixed effects model with continuous test scores are relatively consistent with the 1.97 and 1.47 odds estimated effect from the school fixed effects model in Table 8 (on page 178), which uses test performances levels. It should be noted that the estimated positive effects of EC decreased from college enrollment to college success while those of ICP increased.

Table 10. Effects Using Continuous Test Scores from 2020-21 and 2021-22 (School Fixed Effects)

	Effects on College Readiness	(SE)	Effects on College Access	(SE)	Effects on College Success	(SE)
EC	1.17	(0.17)	1.84***	(0.15)	1.61***	(0.15)
ICP	1.48	(0.42)	1.51***	(0.15)	1.68***	(0.22)
Black	1.19*	(0.10)	1.50***	(0.13)	1.45**	(0.18)
Other	1.07	(0.10)	1.04	(0.06)	0.96	(0.08)
Latinx	0.92	(0.08)	0.74***	(0.04)	0.63***	(0.04)
Low-Income	0.64***	(0.05)	0.64***	(0.02)	0.63***	(0.04)
Male	0.75***	(0.06)	0.62***	(0.03)	0.61***	(0.03)
English Learner	1.11	(0.18)	0.95	(0.10)	1.10	(0.20)
Disability	0.48***	(0.06)	0.68***	(0.05)	0.64***	(0.06)
Chronically Absent in G8	0.50***	(0.03)	0.55***	(0.03)	0.49***	(0.04)
Suspended in G8	0.62***	(0.06)	0.51***	(0.03)	0.46***	(0.04)
Next Gen ELA Test	1.01***	(0.00)	1.01***	(0.00)	1.02***	(0.00)
Next Gen Math Test	1.01***	(0.00)	1.02***	(0.00)	1.02***	(0.00)
School Year=2022	1.17	(0.16)	0.86***	(0.03)	1.00	(.)
Observations	24772		25727		11715	

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

As an additional robustness check for these logistic regression models, one may regress the same variables as linear probability models. In expectation, relationships between the dependent variable and the independent variables should remain similar across logistic and linear probability models (Papke & Wooldridge, 1996). Including all the years in the data, linear probability models estimated that Early College participants had a 14% higher probability of enrolling in college and ICP participants have an 8% higher probability of enrolling in college, relative to students who participated in neither intervention (Table 11). The models also estimated that ICP students had a 6% higher probability of being college ready and EC students had an 8% higher probability of persisting for a second year in college. All models across all approaches—continuous tests scores or factor test

performance levels, logistic regressions or linear probability models—estimate that Early College and Innovation Career Pathways participation have a positive effect on college enrollment.

Table 11. Estimated Effects Using Linear Probability Models (School Fixed Effects)

	Effects on College Readiness	(SE)	Effects on College Access	(SE)	Effects on College Success	(SE)
EC	0.01	(0.02)	0.14***	(0.01)	0.08***	(0.01)
ICP	0.06*	(0.03)	0.08***	(0.02)	0.04	(0.02)
Black	-0.01	(0.01)	0.07***	(0.01)	0.03*	(0.01)
Other	0.00	(0.01)	0.00	(0.01)	-0.01	(0.01)
Latinx	-0.02	(0.01)	-0.07***	(0.01)	-0.06***	(0.01)
Low-Income	-0.04***	(0.01)	-0.09***	(0.01)	-0.05***	(0.01)
Male	-0.03***	(0.01)	-0.11***	(0.01)	-0.08***	(0.00)
English Learner	-0.01	(0.02)	-0.04*	(0.02)	-0.02	(0.01)
Disability	-0.07***	(0.02)	-0.09***	(0.01)	-0.05***	(0.01)
Chronically Absent in G8	-0.08***	(0.01)	-0.11***	(0.01)	-0.06***	(0.01)
Suspended in G8	-0.06***	(0.01)	-0.12***	(0.01)	-0.07***	(0.01)
Missing ELA Test	-0.02	(0.02)	0.01	(0.02)	-0.04*	(0.02)
Partially Meeting ELA	0.04***	(0.01)	0.06***	(0.01)	-0.01	(0.01)
Meeting ELA	0.06***	(0.01)	0.15***	(0.01)	0.04***	(0.01)
Exceeding ELA	0.08***	(0.01)	0.19***	(0.01)	0.11***	(0.01)
Missing Math Test	0.04	(0.02)	0.13***	(0.03)	0.15***	(0.03)
Partially Meeting Math	0.06***	(0.01)	0.05***	(0.01)	0.06***	(0.01)
Meeting Math	0.09***	(0.01)	0.15***	(0.01)	0.12***	(0.01)
Exceeding Math	0.10***	(0.02)	0.21***	(0.01)	0.24***	(0.01)
School Year=2019	0.01	(0.02)	0.10***	(0.01)	0.06***	(0.01)
School Year=2021	0.04	(0.02)	0.04***	(0.01)	0.03***	(0.01)
School Year=2022	0.06*	(0.02)	0.01	(0.01)	-0.40***	(0.02)
Constant	0.75***	(0.02)	0.50***	(0.01)	0.45***	(0.01)
Observations	40991		40991		40991	

Discussion

An emergent share of the literature does not make a clear distinction between preparing students for college and preparing them for a career. This is reflected by the US Department of Education which aims to prepare every student to effectively transition to adulthood and become college and career ready (Xing et al., 2019). Indeed, American Diploma Partnership (ADP, 2004) found convergence around core knowledge and skills needed in high-performance workplaces and in credit-bearing college courses, and American College Testing (ACT, 2006) found that high school graduates need comparable proficiency in reading and mathematics whether they were planning to pursue a college degree or join a workforce training program. Yet, the literature proposes nuanced theories of

change for college and career preparation's respective effects on educational attainment, and this study finds variations in outcomes, including by socio-economic groups, when looking at their comparative effects.

In addition to the outcomes, there are observable systematic differences between the average enrollment profile of Early College programs and the average enrollment profile of Innovation Career Pathways programs, due to them being offered at demographically different schools. How could the two interventions adhere to the same equitable access guiding principle, yet tend to end up being implemented in communities with different demographics? Assuming all schools had an equal opportunity to apply for and offer either intervention, some chose Early College while others chose Innovation Career Pathways. In the schools that offer both, participants chose one over the other. This warrants further investigation, perhaps by interviewing school and district leaders, state designation officers for the two interventions, and in cases where a school offered both, also the student participants and their guidance counselors.

In a world of infinite resources, if the aim is to promote college enrollment and persistence, especially for students historically underrepresented in American higher education, findings from this study would suggest that districts and schools should offer Early College. However, in a world of particularly scarce resources, it may be more practical to offer Innovation Career Pathways, if the associated costs are much less. Although their study focused on whole school CTE programs, as opposed to within-school model of ICP, Dougherty and Smith (2022) find that the estimated benefits of CTE in Massachusetts likely outweigh their costs under most conservative plausible estimates of the lifetime public benefits and costs. Conversely, Belfield et al. (2023) caution that dual enrollment, a prominent feature of Early College, may not be financially sustainable in states where it is offered at a discount to students.

Nevertheless, it is not clear that college preparation and career preparation, thus EC and ICP, are entirely separate pathways. The definitions of college and career readiness converged in most states (Mishkind, 2014); ADP (2004) and ACT (2006) find considerable overlap in knowledge and skills needed for either college or the workforce; while practically all students, including those who go to college, aspire to join the workforce eventually (Conley, 2012). Furthermore, Edmunds et al. (2022) did propose that it is the practice of offering dual enrollment courses by students in career preparation programs, a college preparation feature, that drives the relationship between career preparation in high school and college enrollment. The variation in implementation permitted by the state creates a possibility that there can exist an EC program that is more similar to an ICP program than other EC programs.

It should be noted that findings from initial impact evaluations of such interventions sometimes do not necessarily hold steady over time. The AIR randomized controlled trial saw the positive difference of Early College participation decrease from 40 percentage points more likely to enroll in college immediately after high school to 7 percentage points more likely to enroll in college 6 years after high school (Song & Seizer, 2019). While both EC and ICP have positive effects on immediate college enrollment, it would be interesting to see their effects on college enrollment five years after high school graduation. Furthermore, college enrollment is of interest to the extent it contributes to college completion, a measure on which the impact of EC and ICP have not yet been studied. Likewise, educational attainment is in many ways an intermediary measure for other life outcomes, such as employment and earnings. It would be prudent to see the comparative effects of Early College and Innovation Career Pathways on these more distal outcomes before making conclusive judgements or swift policy decisions based on this study.

With the framing of offering Early College and Innovation Career Pathways as human capital investments, 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. 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. Lastly, there isn't any overlap between EC and ICP participants in their likelihood of being assigned one another's interventions as illustrated via the boxplots in Figure 1 (on page 175). However, there are no specific rules for what constitutes sufficient overlap; separation in the propensity score box plots does not imply that weighting cannot balance pretreatment variables; and there are instances when tuning a model to achieve greater balance in the covariates with weights results in greater separation of the propensity score box plots (McCaffrey et al., 2013). Nevertheless, IPTW regression results from trimmed weights, with estimates nearly identical to the untrimmed weights regressions, can be seen in Appendix B.

Lastly, it should be noted that there is limited ability to estimate the effect of program participation on MassCore completion, the approximation for college readiness used in this study, when incorporating fixed effects. This is because many schools in Massachusetts have all their high school graduates completing MassCore, although it is suggested and not a required program of study from the state. When fixed effects are included in a logistic regression model with a binary-dependent variable, groups or clusters with no variation in the dependent variable are dropped because the fixed effects perfectly predict the outcome (Beck, 2020). This in turn substantially reduces the sample size, and is perhaps why the estimated effects on MassCore completion are not statistically significant in many of the models.

Conclusion

Although college and career preparation in high school may be ascribed to different theories of change, recent research suggests they both positively influence college enrollment and completion. What isn't commonly found in the literature are comparisons between the two approaches in one study. Given persistent and considerable gaps in educational outcomes by race and socioeconomically disadvantaged status, and the co-existence of the Early College and Innovation Career Pathways in Massachusetts, this study investigated the comparative effects of participation in either intervention on college readiness, access, and success, with particular consideration for their respective impacts on Black, Latinx, and low-income students. Using inverse probability of treatment weighting by way of generalized propensity scores, this study finds that both Early College and Innovation Career Pathways promote college access and success, albeit to varying degrees with different effect sizes across models and outcomes. Early College had statistically significant positive interactions with low-income status and college enrollment as well as college persistence. This initial impact evaluation does not include critical distal outcomes of college completion, employment, and earnings, so there is much more to investigate regarding EC and ICP.

Chapter 7: Discussion and Conclusion

This integrated thesis contributes to and/or engages literature in at least five distinct and meaningful ways. Firstly, the thesis responds to suggestions for further research from the Early College literature and adds to the nascent evidence that Early College is effective in promoting educational attainment. Secondly, the thesis addresses an ambiguity highlighted in the career and technical education (CTE) literature, namely the unclear effects of career preparation in high school on college enrollment and persistence. Thirdly, the thesis adds to the emergent joint college and career preparation literature by estimating the comparative effects of Early College and Innovation Career Pathways. Fourthly, the thesis contributes to the body of research that investigates and identifies college and career preparation interventions that promote equitable educational attainment across racial and economic groups. Lastly, the three papers engage human capital theory, by framing their respective impact evaluations as return on human capital investment analyses. Furthermore, the three papers in the thesis raise a series of questions worth discussing. For example, the Massachusetts interventions of Early College and Innovation Career Pathways target Black, Latinx, and low-income students. However, those demographic groups are not the only ones underrepresented in higher education. Furthermore, it must be underscored that there is not empirical evidence to explain the theory of change for either Early College or Innovation Career Pathways, beyond what is proposed in the literature. Some other discussion points include alternative and distal measures of effectiveness, and future complications for evaluations of Massachusetts Early College and Innovation Career Pathways.

Contribution to College Preparation/Early College Literature

Dating back to the 2002 Bill and Melinda Gates Early College High School Initiative (Berger et al., 2010), Early College interventions in the United States were always whole school models, where all students at the school receive the treatment. As such, Edmunds et al. (2017; 2020) who conducted an

impact evaluation of Early College in North Carolina only included whole schools. Likewise, Berger et al. (2013) and Haxton et al. (2016) conducted their Early College Impact evaluations only including whole schools. Although the efforts of these researchers serve as the empirical evidence for the efficacy of Early College, a limitation to their external validity is that their findings only apply to program participants who attend whole school models. Because of this, Edmunds et al. (2017) indicate in their discussion that an area for further research is the investigation of the efficacy of Early College strategies within schools. By evaluating the impact of Massachusetts Early College, which is nearly entirely a program within a school model, with an average of 21% of 12th grade students at any designated school participating and only one school having 100% of its students participate, the thesis responds directly to this suggestion.

The first research paper in the integrated thesis found that Early College participants have an estimated 2.01 times the odds of enrolling in college, relative to their matched comparison group, from a multivariate logistic regression. This translates to a 14-percentage point positive difference when using a linear probability model. At a 14-percentage point positive impact estimate on college enrollment, the findings from that paper are consistent in direction and magnitude with the 15.6-percentage point positive impact estimate found by Edmunds et al. (2017; 2020). The 14-percentage point positive impact estimate is also relatively consistent with Haxton et al. (2016), who found Early College to have a 9-percentage point positive impact estimate on college enrollment from a longitudinal randomized controlled trial. Thus, the thesis, in addition to studies by Edmunds et al. (2017; 2020), Berger et al. (2013), and Haxton et al. (2016)—provides further evidence that Early College promotes educational attainment.

It is more costly, politically challenging, and logistically complex to implement a whole school reform, relative to offering an intervention to a subset of a school. Given that the mostly within school model of Early College has similar effects to whole school Early College programs, schools and districts in

local control states, such as Massachusetts, who wish to promote post-secondary school enrollment and persistence via Early College but cannot afford the whole school model may consider this lower barrier to entry within school model. Likewise, education agencies within state control political climates, as opposed to local control, may have an easier time convincing their legislatures who are reluctant to pursue whole school reforms to offer Early College to shares of the school, with the expectation of yielding results for participants that are consistent with whole school models.

Contribution to Career Preparation/Career Technical Education Literature

Much of the empirical research on career and technical education (CTE) in high school focus on its effects on completing high school, employment prospects, and future earnings of program participants. Consequently, there is a certain dearth in the literature, where there isn't much empirical research on how well CTE programs contribute to college enrollment and success. Dougherty (2018; 2023), who conducts research on the effects of CTE, describes the literature on how well CTE programs prepare students for college as emergent; argues that CTE's impact on college readiness, access, and success is less clear than its effects on high school success; and suggests this is an area for further research. By evaluating the effects of Massachusetts Innovation Career Pathways on college enrollment and persistence, the thesis responds directly to this suggestion and addresses the ambiguity in the literature.

The second research paper in the integrated thesis found that Innovation Career Pathway participants have higher odds of enrolling in college, relative to non-participants at their schools using an inversely weighted multivariate regression. More specifically, program participants had a 7-percentage point increase in college enrollment, relative to non-participants. This is a smaller effect size than both the 10 and 7.8 percentage points positive differences found by Brodersen et al. (2021) and Witzen (2018), respectively, but it is in the same direction and relatively close in magnitude as that of Witzen (2018).

Thus, this paper corresponds with and contributes to the emergent literature on the effects of CTE participation on college enrollment. Given the relative consistency of findings that CTE promotes educational attainment, namely college enrollment, in the emergent literature, including this thesis, CTE should be increasingly mentioned in the list of interventions that promote college going.

Contribution to Emergent Joint College and Career Preparation Literature

Although this was not the case in the previous century, presently, it is not clear that college preparation and career preparation are entirely separate pathways. American Diploma Partnership (ADP, 2004) found considerable convergence in the knowledge and skills that students would need in a high-performance workplace and in higher level college courses. Likewise, American College Testing (ACT, 2006) found that high school graduates need comparable proficiency in reading and mathematics whether they were planning to pursue a college degree or join a workforce training program. Along the same lines, most states have a combined college and career readiness definition (Mishkind, 2014), and the U.S. Department of Education states that it aims to prepare every student to effectively transition to adulthood and become college and career ready (Xing et al., 2019).

To further substantiate this idea that college and career readiness may not be entirely different, research referenced in papers one and two find that college and career preparation respectively have positive effects on the same outcome of educational attainment (Edmunds et al., 2020; Song & Zeiser, 2019; Brodersen et al., 2021; Dougherty et al., 2019). Moreover, the literature suggests that both college preparation and career preparation interventions specifically have positive effects on educational attainment for students historically underrepresented in American higher education (ACT, 2013; Allen, 2010; Cave & Quint, 1990; Kemple, 2004). Most pertinently, the findings from papers one and two are that Early College, a college preparation intervention, and Innovation Career Pathways, a career preparation intervention, each have positive effects on college enrollment and

persistence. Despite this lack of clarity regarding how distinct those two types of interventions may be, there are no empirical studies that directly investigate the comparative effects of college preparation and career preparation on any outcome. By estimating the comparative effects of Early College and Innovation Career pathways in one study, the third paper of the thesis addresses this gap in the research and engages the emergent joint college and career preparation literature, providing evidence that both promote educational attainment and perhaps that the two are more alike than different.

Promoting Equity in Educational Attainment via College and Career Preparation

In the United States, students from low-income from families as well as students who identify as Black or Latinx continue to have lower levels of educational attainment than their non-low-income and White counterparts. In Massachusetts, less than 50% of socioeconomically disadvantaged students attended college or university, compared to 75% of higher-income students (Murnane et al., 2014). Furthermore, while 40 percent of White Americans between the ages of 25 and 29 had completed at least a bachelor's degree in 2015, less than 17 percent of Latinx Americans did so (U.S. Census Bureau, 2015 as cited in Gándara & Mordechay, 2017). There likewise remains a disparity in the rates at which Black students are attending and completing college relative to White ones, although the share of Americans pursuing and earning degrees has increased (Jeffrey, 2020).

There is literature suggesting that some college preparation and some career preparation interventions may specifically have positive effects on educational attainment for students historically underrepresented in American higher education. ACT (2013) found college course taking in high school, a prominent feature of Early College, to be a vehicle to reduce gaps in persistence and degree completion among racial and socioeconomic groups, using weighted hierarchical logistic models. In their randomized controlled trial, Cave and Quint (1990) found that participants in Career Beginnings,

a career preparation intervention in an urban low-income community, were likely to enroll in college at a rate 4.7 higher percentage points higher than their control group.

This thesis contributes to this strand of literature in two ways. Firstly, in regression models estimating effects of Early College participation on college enrollment and college persistence, respectively, there is an interaction between program participation and having a low-income background for college enrollment and college persistence, both of which result in increased odds of these underrepresented students reaching those milestones. Secondly, when looking at the effects of Innovation Career Pathways participation on college enrollment and persistence for students underrepresented in higher education, we argue that targeted recruitment which result in overrepresentation of Black, Latinx, and low-income students in the intervention would promote educational equity, since the effects were positive on average and there were no statistically significant interactions suggesting effects vary by group.

Engaging and Justifying the Use of Human Capital Theory

Throughout the thesis, the offering of Early College and Innovation Career Pathways are framed as human capital investments, and the impact evaluations are framed as analyses of returns on these investments. Schultz (1961) and Becker (1962) similarly define human capital as intentional pursuit of knowledge and skills through schooling or training, including while foregoing earning or on the job, that may potentially result in increased economic value. Given that college graduates earn substantially more than those who do not attend college (Lobo & Burke-Smalley, 2018; Rose, 2013), and that Early College seeks to promote college readiness, access, and success (Massachusetts Department of Higher Education & Massachusetts Department of Elementary and Secondary Education, 2017), it is appropriate to frame it as a human capital investment.

Although Innovation Career Pathways does not intend to promote college enrollment and completion as exclusively and explicitly as Early College, it is appropriate to frame its offering as a human capital investment for at least two reasons. Firstly, the ICP designation criteria states that participants enroll in a series of courses, which are often post-secondary level, and that recruitment should be focused on students underrepresented in post-secondary education enrollment and completion, which implies some element of preparing students for college (Massachusetts Executive Office of Education & Massachusetts Department of Elementary and Secondary Education, 2020). More most relatedly, the ICP designation criteria indicates that the intentions of the program are to provide students career awareness and work-based learning activities, which corresponds to the job training component of human capital (Schultz, 1961; Becker, 1962).

In addition to framing the two interventions as human capital investments, the author frames the impact evaluations as return on investment analyses. Although none of the papers estimate the effects of participating in either program on earnings, Sweetland (1996) suggests that returns on human capital investments may be determined by years of schooling. Even if that were not the case, the World Bank estimates that each additional year of education produces a private rate of return to schooling of about 5–8% per year, using the Mincer Equation (Patrinos, 2016), thus effects on earnings may be approximated from years schooling. Given the inclusion of college persistence as an outcome in the three papers, and the definition of college persistence as enrolling in college for two consecutive academic years, an estimate on the effects of either intervention on years of schooling is automatically included.

Although Schultz (1961) and Becker (1962) acknowledge differences in employability and earnings by race, they similarly attribute much of the variation in income by race to differences in human capital investments. However, there is a body of literature challenging Human Capital Theory's consideration of race, which should be considered when framing Early College and Innovation Career

Pathways as human capital investments. Tomaskovic-Devey et al. (2005) argue that human capital acquisition is more of a social product, than it is an individual investment decision, with discrimination influencing both the gaining of knowledge and skills as well as income inequality. In their regression models that estimate career earnings, they found interactions between human capital and race, where the effects on income were substantially less for Black and Latinx men relative to White men. One may interpret this to mean that neither the targeted recruitment of Black, Latinx, and low-income students, by Massachusetts nor the students' decisions to participate are ultimately going to address the distal income inequality, absent other supportive policies and practices affecting the broader societal structures affecting workforce/economic equity.

However, Thompson (2021) investigated the relationship between human capital, measured by educational attainment and test performance, with the racial earnings gap in three separate samples of men spanning 1966 through 2017, and found that decreases in racial earnings gap were greater over time, when controlling for human capital, in all the data sets. This means that, differences in human capital investment become better at explaining variation in earnings by race over time, or that the differences that exist in earnings by race are increasingly explained by differences in human capital investments. This is consistent with Simth's (1984) findings that there were gradual improvements in closing the disproportionality in earnings over time, when comparing men of similar education levels but different racial backgrounds, and bolsters the original arguments made by Schultz (1961) and Becker (1962), although it does not entirely disprove the argument that human capital effects vary by race.

Underrepresented Students

Findings from the three papers of the integrated thesis suggest that Massachusetts Early College and Innovation Career Pathways may indeed be ways to promote equitable educational attainment by

either increasing the odds by which Black, Latinx, and low-income students are college ready, enroll in college, and persist in college, relative to White and non-low-income students; or by overrepresenting Black, Latinx, and low-income students in those interventions, relative to their share in school enrollment when there is no evidence in variation by racial and income groups. However, Black, Latinx, and low-income students are not the only groups underrepresented in higher education. Other such groups are English learners, students with a disability, and boys. They may have benefited from the targeted recruitment of Black, Latinx, and low-income students.

Although the share of students who are English learners in the United States public schools is rapidly increasing, such students are underrepresented in higher education, with roughly 40% not finishing high school and only 18% of continuing on to a 4-year college (LaCosse et al., 2020). Looking at the data from this study, English learner students make up 15% of all students who enroll in all Early College offering schools and 11% of all students who enroll in Innovation Career Pathways offering schools. However, their participation rates in the two interventions are 7% and 9%, respectively. Likewise, Fernando et al. (2022) found that despite the increase in the presence of students with physical disabilities, autism spectrum disorder, and learning disabilities in education, they still have inequitable access to higher education. Students with a disability make up 15% of students who enroll in all Early College offering schools and 12% of all students who enroll in Innovation Career Pathways offering schools. However, their participation rates in the two interventions are 4% and 7%, respectively.

When Fry (2023) investigated national higher education enrollment trends from 2011 to 2022, he observed that 1 million fewer young men enrolled in college, relative to 0.2 million fewer young women. Consequently, the 44% share of college students who are male in 2022 was 3 percentage points less than the 47% from 2011. In this study's data, male students make up 51% of all students who enroll in all Early College offering schools and 50% of all students who enroll in Innovation

Career Pathways offering schools. However, their participation rates in the two interventions are 36% and 46%, respectively.

While targeted recruitment of Black, Latinx, and low-income students in Early College and Innovation Career Pathways is a way to promote equitable educational attainment, as evidenced by the findings of the three papers, Massachusetts may potentially further promote equity in education by also targeting students who are English learners, have a disability, or identify as male, as they are also underrepresented. Likewise, it would be interesting for further research to investigate the effects of program participation on the groups, as was done with racial and income groups via interactions in the three papers of this thesis.

Theories of Change

The impact evaluations on Early College referenced in the thesis provide empirical evidence for their theories of change, beyond frameworks and literature. Edmunds et al. (2020) investigated a variety of mechanisms by which Early College may have an effect on college readiness, access, and success in their study. Quantitatively, they confirmed that a significantly higher proportion of Early College students successfully completed college preparatory courses and that Early College students completed many more college credits while in high school than the control group. Qualitatively, they interviewed students and concluded that the "schools emphasized a set of rigorous and relevant instructional practices that required students to engage in critical thinking, extensive writing, cooperative work, and ongoing class discussion" (p. 260). Furthermore, they learned from the schools that Early College programs assisted students in applying for college and for financial aid.

Likewise, Berger et al. (2013) explored a variety of features of Early College to understand the extent to which the treatment and control group differed in their high school experiences. Firstly, they found that Early College participants were substantially and statistically significantly more likely to

enroll in a college course than the control group and the national average in every grade in high school. Furthermore, they found Early College participants accumulated more transferrable college credits than the control group, with nearly half Early College students earning one year's worth of college credits in high school, compared just over 5% of the control group. They also analyzed the extent to which the academic transcripts of Early College participants differed in rigor from the control group, and found a significant difference in science rigor, in favor of Early College students. Lastly they surveyed students and found significant differences in favor of program participants regarding having college-going culture and a variety of non-academic college preparation supports.

Unlike those for Early College, the impact evaluations for career and technical education (CTE) whose effects sizes are referenced in the thesis do not provide empirical evidence to substantiate a theory of change as to how such interventions promote college readiness, access, and success (Brodersen et al., 2021; Witzen, 2018). It is from a combination of the intervention descriptions, the literature, and logic, that one may reasonably infer the mechanisms by which program participation is conducive to college going. For example, a student may discover their desired profession requires a college degree from a career exploration feature of a CTE program (Hughes et al., 2001).

When it comes to the thesis itself, there is a lack of sufficient and consistent data collected in Massachusetts for the years included in the study to investigate the mechanisms by which Early College or Innovation Career Pathways are promoting educational attainment. For Early College, looking at the rigor of the courses that were offered, exploring how many credits were earned, and determining how many credits were transferred could have been insightful. For Innovation Career Pathways, knowing what career fields were chosen, how many credentials were earned, and even how many internship hours were accumulated would be similarly informative.

The Student Course Schedule (SCS) is a database that includes the courses taken by students in the public-school districts of Massachusetts and their performance in these courses at the student level (DESE, 2023). One of the variables in the data is course level, which includes values for advanced or college level courses. However, neither Early College nor Innovation Career Pathways programs consistently reported values for those variables during the years of the study. Alternatively, a researcher could have used course names to identify the courses, but unlike Florida, Massachusetts does not have consistent course names across neither its secondary nor tertiary educational institutions, so courses with the same name could cover different content and vice versa. Credits earned per course in high school are perhaps another way a researcher may have investigated the higher-level course taking mechanism, however that information is not collected on the same scale across schools.

Early College is a collaboration between secondary schools and tertiary institutions, where students are taking courses offered by the college while in high school, and as such the colleges should have records of these courses. However, this record keeping did not start until the last year of the study, 2022, and the data was not collected consistently across institutions. This does present two credit related opportunities for further Early College research. Firstly, given that higher education institutions started collected the Early College credit information in 2022, future evaluations can specifically explore the relationship between credits earned and college enrollment, in a manner analogous to dosage of medicine studies in healthcare. Furthermore, for the students who remain in-state for college, the amount of college credits a student enters their first year with would be a valid proxy for how many college credits they earned in high school. Because not all college credits earned in high school are automatically accepted by the colleges they attend, this measure can only be an approximation.

Distal and Alternative Measures

It was iterated in the discussion sections of each paper that college readiness, enrollment, and persistence are intermediary measures for college completion. After all, readiness, enrollment, and persistence do not mean as much if the degrees are not earned. As such, in a few years' time, the initial impact evaluations should be updated not just to confirm that the initial estimate effects on readiness, enrollment, and persistence hold relatively consistently over time, but also to include the ultimate outcome of college completion. Indeed, college completion is an outcome measure in the impact evaluations for interventions whose estimated effects on college enrollment are compared to the estimates from the three papers in the thesis.

Edmunds et al. (2017; 2020) had attainment of a postsecondary credential as their primary outcome. Their definition of a postsecondary credential includes bachelor's degrees, associate degrees, and technical credentials. They measured student attainment of these credentials 4 years after completing high school as well as 6 years after completing high school. Berger et al. (2013) also include college completion as an outcome in their study, but not as the main one, because they conducted their analysis within a few short years of the participants graduating high school and "a complete understanding of how long the Early College impact persists would require tracking degree attainment and workforce outcomes over a more extended time period" (p. 45). Their Early College effects on college completion were still positive and statistically significant, but smaller than those on college enrollment.

For the career and technical education studies whose estimates are referenced, Brodersen et al. (2021) included college completion within two years for associate degrees and within five years for bachelor's degrees as outcomes, while Witzen (2018) include attainment of any college degree within 6 years as an outcome in their respective studies. The fact that all the studies highlighted

include college completion, speaks to the importance of investigating the effects of Early College and Innovation Career Pathways on that outcome. By the submission of this thesis, none of the four cohorts will have been out of high school for 6 years and only the first cohort, which is the smallest, will have college graduation within 4 years of completing high school data available.

There are alternative measures to which the researchers did not have access that may also be used to investigate effects of Early College and Innovation Career Pathways. For example, one of the aims of the intervention is to reduce the high costs of higher education. The Center for College Affordability and Productivity (2010) determined that cost of college may be reduced by up to 12.5% when a student participates in a program that enables dual enrollment, like Early College. It would be interesting to see if program participants for either Early College or Innovation Career Pathways who did enroll in a post-secondary institution ended up spending less money than college enrollees who did not. Likewise, another aim of Early College is to reduce the time to completion. Had the college completion information been available for all cohorts over a long period of time, it would also be interesting to calculate and compare time to completion of program participants and non-participants for both Early College and Innovation Career Pathways.

Indeed, Edmunds et al. (2020) explore time to college completion and cost savings in the impact evaluation of Early College and cover the effects of program participation on those two measures in their results and discussions sections, even though the two measures were not explicit outcomes in their research questions. After determining the Early College participants earned degrees more rapidly than the control group, they argue that an "advantage to students completing their degree more quickly [is that] it may end up costing students and taxpayers less" (p. 267). Berger et al. (2013) likewise cover time to completion and cost reductions in their results, indicating that Early College participants earned degrees faster than the control group and arguing that earning a college degree faster can save students and their families money. Time to degree completion and cost reductions of

college were not covered in the studies regarding the effects of CTE on college enrollment and completion.

Furthermore, it can be said that educational attainment in general, including college completion, is an intermediary measure for other life outcomes, such as employment and earnings. Therefore, effects of program participation on such outcome measures would be worthwhile to investigate in the future. Although they do not include employment and earnings as outcomes in their respective impact evaluations, Edmunds et al. (2020) posit that Early College participants may find employment more rapidly due to accelerated completion while Berger et al. (2013) argue that "students who earn degrees earlier have the opportunity to enter the workforce earlier and potentially realize additional lifetime earnings" (p. 45). This suggests that studying the effects of Early College on employment and earnings is of interest to the field. Regarding career and technical education, employment and earnings are typically among the outcomes of interest in the research (Dougherty et al., 2019; Witzen, 2018), so it is natural to pursue such questions for Innovation Career Pathways. The emphasis on creation and maintenance of State longitudinal data systems in the United States, linking education and workforce data, provides a rich opportunity for the investigation of such distal post-college outcomes.

Future Complications for Evaluations

Starting in the 2022-23 academic year, the year immediately after the data points in this study, Massachusetts designation policy changed such that some students can participate in both Early College and Innovation Career Pathways, which further complicates any future evaluations. For the schools that enable participation in both interventions, it will be difficult to determine which and to what extent each intervention is contributing to college readiness, access, and success. It's already debatable whether college preparation and career preparation are distinct activities (ADP, 2004; ACT,

2006) when they are separate, so the combination of the two will further blur the line. Those students would likely have to be excluded from future impact evaluations.

During that same year, the state approved and many schools started offering Early College promise, which is a 13th year of school to enable students to earn more college credits and potentially earn a 2-year degree while still in high school. As a result, many students will not enroll in a post-secondary institution after high school. The National Student Clearinghouse database that captures college enrollment only does so for those who matriculate in the colleges. Depending on what share of students participate in the Early College Promise and earn enough credits to be awarded a degree, future evaluations may underestimate the effects of the Early College program on college enrollment, persistence, and completion, unless there is supplemental data collection system to indicate that students earned degrees despite not ever having formally matriculated in a college or university.

Lastly, although there was only one whole-school Early College program from 2019-2022, with the rest being a share of the school, Massachusetts has since approved additional whole school Early College programs. The sampling methodology used in the papers that evaluate either intervention, compares program participants to non-participants in intervention offering schools balanced by matching or weighting on propensity scores. The increase in whole-school models would mean that these schools would get excluded from the regression models when school fixed effects are incorporated, as they would not have school peers with whom to be compared. This does perhaps present an opportunity for other non-experimental causal methods, such as differences-in-differences, which would compare the whole school to another comparable school in the state, or interrupted time series which would compare the school to itself in the past. Edmunds et al. (2017; 2020), Berger et al. (2013), and Haxton et al. (2016) investigated whole school models exclusively, but with randomized controlled trials.

Alternative Methods

This did not need to be discussed in the methods section of the papers or the methods chapter of the thesis, but it should be noted that there are non-experimental causal methods, other than propensity score based ones, that may be used to estimate causal impacts of interventions. Four such commonly used in methods in education research are Differences-in-Differences, Regression Discontinuity Designs, Instrumental Variables, and Interrupted Time Series. Due to certain criteria that must be met before their use, those methods could not be used to estimate the impacts of either Early College or Innovation Career Pathways. Nevertheless, it is useful to cover the alternative methods as a discussion point.

First introduced by Card and Krueger (1992), Difference-in-Differences assumes parallel secular trends when a group receives a treatment and an otherwise comparable group does not, to compare pre-treatment differences between the two groups, to post-treatment differences between the groups. In their case, Card and Krueger (1992) used adjacent towns that were on different sides of the state line, and thus subject to different policies, even though they were culturally and demographically similar. They used that methodology to demonstrate that a rise in minimum wage did not reduce employment. This methodology could have been used to evaluate Early College or Innovation Pathways, had they both been whole school programs, with neighboring schools that are similar demographically but do not offer the interventions. Neither of these criteria were met by either intervention.

Regression Discontinuity Designs require that treatment assignment be based on a threshold, where subjects within a minimum distance of each other, but on different sides of the threshold are compared to each other. As Calonico and Cattaneo (2014) explain, “the key feature of the design is that the probability of receiving treatment conditional on this covariate jumps discontinuously at the

cutoff, inducing variation in treatment assignment that is assumed to be unrelated to potential confounders" (p. 909). Hypothetically speaking, if participation in either Early College or Innovation Career Pathways required a score of 75% on some assessment, Regression Discontinuity Design would compare untreated students of 73% and 74% to treated students at 75% and 76%. Neither intervention had such cutoff scores, thus this methodology could not be used to estimate effects of the two interventions.

According to Baiocchi et al. (2014) Instrumental Variables analysis is a non-experimental causal research method that controls for unmeasured confounding variables. It requires the measurement of a valid instrumental variable that is independent of the unmeasured confounding, affects the treatment, and affects the outcome only through the treatment. It is difficult and rare for a variable to meet the three criteria to be considered an instrument and there are no known such variables in the data set that influence college readiness, access, and success only through participation in either Early College or Innovation Career Pathways. For example, distance is a commonly used instrumental variable (Baiocchi et al., 2014), but student home addresses are not included in the DESE data so we could not calculate their geographic proximity of Early College or Innovation Career Pathways offering schools. Thus, Instrumental Variables analysis could not be used to estimate the effects of either of the two interventions studied in this thesis.

Lastly, Interrupted Time Series Analysis approach involves constructing a time series of population-level rates for a particular effect and testing statistically for a change in the outcome rate in the time periods before and time periods after the intervention designed to change the outcome (Penfold & Zhang, 2013). This methodology could not be used for a couple of reasons. Firstly, as previously discussed, the pandemic occurred during the years of the intervention, therefore the pre-intervention measures of college readiness, access, and success are not comparable to the same measures post intervention as there is an unknown pandemic effect. Secondly, the number of

schools, the number of students, and the share of students participating in either intervention changed each year, as the state continued to grant and retract designation from schools. In other words, post-intervention is not sufficiently stable across the entire treatment group for it to be compared to pre-intervention, but perhaps might be used to understand more about such interventions if implemented elsewhere in future without the disruption of the pandemic.

Conclusion

Despite often being perceived as or claimed to be "the land of opportunity," there has historically been and remains inequity in educational attainment by race and socioeconomic group in the United States. In addition to the temporal dimension of educational inequity, there is spatial dimension as well, with empirical evidence of it across regions and states. As a top performing state in primary, secondary, and tertiary educational outcomes, Massachusetts sought to address the disproportionate rates at which its Black, Latinx, and low-income students were enrolling in and succeeding in colleges and universities by launching Early College.

Early College is a high school model that enables simultaneous enrollment in high school and college courses. Unlike those in other states, e.g., North Carolina and California, Massachusetts Early College enables a within-school as well as a whole-school intervention, in which each participating school may enroll some or all of its students in the program. Furthermore, Massachusetts Early College targets the recruitment of students historically underrepresented in higher education, sequences course taking on pathways conducive to a college major and a career, and provides various academic support services.

Randomized control trials show that the Early College high school model in other states has positive effects on college enrollment and completion for all students, including those historically underrepresented. The theories of change, or mechanisms by which Early College is having those

effects, include reducing the otherwise high costs of college or university attendance; better preparing students for college courses through higher level and rigorous course taking in high school; enabling students to gain momentum toward completion via credit accumulation before starting; and favorable perception by college admissions officers.

In this thesis, the researcher uses propensity score matching to identify and compare participating and non-participating students in Early College offering schools with a similar probability of having participated, based on a vector of attributes. The finding is that Early College participants have higher odds of being college ready, immediately enrolling in college after high school graduation, and persisting to a second year in college, compared to similar students who do not participate, on average. Furthermore, interaction terms incorporated in the regression models demonstrate that while the effects are positive across the three measures for all groups average, they are more pronounced for low-income students in college enrollment and college persistence.

Simultaneous to the launch of Early College, the state of Massachusetts also launched Innovation Career Pathways, optional career and technical education (CTE) programs within traditional public high schools, to grant students access to preparation for in demand careers through technical courses and hands-on learning experiences. The literature suggests that in addition to being conducive to economic opportunity directly by promoting career readiness, CTE programs may also do so indirectly by having a positive effect on educational attainment. This is a shift from the historical understanding that CTE would prepare students for working class jobs.

From the literature, the proposed mechanisms by which CTE promote educational attainment of participants include: the discovery that their desired job or profession requires a college degree via career exploration components of a CTE program; the pedagogical emphasis on applied learning in CTE programs can stimulate students who might have otherwise disengaged with academic study;

improvements in non-cognitive intermediary outcomes such as improved attendance in the early high school years; and students receive more personal, academic, and social support.

This thesis 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, without statistically significant interactions, the researcher propose 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.

Lastly, the thesis conducts a comparative impact evaluation of Early College and Innovation Career pathways. While impact evaluations of Early College and Innovation Career Pathways were conducted, respectively, the estimates from those two studies should not be directly compared, as they were derived from different subsets of the sample and thus do not represent the same populations. Furthermore, the estimates were calculated using different methods—Propensity Score Matching (PSM) and Inverse Probability of Treatment Weighting (IPTW)—which can yield different results, albeit in very particular circumstances, potentially further complicating comparisons.

Findings from the third evaluation are relatively consistent with the former two. Early College and Innovation Career Pathways have positive effects on college enrollment and persistence on average, with Early College having higher effects and having interactions with income group for college enrollment and persistence, suggesting that the effects are greater for these groups. The third paper also points out it remains unclear whether college preparation interventions and career preparation interventions are sufficiently distinct to be separated or sufficiently similar to be bundled and that

future research should seek to clarify this. Likewise, there are potential costs differences to offering either intervention and Massachusetts should pay attention as one may be more efficient use of taxpayer dollars.

The three papers in the thesis apply the Research Framework for Reducing the College Success Gap to provide structure and direction to the systematic investigation. The research framework has four transitions in the longitudinal student journey— college readiness, college enrollment, college achievement, and post-college attainment. Approximations for college readiness and college achievement, and a direct measure of college enrollment are the three outcomes of interest in all three papers. Likewise, the framework has four layers of context to understanding student progress through the four transitions—internal, family, school, and sociopolitical. All of four contexts are captured in covariates for regressions used to calculate propensity scores, as well as regressions used to estimate program effects, with the latter further incorporating all layers as either interactions or fixed effects.

Lastly, all three papers, and therefore the entire thesis, are framed by Human Capital Theory, as defined by Schultz (1961) and Becker (1962). Human Capital Theory posits that any deliberate acquisition of knowledge and skills that adds economic value is a human capital investment. If further suggests that educational attainment and on-the job training are the most common forms of human capital investment. In this regard, both Early College and Innovation Career Pathways are human capital investments for the state of Massachusetts, the schools that offer the interventions, and the students who participate. The three papers would suggest the returns on those investments are largely? positive.

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Appendix A. Trimmed Weights ICP IPTW Regressions

	Effects of Treatment on College Readiness with School Fixed effects	(SE)	Effects of Treatment on College Access with School Fixed effects	(SE)	Effects of Treatment on College Success with School Fixed effects	(SE)
ICP	1.86**	(0.37)	1.41**	(0.17)	1.28	(0.21)
Black	0.90	(0.11)	1.50***	(0.13)	1.39***	(0.13)
Other	0.83*	(0.06)	0.97	(0.17)	0.94	(0.19)
Latinx	0.89	(0.10)	0.73***	(0.05)	0.63***	(0.05)
Low-Income	0.71***	(0.07)	0.63***	(0.05)	0.65***	(0.07)
Male	0.76*	(0.09)	0.61***	(0.04)	0.54***	(0.06)
Disability	0.38***	(0.06)	0.54**	(0.11)	0.44***	(0.05)
English Learner	0.70	(0.15)	0.65	(0.17)	0.66	(0.19)
Chronically Absent in G8	0.51***	(0.05)	0.54***	(0.05)	0.49***	(0.08)
Suspended in G8	0.61***	(0.06)	0.60***	(0.08)	0.49***	(0.08)
Missing ELA Test	1.17	(0.22)	1.98*	(0.61)	1.38	(0.59)
Partially Meeting ELA	1.84***	(0.23)	1.70***	(0.19)	1.96***	(0.40)
Meeting ELA	2.50***	(0.38)	2.70***	(0.31)	3.11***	(0.84)
Exceeding ELA	2.50***	(0.52)	4.21***	(0.78)	5.59***	(1.75)
Missing Math Test	1.90	(0.80)	1.60*	(0.37)	1.52	(0.42)
Partially Meeting Math	1.33*	(0.17)	1.29*	(0.14)	1.05	(0.18)
Meeting Math	1.96***	(0.34)	2.04***	(0.26)	1.67**	(0.30)
Exceeding Math	1.74**	(0.34)	3.00***	(0.50)	2.59***	(0.60)
School Year=2019	0.77	(0.20)	1.55***	(0.16)	1.31*	(0.15)
School Year=2021	3.34*	(1.96)	1.53***	(0.14)	1.56***	(0.12)
School Year=2022	4.01*	(2.27)	1.23*	(0.12)	1.00	(.)
Constant	1.56	(0.45)	0.66**	(0.10)	0.49**	(0.13)
Observations	20100		20796		13796	

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

Appendix B. Trimmed Weights EC vs. ICP IPTW Regressions

	Effects of Treatment on College Readiness with School Fixed effects	(SE)	Effects of Treatment on College Access with School Fixed effects	(SE)	Effects of Treatment on College Success with School Fixed effects	(SE)
EC	1.19	(0.18)	1.96***	(0.13)	1.99***	(0.15)
ICP	1.92**	(0.47)	1.47***	(0.15)	1.48**	(0.20)
Black	0.98	(0.09)	1.41***	(0.10)	1.31**	(0.13)
Other	1.01	(0.08)	1.01	(0.07)	0.95	(0.08)
Latinx	0.86*	(0.07)	0.73***	(0.04)	0.61***	(0.03)
Low-Income	0.69***	(0.04)	0.65***	(0.02)	0.65***	(0.03)
Male	0.74***	(0.05)	0.58***	(0.02)	0.54***	(0.02)
Disability	0.53***	(0.05)	0.65***	(0.04)	0.64***	(0.05)
English Learner	0.96	(0.13)	0.78*	(0.09)	0.90	(0.10)
Chronically Absent in G8	0.54***	(0.03)	0.57***	(0.02)	0.51***	(0.03)
Suspended in G8	0.63***	(0.04)	0.53***	(0.03)	0.50***	(0.03)
Missing ELA Test	0.77	(0.11)	0.90	(0.14)	1.16	(0.23)
Partially Meeting ELA	1.31**	(0.12)	1.38***	(0.07)	1.61***	(0.11)
Meeting ELA	1.67***	(0.19)	2.01***	(0.13)	2.44***	(0.21)
Exceeding ELA	2.16***	(0.33)	2.70***	(0.22)	3.70***	(0.36)
Missing Math Test	1.29	(0.21)	1.86***	(0.24)	2.30***	(0.31)
Partially Meeting Math	1.55***	(0.13)	1.28***	(0.05)	1.33***	(0.07)
Meeting Math	2.20***	(0.22)	2.05***	(0.11)	2.14***	(0.16)
Exceeding Math	2.47***	(0.36)	3.01***	(0.20)	3.35***	(0.31)
School Year=2019	1.10	(0.19)	1.72***	(0.10)	1.54***	(0.10)
School Year=2021	1.53	(0.36)	1.21***	(0.05)	1.28***	(0.06)
School Year=2022	1.80*	(0.42)	1.05	(0.05)	1.00	(.)
Constant	2.86***	(0.53)	0.98	(0.06)	0.53***	(0.05)
Observations	39005		40167		26375	

Exponentiated coefficients; Standard errors in parentheses

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

Central University Research Ethics Committee (CUREC)

CUREC 1A Form for Application form for research projects in the social sciences and humanities with less complex ethical issues

The University of Oxford places a high value on the knowledge, expertise, and integrity of its members and their ability to conduct research to high standards of scholarship and ethics. The research ethics review process has been established to ensure that research involving human participants is conducted in a way that respects the dignity, rights, and welfare of participants, and minimises risk to participants, researchers, third parties, and to the University itself. It is assumed that all members of the University will take their responsibilities and obligations seriously, and will ensure that their research involving human participants is conducted according to established principles and good practice in their field and in accordance, where appropriate, with legal requirements.

Before completing this form, please refer to the guidance and flowchart on the Research Support website. Only type-written forms form will be accepted. Completed application forms should be emailed, along with relevant supporting documents, to your Departmental Research Ethics Committee (DREC) or to ethics@socsci.ox.ac.uk from your ox.ac.uk email address.

Please contact your DREC or the SSH IDREC if you have any questions about completing this form or the review process.

Section A: Filter for CUREC 2 application		
This section determines whether the application for ethics review should be made using this form (CUREC 1A) or the CUREC 2 form (for research with more complex ethical issues).		
Please indicate with an 'X'.	**Yes**	**No**
1. Does the research involve the deception of participants?	☐	☒
2. Are the research participants vulnerable in the context of the research, or classed as people whose ability to give free and informed consent is in question? For example, • Participants aged 16 or under (also answer question A5); • Participants aged 16 – 18 (refer to competent youths for guidance); • adults at risk; Note the University's Safeguarding Guidance and Code of Practice and its implications for researchers involving young people or adults at risk.	☐	☒
3. By taking part in the research, will participants be at risk of criminal prosecution or significant harm?	☐	☒
4. Does your research raise issues relevant to the Counter-Terrorism and Security Act (the Prevent Duty), which seeks to prevent people from being drawn into terrorism? Best Practice Guidance 07 on the Prevent Duty provides further guidance.	☐	☒
If you answered **'No'** to all the questions above, go to Section B. If you answered **'Yes'** to any question above, continue to question 5 below.		
5. Is your project covered by a CUREC Approved Procedure?	☐	☐
If yes, list the CUREC Approved Procedure(s) you will follow		
If you have answered '**No**' to all questions 1-4, go on to **Section B**. If you answered '**Yes**' to ANY of questions 1-4, and answered '**No**' to question 5, **stop** completing this form and do not submit it for ethical review. You will instead need to submit a CUREC 2 application form. If you answered '**Yes**'		

to **any** of questions 1-4, and your project is covered by an Approved Procedure, **go on to Section B**. If more than one Approved Procedure applies, contact the SSH IDREC or your DREC for advice on whether a CUREC 2 form should be submitted instead.

Section B: Researchers		
1. Name of Principal Investigator or student's supervisor	Ariel Lindorff/Steve Strand	
2. Department or Institute	Department of Education	
3. University of Oxford email address	ariel.lindorff@education.ox.ac.uk steve.strand@education.ox.ac.uk	
Copy and paste the following six rows as necessary to complete for each additional researcher who will be involved in this study, including student(s) and those external to the University.		
4. Name of researcher or student	Pierre Lucien	
5. Department or Institute	Department of Education	
6. University of Oxford email address	pierre.lucien@education.ox.ac.uk	
7. Role in research	Student/Researcher	
8. Degree programme, if student research	DPhil	
The whole research team		
9. Have the researchers undertaken research ethics and integrity training?	**Yes** ☒	**No** ☐
10. Please provide details of any research ethics and integrity training undertaken, including the dates of the training. Alternatively state relevant research experience.	research ethics and integrity training completed with 91.3% test score on June 25, 2022.	
11. State any conflicts of interest and explain how these will be addressed.	The student researcher is a Policy Analyst at the Massachusetts Department of Elementary and Secondary Education, where his salary is being paid for by a three-year grant from the Smith Family Foundation, for the purpose of conducting an impact evaluation of the Early College program, the subject of the research. Many schools in the state of Massachusetts are recipients of grants from the Smith and Family Foundation, for the purpose of implementing the Early College program. *The student researcher solicited and raised funds among high net-worth friends and associates to help pay course fees and defray the cost of living in Oxford during the DPhil. Among the contributors to the fundraiser was a member of the Massachusetts Board of Higher Education, to whom the researcher sometimes presents research updates and preliminary*	

	*findings, as the thesis includes an impact evaluation of the Massachusetts Early College program. The researcher did not originally think this contribution warranted a disclosure, as the donor is a mentor/friend and personal funds were used. However, the researcher's perspective on this evolved. Consequently, the funds were returned to the donor, and this exchange is being disclosed, as to not create the perception of any conflict of interest.** *Italicized portion was amended on 10/23/23

Section C: The research project	
1. Title of the research project	
Are college preparation and career preparation effective tools to promote college enrolment, persistence, and completion for students historically underrepresented in American higher education?	
2. Anticipated start date of the aspect of the research project involving human participants and/ or personal data (**dd/mm/yy**).	August 1st, 2022 **(01/08/22)**
3. Anticipated research end date (**dd/mm/yy**).	August 1st, 2025 **(01/08/25)**
4. Provide a brief lay summary of the aims and objectives of the research. This should cover the questions it will answer and any potential benefits. (max 300 words)	
There is persistent and pervasive disparity in education outcomes based on race and socioeconomically disadvantaged status in the United States. Schools, districts, and state education agencies continue to explore interventions to close these gaps. Early College and Innovation Pathways are two such interventions in the state of Massachusetts. Early College (EC) is an intervention within a school that enables participating secondary school students to simultaneously enrol in credit-bearing post-secondary courses, to promote subsequent enrolment at colleges and universities. Innovation Pathways (IP) is a career preparation intervention within a school that offers secondary school students coursework and experience in a specific high-demand industry, to promote consequent career readiness. This study evaluates the effects of the Massachusetts Early College and Innovation Pathways interventions on educational attainment, with a focus on racial minority and socioeconomically disadvantaged students, by comparing college enrolment, persistence, and completion rates of EC participants and IP participants with separate matched comparison groups of students who participated in neither. Program participants and their comparison groups are similar on observable characteristics, pre-intervention test scores, and probability of participating in the respective interventions, per propensity scores. Findings will help determine if EC and IP are effective at gaps in educational attainment between racial minority and socioeconomically disadvantaged students and their non-minority and non-disadvantaged peers.	
5. Please indicate the methods to be used (indicate with an '**X**'):	

Analysis of existing records	☒
Snowball sampling (recruiting through contacts of existing participants)	☐
Use of casual or local workers e.g. interpreters (refer to guidance in BPG 01: Researcher safety)	☐
Participant observation	☐
Covert observation	☐
Observation of specific organisational practices	☐
Participant completes questionnaire in hard copy	☐
Participant completes online questionnaire or other online task (refer to guidance in BPG 06: Internet-mediated research)	☐
Using social media to recruit or interact with participants (refer to guidance in BPG 06: Internet-mediated research)	☐
Participant performs paper and pencil task	☐
Participant performs verbal or aural task (e.g. for linguistic study)	☐
Focus group	☐
Interview (refer to guidance in BPG 10: Conducting research interviews)	☐
Audio recording of participant (you will generally need specific consent from participants for this)	☐
Video recording of participant (you will generally need specific consent from participants for this)	☐
Photography of participant (you will generally need specific consent from participants for this)	☐
Others (please specify below)	☐

6. Provide a brief summary of the research design and methods. What will research participants be asked to do? (max 300 words)
   Please also submit a copy of the questions participants will be asked, if applicable, or some information about the sorts of topics that will be covered.

Quasi-experimental design:

This study seeks to evaluate the impact of a college preparation program (Early College) and a career preparation program (Innovation Pathways) in Massachusetts on students historically underrepresented in American higher education. Using secondary data, this research applies propensity scores to match program participants to similar non-participants, based on observable characteristics, and compare differences in outcomes.

The secondary data are administrative datasets from Massachusetts, including information on individual student demographics (e.g., race, gender, disability status, etc.), standardized test scores, course enrolment and performance, and college enrolment, persistence, and completion from 2015 to 2024 for students who graduated Massachusetts high schools in 2019, 2020, 2021, and 2022.

Propensity score matching is a strategy within the quasi-experimental framework. Results will show whether there is a "treatment effect" of each programme, and the size of such effects, taking appropriate covariates into account.			
7. List the location(s) where the research will be conducted, including any other countries.	The research will be conducted remotely from Oxford as all the Massachusetts education data is accessible online via a government issued virtual private network (VPN).		
8. Clarify which parts of the research will be conducted in-person and which will take place remotely, e.g. online.	The entire research will be conducted in the manner described above.		
9. If your research involves fieldwork or travel and your department requires a travel risk assessment, will you have completed and returned a risk assessment form beforehand? Please indicate with an '**X**'. (This must be approved by your department before you travel. If you are travelling overseas, you are advised to take out University travel insurance.) Refer to guidance available from your Department, the Safety Office, the Social Sciences Division, and the Humanities Division, and on travel for University business.		Yes	☐
		No	☐
		Not required in this instance	☒
10. In the case of international or collaborative research, explain how you will address any ethical issues specific to the local context. Please provide details of the local review, approval or permission obtained or required. Refer to the BPG 16: Social science research conducted outside the UK. If there will be no local review, explain why not. Please mention any stakeholder or community engagement that has been/ will be undertaken in relation to the research. Please also address any physical or psychological risks for Oxford researchers and local fieldworkers in Section G.			
The researcher will be providing routine updates on the progress of the research to the Massachusetts Department of Elementary and Secondary Education (DESE). Moreover, DESE requires that the researcher gain their clearance at least 30 days before submission of any material for publication.			
11. Name of departmental/ peer reviewer (if applicable)	N/A		
12. External organisation funding the research and grant reference (if applicable)	Massachusetts Department of Elementary and Secondary Education/ Smith Family Foundation		
13. Please refer to the CUREC Best Practice Guidance and list any that have been used to develop your research.	BGP 09		

Section D: Recruitment of research participants		
1. Number of participants	N/A	
2. How was the number of participants decided?	N/A	
3. Age range of participants	N/A	
4. Inclusion criteria		
5. Exclusion criteria		
6. Indicate with an '**X**' all intended recruitment methods **Please submit copies of the recruitment material that will be used, e.g. advertisement text, introductory email text.**	Poster advert	☐
	Flyer	☐
	Email circulation	☐
	Social media (e.g. Twitter, Facebook)	☐
	Website	☐
	In-person approach	☐
	Snowball sampling	☐
	Recruitment sites (e.g. Mechanical Turk)	☐
	Existing contacts or volunteer database	☐
	Other (please specify):	☐
7. How will potential participants be identified and approached?	N/A	
8. Will informed consent be obtained from the research participants or their parents/ guardians? If not, please explain why not.	N/A	
9. For each activity or group of participants, explain how informed consent will be obtained from the participants themselves and/ or their parents/ guardians, if applicable. How will their consent be recorded? **Please submit copies of all participant-facing materials for review.** E.g.: • Recruitment material (e.g. emails, posters) • Information for participants to read (or hear) before they agree to take part (e.g. written information or, if applicable, an outline oral information script). • A document to record informed consent. Further guidance and templates.	N/A	

10. Provide details of any payments and incentives and the rationale for providing these. Further guidance in Best Practice Guidance: 05 Payments and incentives in research.	N/A
11. Describe how participants • may withdraw from the study • may withdraw any personal information they have provided from the study State any limits to withdrawal, for example once the data has been anonymised or at some other specified stage prior to publication. Make sure participants are aware of any withdrawal limits.	N/A

Section E: Research data

All information provided by participants is considered research data for the purpose of this form. Any research data from which participants can be identified is known as personal data; any personal data which is sensitive is considered special category data. Management of personal data, either directly or via a third party, must comply with the requirements of the UK General Data Protection Regulation (UK GDPR) and the Data Protection Act 2018, as set out in the University's Guidance on Data Protection and Research.

In answering the questions below, please also consider the points raised in the Data Protection Checklist and Data Protection Screening Assessment and whether, for higher-risk data processing, a separate Data Protection Impact Assessment may also be required for the research. Advice on research data management and security is available from Research Data Oxford and your local IT department. Advice on data protection is available from the Information Compliance team.

For guidance on conducting internet-mediated research, refer to CUREC's Best Practice Guidance 06: Internet-mediated research.

1. What data will be collected? (Indicate with an '**X**')

Screening documents	☐	Task results (e.g. questionnaires, diaries)	☐
Consent records (e.g., written consent forms, audio-recorded consent, assent forms)	☐	IP addresses (refer to Best Practice Guidance 09: Data collection, protection and management for guidance)	☐
Contact details for the purpose of this research only	☐	Field notes	☐
Contact details for future use (guidance)	☐	Photographs	☐
Opt-out forms	☐	Information about the health of the participant (including mental health)	☐
Audio recordings	☐	Previously collected (secondary) data	☒
Video recordings	☐	Data already in the public domain. Specify the source of the data:	☐

Transcript of audio/ video recordings		☐	Other, please specify:	☐
2. During the course of the research, where will **each type of** research data be stored?	This study is being conducted exclusively with secondary administrative data, that are all in a multifactor authentication guarded database that can only be accessed via the state government issued virtual private network. Within the data sets, all personally identifiable information, including name, date of birth, and address have been removed. Students are identified by a state generated ID number which is used exclusively for education administration and research purposes. As an agent of the Massachusetts Department of Elementary and Secondary Education, the researcher has governmental approval to not only view the data but has been assigned the task of using the data to conduct this analysis. The machine being used is an encrypted PC issued by the state of Massachusetts government for the purpose of this research.			
3. Who will have access to the research data during the project?	Only the student researcher will have access to the data during the project.			
4. Please complete this section if your research involves the use of secondary (i.e. previously collected) data.	**Please indicated with an 'X'.**		**Yes**	**No**
	Are data access agreements in place for access to and use of this secondary data? (If so, please attach these.)		☒	☐
	Did the individuals agree that their data could be used for this purpose?		☐	☒
	Could anyone (including members of the research team) link the data back to an individual or individuals? If this is a possibility, please explain how the associated ethical issues will be addressed: This study is being conducted exclusively with secondary administrative data, that are all in a multifactor authentication guarded database that can only be accessed via the state government issued virtual private network.		☒	☐
5. How do you intend to share the research data at the end of the project?	Depositing in a specialist data centre or archive		☐	
	Submitting to a journal to support a publication		☐	
	Depositing in an institutional repository		☐	
	Dissemination via a project or institutional website		☐	
	No plans to share the data		☒	
	Other (please specify):		☐	
	Thesis publication		☒	

6. How do you intend to report and disseminate the results of the research? (Indicate with an 'X')	Publication in a peer reviewed journal	☒
	Publicly available report	☒
	Conference presentation	☒
	Publication on a website	☒
	Pre-registration	☐
	Report to a research funder	☒
	Providing participants with a lay summary of the results	☐
	Submission for academic assessment	☐
	Other (please specify):	☐

7. Explain what will happen to the data at the end of the research project. This question must be answered for each type of data, including completed consent forms.
The data will remain in the Massachusetts Department of Elementary and Secondary Education Database and will not be held beyond the project.

Section F: Protection of research participants and their personal data		
1. How identifiable will the participants be from the **research outputs**? (Indicate with an 'X')	Directly identifiable from the information included	☐
	Pseudonymised/ indirectly identifiable	☐
	Not identifiable – data is anonymous	☒
	Other, please specify:	☐
2. To what extent will the **data** be de-identified? How identifiable will any individuals be from the research data? Describe any measures you will take towards assuring confidentiality, potential risks to confidentiality.	The research outputs are going to be aggregate results for treatment and comparison groups, so there will not be any personally identifiable information in the dissertation, publications, presentations, or reports. The Massachusetts Department of Elementary and Secondary Education's Office of Planning and Research (OPR) requires that academic performance data for which the underlying number of students is 10 or fewer be suppressed. For non-academic data, OPR requires suppression if the underlying number of students is 6 or fewer. Lastly, OPR requires that the researcher gain their clearance at least 30 days before submission of any material for publication.	
3. How will you ensure that third parties (e.g., interpreters and transcribers) are aware of and adhere to the	There are no third-party viewers of the data.	

measures described in this form?	

Section G: Risks and benefits of the research

1. Will the research involve topics that could be considered sensitive? If so:
    a. Please provide more detail or supporting information (such as the interview questions) to show the range of questions;
    b. Explain what steps will be taken to reduce risk of distress;
    c. Consider seeking advice from within your Department or from the ethics committee including whether the application might benefit from additional ethics review (e.g., via a CUREC 2 application).

2. Describe any additional burden or risks to the participants and the steps you will take to address these.

N/A

3. Describe any physical or psychological risks to the researcher(s) (including local fieldworkers or research assistants) and the steps you will take to address these.

N/A

4. Describe any benefits of the research, both to participants and to others.

The findings will inform multi-million-dollar decisions in the state of Massachusetts about how to support the educational attainment of students underrepresented in American higher education.

5. Give details of any other ethical issues or relevant information.

Section H: Professional guidelines

Please indicate with an '**X**' at least one set of professional guidelines you will follow.

Research specialism/ methodology	Association and guidance	
Anthropology	Association of Social Anthropologists of the UK	☐
Computer Science	ACM Code of Ethics and Professional Conduct	☐
Criminology	British Society of Criminology Statement of Ethics	☐
Education	British Educational Research Association Ethical Guidelines for Educational Research	☒
Geography	American Association of Geographers Statement on Professional Ethics	☐
History	Oral History Society of the UK Ethical Guidelines	☐
Internet-mediated research	Association of Internet Researchers Ethical Guidelines British Psychological Society: Ethics Guidelines for internet-mediated research Association for Computing Machinery Code of Ethics and Professional Conduct	☐
Management	Academy of Management Code of Ethics	☐
Political Science	American Political Science Association (APSA) Guide to Professional Ethics in Political Science	☐
Politics	Political Studies Association. Guidelines for Good Professional Conduct	☐
Psychology	British Psychological Society Code of Ethics and Conduct	☐
Social research	Social Research Association: Ethical Guidelines	☐
Socio-legal studies	Socio-Legal Studies Association: Statement of Principles of Ethical Research Practice	☐
Sociology	The British Sociological Association: Statement of Ethical Practice	☐
Visual research	ESRC National Centre for Research Methods Review Paper: Visual Ethics: Ethical Issues in Visual Research	☐
Other professional guidelines	American Educational Research Association	☒

Section I: Endorsements and signatures

Please ensure this form is endorsed by the Principal Investigator (or student's supervisor), the Head of Department (or nominee) and, if student research, by the student themselves.
The SSH IDREC Secretariat accepts either option below. If you have a DREC, check which signature option it prefers.

- **Option 1: direct email endorsements**
  Each of the signatories should submit an email from a University of Oxford email address, indicating their acceptance of the responsibilities listed below.
- **Option 2: signatures**
  Please scan the signed form and email it to us as a PDF. Pasted images of signatures cannot be accepted.

Endorsement by the Principal Investigator/ student supervisor and student, if applicable

I/ we the researchers understand my/ our responsibilities as Principal Investigator (and student, if applicable) as outlined in the guidance on the CUREC website. I/ we declare that the answers above accurately describe the research as presently designed, and that the ethics committee will be informed of any changes to the project which affect the answers to this form. I/ we will inform the relevant IDREC if the Principal Investigator changes.	
Name of Principal Investigator	Ariel Lindorff and Steve Strand
Principal Investigator's signature	
Date	June 30th, 2022
Name of student (if applicable)	Pierre Lucien
Student's signature	
Date	June 29th, 2022

Departmental endorsement – from the Head of Department or nominee (Another senior member of the department may sign where the head of department is the Principal Investigator, or where the Head of Department has appointed a nominee. Example nominees include Deputy Head of Department, Director of Research, or Director of Graduate/ Undergraduate Studies.)	
On the basis of the information available to me, I confirm that: • I am aware of the research proposed and have read this application; • To the best of my knowledge, the proposed design and scientific methodology do not raise ethical concerns; • I support this research in principle, subject to ethical and other necessary reviews.	
Signature	
Name	Trevor Mutton
Role	Director of Graduate Studies
Date	03/07/2022

SOCIAL SCIENCES & HUMANITIES
INTERDIVISIONAL RESEARCH ETHICS COMMITTEE
DEPARTMENTAL RESEARCH ETHICS COMMITTEE

Department of Education
15 Norham Gardens, Oxford OX2 6PY
research.management@education.ox.ac.uk



Pierre Lucien
Department of Education, Social Sciences Division
University of Oxford

03 August 2022

Dear Pierre,

Research ethics approval

Research title: Are college preparation and career preparation effective tools to promote college enrolment, persistence, and completion for students historically underrepresented in American higher education?

Research ethics reference: CIA-22TT-130

The above research has been considered on behalf of the Department of Education Departmental Research Ethics Committee (DREC) in accordance with the University's procedures for ethical approval of all research involving human participants.

I am pleased to confirm that, on the basis of the information provided to the DREC, ethics approval has now been granted for this research.

Please note the following:

Personal data: It is the responsibility of the PI to ensure that all personal data collected during the project is managed in accordance with the University's guidance and legal requirements.

In-person activities: Any data collection involving in-person interactions with participants must have an up-to-date fieldwork risk assessment in place; further guidance is available from the Safety Office's website.

Amendments: Please notify the committee if you intend to make any amendments to the information in your ethics application as submitted at date of this approval, as all changes must receive ethical approval prior to implementation. The amendment form is available on the SSH IDREC webpage.

We welcome feedback on your experience of the ethical review process and suggestions for improvement. Please email any comments to research.management@education.ox.ac.uk or ethics@socsci.ox.ac.uk.

Yours sincerely

Aliya Khalid

DREC member

cc: Ariel Lindorff, ariel.lindorff@education.ox.ac.uk

SOCIAL SCIENCES & HUMANITIES
INTERDIVISIONAL RESEARCH ETHICS COMMITTEE
DEPARTMENTAL RESEARCH ETHICS COMMITTEE

Department of Education
15 Norham Gardens, Oxford OX2 6PY
research.management@education.ox.ac.uk



Pierre Lucien
Department of Education, Social Sciences Division
University of Oxford

07 November 2023

Dear Pierre,

Research ethics approval

Research title: Are college preparation and career preparation effective tools to promote college enrolment, persistence, and completion for students historically underrepresented in American higher education?

Research ethics reference: CIA-22TT-130

Date of amendment:

Amendment number: CIA-22TT-130_Amendment_01

The above amendment has been considered on behalf of the Department of Education Departmental Research Ethics Committee (DREC) in accordance with the University's procedures for ethical approval of all research involving human participants.

I am pleased to confirm that, on the basis of the information provided to the DREC, ethics approval has now been granted for this amendment.

As part of the amendment, the following paragraph was added to section B.11 on the CUREC application form:

The student researcher solicited and raised funds among high net-worth friends and associates to help pay course fees and defray the cost of living in Oxford during the DPhil. Among the contributors to the fundraiser was a member of the Massachusetts Board of Higher Education, to whom the researcher sometimes presents research updates and preliminary findings, as the thesis includes an impact evaluation of the Massachusetts Early College program. The researcher did not originally think this contribution warranted a disclosure, as the donor is a mentor/friend and personal funds were used. However, the researcher's perspective on this evolved. Consequently, the funds were returned to the donor, and this exchange is being disclosed, as to not create the perception of any conflict of interest.

Please note the following:

Personal data: It is the responsibility of the PI to ensure that all personal data collected during the project is managed in accordance with the University's guidance and legal requirements.

In-person activities: Any data collection involving in-person interactions with participants must have an up-to-date fieldwork risk assessment in place; further guidance is available from the Safety Office's website.

Amendments: Please notify the committee if you intend to make any further amendments to the information in your ethics application as submitted at date of this approval, as all changes must receive ethical approval prior to implementation. The amendment form is available on the SSH IDREC webpage.

We welcome feedback on your experience of the ethical review process and suggestions for improvement. Please email any comments to research.management@education.ox.ac.uk or ethics@socsci.ox.ac.uk.

Yours sincerely

Irina Lepadatu



DREC member

cc: Ariel Lindorff, ariel.lindorff@education.ox.ac.uk

```
/*******************************************************************************
File Name: dese_hs_time_invariant_demographics
Author: Pierre M. Lucien
Purpose: Produces a file of time invariant attributes for all h.S. students in state
*******************************************************************************/

//top matter
clear all
cap log close
set more off

//globals
global clean "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\clean_data"
global intermediate "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\intermediate_data"
global raw "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese data\raw data"

forval year = 17/24 {
    //global inputs
    global sims_`year' "$raw\sims_`year'.dta"

    //load the file
    cap confirm file "${sims_`year'}"
        if !_rc {
            use "${sims_`year'}" if inlist(GRADE, "09", "10", "11", "12") & inlist(ENSTAT, "01", "04", "10", "11") ///
            & ATTEND !=555
        }

    //rename all variables to lower case
    rename *, lower

    //fix dob variable
    gen dob_num = date(dob, "MDY")
    format dob_num %td
    drop dob
    rename dob_num dob

    //generate school year variable
    tab period_name
    gen school_year = substr(period_name, strpos(period_name,"F") + 2, 4)
    destring school_year, replace

    //fix race variable
    destring race, replace
        //convert 6 to 31 into multi racial
        count if inrange(race, 7, 31)
        replace race = 6 if inrange(race, 6, 31)
        //convert 33 and up to hispanic
        count if race >= 33
        replace race = 7 if race >= 33

    #delimit ;
    label define race
        1 "White"
        2 "Black"
        3 "Asian"
        4 "Native American"
        5 "Pacific Islander"
        6 "Multiracial"
        7 "Hispanic";
    #delimit cr

    label values race race

    //fix gender variable
    assert !mi(gender)
    gen male = (gender == "M") if !mi(gender)
```

```
67        drop gender
68        label define male 1 "Male" 0 "Female"
69        label values male male
70
71        //check uniqueness of file
72        unique sasid
73
74        //drop duplicates
75        keep school_year sasid race male
76        duplicates drop
77        isid sasid
78
79        //temporarily save each year
80        save "$intermediate\time_invariant_demographics_`year'", replace
81    }
82
83    //append all the files together
84    use "$intermediate\time invariant demographics 17.dta", clear
85    append using "$intermediate\time_invariant_demographics_18.dta"
86    append using "$intermediate\time_invariant_demographics_19.dta"
87    append using "$intermediate\time_invariant_demographics_20.dta"
88    append using "$intermediate\time_invariant_demographics_21.dta"
89    append using "$intermediate\time_invariant_demographics_22.dta"
90    append using "$intermediate\time_invariant_demographics_23.dta"
91    append using "$intermediate\time_invariant_demographics_24.dta"
92
93    //bring uniqueness level to student ID by keeping the last reported values
94    bys sasid (school_year): keep if school_year == school_year[_N]
95    drop school_year
96    duplicates drop
97    isid sasid
98
99    //add ever EL
100   preserve
101       //global inputs
102       global sims_14 "$raw\sims_14.dta"
103       global sims_15 "$raw\sims_15.dta"
104       global sims_16 "$raw\sims_16.dta"
105       global sims_17 "$raw\sims_17.dta"
106       global sims_18 "$raw\sims_18.dta"
107       global sims_19 "$raw\sims_19.dta"
108       global sims_20 "$raw\sims_20.dta"
109       global sims_21 "$raw\sims_21.dta"
110       global sims_22 "$raw\sims_22.dta"
111       global sims_23 "$raw\sims_23.dta"
112       global sims_24 "$raw\sims_24.dta"
113
114       forval x=14/24 {
115           // load the file
116           use SASID GRADE LEP using "${sims_`x'}" if inlist(GRADE, "09", "10", "11", "12"),
      clear
117
118           //rename
119           rename *, lower
120
121           // generate school year
122           gen school_year = 20`x'
123
124           //fix ELL variable
125           destring lep, replace
126           rename lep el
127           assert inrange(el, 0, 1)
128
129           //save the files
130           save "$intermediate\ever_el_students_`x'.dta", replace
131       }
132
133       //append the files
134       use "$intermediate\ever_el_students_14.dta"
135       append using "$intermediate\ever_el_students_15.dta"
```

```
136         append using "$intermediate\ever_el_students_16.dta"
137         append using "$intermediate\ever_el_students_17.dta"
138         append using "$intermediate\ever_el_students_18.dta"
139         append using "$intermediate\ever_el_students_19.dta"
140         append using "$intermediate\ever_el_students_20.dta"
141         append using "$intermediate\ever_el_students_21.dta"
142         append using "$intermediate\ever_el_students_22.dta"
143         append using "$intermediate\ever_el_students_23.dta"
144         append using "$intermediate\ever_el_students_24.dta"
145
146         //create ever EL
147         assert !mi(el)
148         bys sasid: egen ever_el = max(el)
149         assert ever_el >= el
150
151         //drop excess variables
152         drop el grade school_year
153
154         //make one row per student
155         duplicates drop
156         isid sasid
157
158         //save the file
159         tempfile ever_el
160         save `ever_el'
161     restore
162
163     //merge ever el on
164     merge m:1 sasid using `ever_el', keep(1 3) nogen
165     replace ever_el = 0 if mi(ever_el)
166
167     //save clean file
168     save "$clean\1. dese_hs_time_invariant_demographics.dta", replace
169
```

```
/*******************************************************************************
File name: dese_hs_time_variant_demographics
Author: Pierre M. Lucien
Purpose: Produces a file of time variant attributes for all h.s. students in state
*******************************************************************************/

//top matter
clear all
cap log close
set more off

//global outputs
global clean "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\clean_data"
global intermediate "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\intermediate_data"
global raw "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese data\raw data"

forval year = 17/24 {
    //global inputs
    global sims_`year' "$raw\sims_`year'.dta"

    //load the data
    cap confirm file "${sims_`year'}"
        if !_rc {
            use "${sims_`year'}" if inlist(GRADE, "09", "10", "11", "12") & inlist(ENSTAT, "01", "04", "10", "11") ///
            & ATTEND !=555
        }

    //rename the variables to lower case
    rename *, lower

    //generate school year variable
    tab period_name
    gen school_year = substr(period_name, strpos(period_name,"F") + 2, 4)
    destring school_year, replace
    label var school_year "School Year"
    drop if mi(school_year)

    //gen SPED variable
    gen sped = !inlist( sped 6to21, "00", "01")

    //fix grade variable
    des grade
    tab grade
    destring grade, gen(grade_level)
    assert inrange(grade_level, 9, 12) if inrange(school_year, 2017, 2022)

    //fix ELL variable
    destring lep, replace
    rename lep el
    assert inrange(el, 0, 1)

    //rename Eco. Dis. variable
    cap confirm var ecodis
        if _rc {
            rename low_income eco_dis_low_inc
        }

        else {
            rename ecodis eco_dis_low_inc
        }

        //label economic variable
        label define eco_dis_low_inc ///
            0 "Non-Low-Income" ///
            1 "Low-Income"
        label values eco_dis_low_inc eco_dis_low_inc
```

```
67
68      //check uniqueness of file
69      unique sasid
70
71      //drop other duplicates
72      keep sasid school_year grade_level sped el eco_dis
73      duplicates drop
74
75      //temporarily save the file
76      isid sasid
77      save "$intermediate\time_variant_demographics_`year'.dta", replace
78  }
79
80  //append all the files together
81  use "$intermediate\time_variant_demographics_17.dta", clear
82  append using "$intermediate\time_variant_demographics_18.dta"
83  append using "$intermediate\time_variant_demographics_19.dta"
84  append using "$intermediate\time_variant_demographics_20.dta"
85  append using "$intermediate\time_variant_demographics_21.dta"
86  append using "$intermediate\time_variant_demographics_22.dta"
87  append using "$intermediate\time_variant_demographics_23.dta"
88  append using "$intermediate\time_variant_demographics_24.dta"
89
90  //save clean file
91  isid sasid school_year
92  save "$clean\2. dese_hs_time_variant_demographics.dta", replace
93
```

```
/*******************************************************************************
File name: dese_high_schools
Author: Pierre M. Lucien
Purpose: Produces a file listing all high schools in the state
*******************************************************************************/

//top matter
clear all
cap log close
set more off

//global outputs
global clean "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\clean_data"
global intermediate "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\intermediate_data"
global raw "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese data\raw data"

forval year = 17/24 {
    //global inputs
    global sims_`year' "$raw\sims_`year'.dta"

    //load the data
    cap confirm file "${sims_`year'}"
        if !_rc {
            use "${sims_`year'}" if ATTEND != 555 & inlist(GRADE, "09", "10", "11", "12") & ENSTAT == "01", clear
            // don't use observations with value 555 for ATTEND
        }

    //rename variables to lower case
    rename *, lower
    rename school school_code


    //generate school year variable
    tab period_name
    gen school_year = substr(period_name, strpos(period_name,"F") + 2, 4)
    destring school_year, replace

    //collapse to the school level
    destring grade, replace
    destring sasid, replace
    collapse (count) enrollment=sasid (max) high_grade=grade (min) low_grade=grade, ///
        by(school_code school_year)

    //retrieve school names
    preserve
        import excel "$raw\public_schools.xlsx", clear firstrow
        rename *, lower
        gen district_name = substr(orgname, 1, strpos(orgname, ":"))
        gen school_name = trim(subinstr(orgname, district_name, "", .))
        replace district_name = trim(subinstr(district_name, ":", "", .))
        rename (orgcode orgtype address1) (school_code school_type address)

        //temporaily save the file
        tempfile school_names
        save `school_names'
    restore

    //merge on the school names
    merge 1:1 school_code using `school_names', keepusing(school_name school_code ///
        school_type district_name address town state zip) keep(3) nogen
    order school_year school_name school_code school_type

    //fix long name(s)
    replace school_name = "North Central Charter" if regexm(school_name, "North Central Charter")
    replace school_name = "Putnam Vocational" if regexm(school_name, "Putnam Vocational")
```

```
66        replace school_name = "New Heights Charter" if regexm(school_name, "New Heights Charter")
67        replace school_name = "Nashoba Valley Tech" if regexm(school_name, "Nashoba Valley Tech")
68        replace school_name = "Fecteau-Leary" if regexm(school_name, "Fecteau-Leary")
69
70        //temporarily save the files
71        isid school_code
72        save "$intermediate\school_names_`year'.dta", replace
73    }
74
75    //append all the files together
76    use "$intermediate\school_names_17.dta", clear
77    append using "$intermediate\school_names_18.dta"
78    append using "$intermediate\school_names_19.dta"
79    append using "$intermediate\school_names_20.dta"
80    append using "$intermediate\school_names_21.dta"
81    append using "$intermediate\school_names_22.dta"
82    append using "$intermediate\school_names_23.dta"
83    append using "$intermediate\school_names_24.dta"
84
85    //save the file
86    isid school_year school_code
87    save "$clean\3. dese_high_schools.dta", replace
88
89
```

```
/*******************************************************************************
File name: dese_hs_student_enrollment_attendance
Author: Pierre M. Lucien
Purpose: Produces a file indicating which schools students enrolled in and for how long
*******************************************************************************/

//top matter
clear all
cap log close
set more off

//global outputs
global clean "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\clean_data"
global intermediate "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\intermediate_data"
global raw "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese data\raw data"


forval year = 17/24{
    //global inputs
    global sims_`year' "$raw\sims_`year'.dta"

    //load the data
    cap confirm file "${sims_`year'}"
        if !_rc {
            use "${sims_`year'}" if inlist(GRADE, "09", "10", "11", "12") & inlist(ENSTAT, "01", "04", "10", "11") ///
            & ATTEND != 555
        }

    //rename the variables to lower case
    rename *, lower
    rename (school grad_core enstat) (school_code graduation_status enrollment_status)

    //generate school year variable
    tab period_name
    gen school_year = substr(period_name, strpos(period_name,"F") + 2, 4)
    destring school_year, replace

    //generate graduated and mass core variables
    gen graduated = (enrollment status == "04")
    gen completed_mass_core = (graduation_status == "01")

    //aggregate  enrollment data
    collapse (sum) attend member truant (max) graduated completed_mass_core, by(sasid school_code school_year)
    cap assert attend <= member

    //drop if attend equals 1 or member is less than 20
    if inlist(school_year, 2019, 2020, 2022) {
        drop if (attend <= 1 | member <= 20)
    } //excluding 2021 because attendance was not recorded properly in covid

    //generate attendance variables
    gen days_absent = member - attend
    gen abs_rate = days_absent/member
    gen excused_absences = days_absent - truant
    rename (attend member truant) (days_present days_enrolled unexcused_absences)

    // keep the school where students attended the most
    duplicates tag sasid, gen(dupe)
    bys sasid school_year (days_present): ///
        keep if days_present == days_present[_N]
    drop dupe

    //keep and order the needed variables
    keep sasid school_code days_enrolled days_present days_absent abs_rate ///
        excused_absences unexcused_absences graduated completed_mass_core school_year
```

```
66          order days_enrolled days_present days_absent abs_rate excused_absences ///
67              unexcused_absences, after(school_code)
68
69          //temporarily save the file
70          isid sasid
71          save "$intermediate\student_enrollment_attendance_`year'.dta", replace
72      }
73
74      //append all the files together
75      use "$intermediate\student_enrollment_attendance_17.dta", clear
76      append using "$intermediate\student_enrollment_attendance_18.dta"
77      append using "$intermediate\student_enrollment_attendance_19.dta"
78      append using "$intermediate\student_enrollment_attendance_20.dta"
79      append using "$intermediate\student_enrollment_attendance_21.dta"
80      append using "$intermediate\student_enrollment_attendance_22.dta"
81      append using "$intermediate\student_enrollment_attendance_23.dta"
82      append using "$intermediate\student_enrollment_attendance_24.dta"
83
84      //save file
85      isid sasid school_year
86      save "$clean\4. dese_school_enrollment_attendance.dta", replace
87
88
```

```
/*******************************************************************************
File Name: dese_8th_grade_mcas_scores
Author: Pierre M. Lucien
Purpose: creates a clean 8th grade test score file for students
*******************************************************************************/

//top matter
clear all
cap log close
set more off

//globals
global clean "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\clean_data"
global intermediate "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\intermediate_data"
global raw "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese data\raw data"

global parcc_15 "$raw\parcc_15.dta"
global parcc_16 "$raw\parcc_16.dta"
global mcas_13 "$raw\mcas_13.dta"
global mcas_14 "$raw\mcas_14.dta"
global mcas_15 "$raw\mcas_15.dta"
global mcas_16 "$raw\mcas_16.dta"
global mcas_17 "$raw\mcas_17.dta"
global mcas_18 "$raw\mcas_18.dta"
global mcas_19 "$raw\mcas_19.dta"

//load the parc files
forval year=15/16 {
    use SASID AssessmentYear AssessmentGrade Subject SummativeScaleScore ///
        using "${parcc_`year'}" if AssessmentGrade == "Grade 8" ///
        & regexm(Subject, "English Language Arts|Math"), clear

    //lower case the variables
    rename *, lower

    //generate test year
    gen test_year = substr(assessmentyear,6, 4)
    destring test_year, replace
    assert test_year == 20`year'
    drop assessmentyear

    //abbreviate subject
    replace subject = "ELA" if regexm(subject, "English Language Arts")
    replace subject = "Math" if regexm(subject, "Math")

    //drop variables missing scale score
    drop if mi(summativescalescore)

    //convert to MCAS scores
    gen parcc_mcass =.
    replace parcc_mcass = 208 if inrange(summativescalescore, 650, 662) & test_year == 2015 & subject == "ELA"
    replace parcc_mcass = 212 if inrange(summativescalescore, 662, 674) & test_year == 2015 & subject == "ELA"
    replace parcc_mcass = 214 if inrange(summativescalescore, 675, 683) & test_year == 2015 & subject == "ELA"
    replace parcc_mcass = 218 if inrange(summativescalescore, 683, 689) & test_year == 2015 & subject == "ELA"
    replace parcc_mcass = 218 if inrange(summativescalescore, 661, 695) & test_year == 2015 & subject == "ELA"
    replace parcc_mcass = 220 if inrange(summativescalescore, 695, 700) & test_year == 2015 & subject == "ELA"
    replace parcc_mcass = 222 if inrange(summativescalescore, 700, 703) & test_year == 2015 & subject == "ELA"
    replace parcc_mcass = 224 if inrange(summativescalescore, 703, 706) & test_year == 2015 & subject == "ELA"
    replace parcc_mcass = 226 if inrange(summativescalescore, 706, 709) & test_year == 2015
```

```
    & subject == "ELA"
60      replace parcc_mcass = 228 if inrange(summativescalescore, 709, 712) & test_year == 2015
    & subject == "ELA"
61      replace parcc_mcass = 230 if inrange(summativescalescore, 712, 714) & test_year == 2015
    & subject == "ELA"
62      replace parcc_mcass = 232 if inrange(summativescalescore, 714, 717) & test_year == 2015
    & subject == "ELA"
63      replace parcc_mcass = 232 if inrange(summativescalescore, 717, 719) & test_year == 2015
    & subject == "ELA"
64      replace parcc_mcass = 232 if inrange(summativescalescore, 719, 721) & test_year == 2015
    & subject == "ELA"
65      replace parcc mcass = 234 if inrange(summativescalescore, 721, 722) & test year == 2015
    & subject == "ELA"
66      replace parcc_mcass = 234 if inrange(summativescalescore, 722, 724) & test_year == 2015
    & subject == "ELA"
67      replace parcc_mcass = 236 if inrange(summativescalescore, 724, 726) & test_year == 2015
    & subject == "ELA"
68      replace parcc mcass = 238 if inrange(summativescalescore, 726, 727) & test year == 2015
    & subject == "ELA"
69      replace parcc_mcass = 240 if inrange(summativescalescore, 727, 729) & test_year == 2015
    & subject == "ELA"
70      replace parcc_mcass = 242 if inrange(summativescalescore, 729, 730) & test_year == 2015
    & subject == "ELA"
71      replace parcc_mcass = 242 if inrange(summativescalescore, 730, 732) & test_year == 2015
    & subject == "ELA"
72      replace parcc_mcass = 242 if inrange(summativescalescore, 732, 733) & test_year == 2015
    & subject == "ELA"
73      replace parcc_mcass = 242 if inrange(summativescalescore, 733, 735) & test_year == 2015
    & subject == "ELA"
74      replace parcc_mcass = 242 if inrange(summativescalescore, 735, 736) & test_year == 2015
    & subject == "ELA"
75      replace parcc_mcass = 242 if inrange(summativescalescore, 736, 737) & test_year == 2015
    & subject == "ELA"
76      replace parcc_mcass = 242 if inrange(summativescalescore, 737, 738) & test_year == 2015
    & subject == "ELA"
77      replace parcc_mcass = 244 if inrange(summativescalescore, 738, 739) & test_year == 2015
    & subject == "ELA"
78      replace parcc_mcass = 244 if inrange(summativescalescore, 739, 741) & test_year == 2015
    & subject == "ELA"
79      replace parcc_mcass = 244 if inrange(summativescalescore, 741, 742) & test_year == 2015
    & subject == "ELA"
80      replace parcc_mcass = 244 if inrange(summativescalescore, 742, 743) & test_year == 2015
    & subject == "ELA"
81      replace parcc_mcass = 244 if inrange(summativescalescore, 743, 744) & test_year == 2015
    & subject == "ELA"
82      replace parcc_mcass = 244 if inrange(summativescalescore, 744, 745) & test_year == 2015
    & subject == "ELA"
83      replace parcc_mcass = 246 if inrange(summativescalescore, 745, 746) & test_year == 2015
    & subject == "ELA"
84      replace parcc_mcass = 246 if inrange(summativescalescore, 746, 747) & test_year == 2015
    & subject == "ELA"
85      replace parcc_mcass = 248 if inrange(summativescalescore, 747, 748) & test_year == 2015
    & subject == "ELA"
86      replace parcc_mcass = 248 if inrange(summativescalescore, 748, 749) & test_year == 2015
    & subject == "ELA"
87      replace parcc_mcass = 248 if inrange(summativescalescore, 749, 750) & test_year == 2015
    & subject == "ELA"
88      replace parcc_mcass = 248 if inrange(summativescalescore, 750, 751) & test_year == 2015
    & subject == "ELA"
89      replace parcc_mcass = 248 if inrange(summativescalescore, 751, 752) & test_year == 2015
    & subject == "ELA"
90      replace parcc_mcass = 248 if inrange(summativescalescore, 752, 753) & test_year == 2015
    & subject == "ELA"
91      replace parcc_mcass = 248 if inrange(summativescalescore, 753, 754) & test_year == 2015
    & subject == "ELA"
92      replace parcc_mcass = 248 if inrange(summativescalescore, 754, 754) & test_year == 2015
    & subject == "ELA"
93      replace parcc mcass = 248 if inrange(summativescalescore, 755, 755) & test year == 2015
    & subject == "ELA"
94      replace parcc_mcass = 248 if inrange(summativescalescore, 755, 756) & test_year == 2015
```

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      & subject == "ELA"
 95       replace parcc_mcass = 248 if inrange(summativescalescore, 756, 757) & test_year == 2015
      & subject == "ELA"
 96       replace parcc_mcass = 248 if inrange(summativescalescore, 757, 758) & test_year == 2015
      & subject == "ELA"
 97       replace parcc_mcass = 250 if inrange(summativescalescore, 758, 759) & test_year == 2015
      & subject == "ELA"
 98       replace parcc_mcass = 250 if inrange(summativescalescore, 759, 760) & test_year == 2015
      & subject == "ELA"
 99       replace parcc_mcass = 250 if inrange(summativescalescore, 760, 761) & test_year == 2015
      & subject == "ELA"
100       replace parcc_mcass = 250 if inrange(summativescalescore, 761, 762) & test_year == 2015
      & subject == "ELA"
101       replace parcc_mcass = 250 if inrange(summativescalescore, 762, 762) & test_year == 2015
      & subject == "ELA"
102       replace parcc_mcass = 250 if inrange(summativescalescore, 762, 763) & test_year == 2015
      & subject == "ELA"
103       replace parcc_mcass = 252 if inrange(summativescalescore, 763, 764) & test_year == 2015
      & subject == "ELA"
104       replace parcc_mcass = 252 if inrange(summativescalescore, 764, 765) & test_year == 2015
      & subject == "ELA"
105       replace parcc_mcass = 252 if inrange(summativescalescore, 765, 766) & test_year == 2015
      & subject == "ELA"
106       replace parcc_mcass = 252 if inrange(summativescalescore, 766, 766) & test_year == 2015
      & subject == "ELA"
107       replace parcc_mcass = 252 if inrange(summativescalescore, 766, 767) & test_year == 2015
      & subject == "ELA"
108       replace parcc_mcass = 252 if inrange(summativescalescore, 767, 768) & test_year == 2015
      & subject == "ELA"
109       replace parcc_mcass = 254 if inrange(summativescalescore, 768, 769) & test_year == 2015
      & subject == "ELA"
110       replace parcc_mcass = 254 if inrange(summativescalescore, 769, 770) & test_year == 2015
      & subject == "ELA"
111       replace parcc_mcass = 254 if inrange(summativescalescore, 770, 771) & test_year == 2015
      & subject == "ELA"
112       replace parcc_mcass = 254 if inrange(summativescalescore, 771, 772) & test_year == 2015
      & subject == "ELA"
113       replace parcc_mcass = 254 if inrange(summativescalescore, 772, 772) & test_year == 2015
      & subject == "ELA"
114       replace parcc_mcass = 254 if inrange(summativescalescore, 772, 773) & test_year == 2015
      & subject == "ELA"
115       replace parcc_mcass = 256 if inrange(summativescalescore, 773, 774) & test_year == 2015
      & subject == "ELA"
116       replace parcc_mcass = 256 if inrange(summativescalescore, 774, 775) & test_year == 2015
      & subject == "ELA"
117       replace parcc_mcass = 256 if inrange(summativescalescore, 775, 776) & test_year == 2015
      & subject == "ELA"
118       replace parcc_mcass = 256 if inrange(summativescalescore, 776, 777) & test_year == 2015
      & subject == "ELA"
119       replace parcc_mcass = 256 if inrange(summativescalescore, 777, 778) & test_year == 2015
      & subject == "ELA"
120       replace parcc_mcass = 256 if inrange(summativescalescore, 778, 779) & test_year == 2015
      & subject == "ELA"
121       replace parcc_mcass = 258 if inrange(summativescalescore, 779, 779) & test_year == 2015
      & subject == "ELA"
122       replace parcc_mcass = 258 if inrange(summativescalescore, 779, 780) & test_year == 2015
      & subject == "ELA"
123       replace parcc_mcass = 258 if inrange(summativescalescore, 780, 781) & test_year == 2015
      & subject == "ELA"
124       replace parcc_mcass = 258 if inrange(summativescalescore, 781, 782) & test_year == 2015
      & subject == "ELA"
125       replace parcc_mcass = 258 if inrange(summativescalescore, 782, 783) & test_year == 2015
      & subject == "ELA"
126       replace parcc_mcass = 258 if inrange(summativescalescore, 783, 784) & test_year == 2015
      & subject == "ELA"
127       replace parcc_mcass = 258 if inrange(summativescalescore, 784, 785) & test_year == 2015
      & subject == "ELA"
128       replace parcc_mcass = 258 if inrange(summativescalescore, 785, 786) & test_year == 2015
      & subject == "ELA"
129       replace parcc_mcass = 260 if inrange(summativescalescore, 786, 787) & test_year == 2015
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      & subject == "ELA"
130       replace parcc_mcass = 260 if inrange(summativescalescore, 787, 788) & test_year == 2015
      & subject == "ELA"
131       replace parcc_mcass = 260 if inrange(summativescalescore, 788, 789) & test_year == 2015
      & subject == "ELA"
132       replace parcc_mcass = 260 if inrange(summativescalescore, 789, 791) & test_year == 2015
      & subject == "ELA"
133       replace parcc_mcass = 260 if inrange(summativescalescore, 791, 792) & test_year == 2015
      & subject == "ELA"
134       replace parcc_mcass = 262 if inrange(summativescalescore, 792, 793) & test_year == 2015
      & subject == "ELA"
135       replace parcc mcass = 262 if inrange(summativescalescore, 793, 794) & test year == 2015
      & subject == "ELA"
136       replace parcc_mcass = 262 if inrange(summativescalescore, 794, 796) & test_year == 2015
      & subject == "ELA"
137       replace parcc_mcass = 262 if inrange(summativescalescore, 796, 797) & test_year == 2015
      & subject == "ELA"
138       replace parcc mcass = 262 if inrange(summativescalescore, 797, 798) & test year == 2015
      & subject == "ELA"
139       replace parcc_mcass = 262 if inrange(summativescalescore, 798, 800) & test_year == 2015
      & subject == "ELA"
140       replace parcc_mcass = 262 if inrange(summativescalescore, 800, 802) & test_year == 2015
      & subject == "ELA"
141       replace parcc_mcass = 264 if inrange(summativescalescore, 802, 803) & test_year == 2015
      & subject == "ELA"
142       replace parcc_mcass = 264 if inrange(summativescalescore, 803, 805) & test_year == 2015
      & subject == "ELA"
143       replace parcc_mcass = 266 if inrange(summativescalescore, 805, 807) & test_year == 2015
      & subject == "ELA"
144       replace parcc_mcass = 266 if inrange(summativescalescore, 807, 810) & test_year == 2015
      & subject == "ELA"
145       replace parcc_mcass = 268 if inrange(summativescalescore, 810, 812) & test_year == 2015
      & subject == "ELA"
146       replace parcc_mcass = 268 if inrange(summativescalescore, 812, 815) & test_year == 2015
      & subject == "ELA"
147       replace parcc_mcass = 270 if inrange(summativescalescore, 815, 819) & test_year == 2015
      & subject == "ELA"
148       replace parcc_mcass = 272 if inrange(summativescalescore, 819, 823) & test_year == 2015
      & subject == "ELA"
149       replace parcc_mcass = 274 if inrange(summativescalescore, 823, 829) & test_year == 2015
      & subject == "ELA"
150       replace parcc_mcass = 276 if inrange(summativescalescore, 829, 843) & test_year == 2015
      & subject == "ELA"
151       replace parcc_mcass = 280 if inrange(summativescalescore, 843, 850) & test_year == 2015
      & subject == "ELA"
152       replace parcc_mcass = 204 if inrange(summativescalescore, 650, 653) & test_year == 2015
      & subject == "Math"
153       replace parcc_mcass = 208 if inrange(summativescalescore, 654, 667) & test_year == 2015
      & subject == "Math"
154       replace parcc_mcass = 212 if inrange(summativescalescore, 667, 675) & test_year == 2015
      & subject == "Math"
155       replace parcc_mcass = 212 if inrange(summativescalescore, 675, 681) & test_year == 2015
      & subject == "Math"
156       replace parcc_mcass = 214 if inrange(summativescalescore, 681, 684) & test_year == 2015
      & subject == "Math"
157       replace parcc_mcass = 214 if inrange(summativescalescore, 684, 688) & test_year == 2015
      & subject == "Math"
158       replace parcc_mcass = 216 if inrange(summativescalescore, 688, 690) & test_year == 2015
      & subject == "Math"
159       replace parcc_mcass = 216 if inrange(summativescalescore, 690, 694) & test_year == 2015
      & subject == "Math"
160       replace parcc_mcass = 216 if inrange(summativescalescore, 694, 695) & test_year == 2015
      & subject == "Math"
161       replace parcc_mcass = 216 if inrange(summativescalescore, 696, 699) & test_year == 2015
      & subject == "Math"
162       replace parcc_mcass = 216 if inrange(summativescalescore, 699, 700) & test_year == 2015
      & subject == "Math"
163       replace parcc mcass = 218 if inrange(summativescalescore, 700, 703) & test year == 2015
      & subject == "Math"
164       replace parcc_mcass = 218 if inrange(summativescalescore, 703, 704) & test_year == 2015
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      & subject == "Math"
165       replace parcc_mcass = 218 if inrange(summativescalescore, 704, 707) & test_year == 2015
      & subject == "Math"
166       replace parcc_mcass = 218 if inrange(summativescalescore, 707, 708) & test_year == 2015
      & subject == "Math"
167       replace parcc_mcass = 218 if inrange(summativescalescore, 708, 710) & test_year == 2015
      & subject == "Math"
168       replace parcc_mcass = 218 if inrange(summativescalescore, 710, 712) & test_year == 2015
      & subject == "Math"
169       replace parcc_mcass = 220 if inrange(summativescalescore, 712, 713) & test_year == 2015
      & subject == "Math"
170       replace parcc mcass = 220 if inrange(summativescalescore, 713, 714) & test year == 2015
      & subject == "Math"
171       replace parcc_mcass = 220 if inrange(summativescalescore, 715, 716) & test_year == 2015
      & subject == "Math"
172       replace parcc_mcass = 220 if inrange(summativescalescore, 716, 717) & test_year == 2015
      & subject == "Math"
173       replace parcc mcass = 220 if inrange(summativescalescore, 718, 719) & test year == 2015
      & subject == "Math"
174       replace parcc_mcass = 222 if inrange(summativescalescore, 719, 721) & test_year == 2015
      & subject == "Math"
175       replace parcc_mcass = 222 if inrange(summativescalescore, 721, 722) & test_year == 2015
      & subject == "Math"
176       replace parcc_mcass = 224 if inrange(summativescalescore, 722, 724) & test_year == 2015
      & subject == "Math"
177       replace parcc_mcass = 224 if inrange(summativescalescore, 724, 724) & test_year == 2015
      & subject == "Math"
178       replace parcc_mcass = 226 if inrange(summativescalescore, 724, 726) & test_year == 2015
      & subject == "Math"
179       replace parcc_mcass = 226 if inrange(summativescalescore, 726, 727) & test_year == 2015
      & subject == "Math"
180       replace parcc_mcass = 228 if inrange(summativescalescore, 727, 728) & test_year == 2015
      & subject == "Math"
181       replace parcc_mcass = 228 if inrange(summativescalescore, 728, 729) & test_year == 2015
      & subject == "Math"
182       replace parcc_mcass = 230 if inrange(summativescalescore, 729, 731) & test_year == 2015
      & subject == "Math"
183       replace parcc_mcass = 230 if inrange(summativescalescore, 731, 732) & test_year == 2015
      & subject == "Math"
184       replace parcc_mcass = 232 if inrange(summativescalescore, 732, 733) & test_year == 2015
      & subject == "Math"
185       replace parcc_mcass = 232 if inrange(summativescalescore, 733, 734) & test_year == 2015
      & subject == "Math"
186       replace parcc_mcass = 234 if inrange(summativescalescore, 734, 735) & test_year == 2015
      & subject == "Math"
187       replace parcc_mcass = 234 if inrange(summativescalescore, 736, 737) & test_year == 2015
      & subject == "Math"
188       replace parcc_mcass = 236 if inrange(summativescalescore, 737, 737) & test_year == 2015
      & subject == "Math"
189       replace parcc_mcass = 236 if inrange(summativescalescore, 738, 739) & test_year == 2015
      & subject == "Math"
190       replace parcc_mcass = 236 if inrange(summativescalescore, 739, 740) & test_year == 2015
      & subject == "Math"
191       replace parcc_mcass = 238 if inrange(summativescalescore, 740, 741) & test_year == 2015
      & subject == "Math"
192       replace parcc_mcass = 238 if inrange(summativescalescore, 741, 742) & test_year == 2015
      & subject == "Math"
193       replace parcc_mcass = 238 if inrange(summativescalescore, 742, 743) & test_year == 2015
      & subject == "Math"
194       replace parcc_mcass = 240 if inrange(summativescalescore, 743, 744) & test_year == 2015
      & subject == "Math"
195       replace parcc_mcass = 240 if inrange(summativescalescore, 744, 745) & test_year == 2015
      & subject == "Math"
196       replace parcc_mcass = 240 if inrange(summativescalescore, 745, 747) & test_year == 2015
      & subject == "Math"
197       replace parcc_mcass = 240 if inrange(summativescalescore, 747, 748) & test_year == 2015
      & subject == "Math"
198       replace parcc mcass = 242 if inrange(summativescalescore, 748, 749) & test year == 2015
      & subject == "Math"
199       replace parcc_mcass = 242 if inrange(summativescalescore, 749, 750) & test_year == 2015
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      & subject == "Math"
200       replace parcc_mcass = 242 if inrange(summativescalescore, 750, 751) & test_year == 2015
      & subject == "Math"
201       replace parcc_mcass = 244 if inrange(summativescalescore, 751, 752) & test_year == 2015
      & subject == "Math"
202       replace parcc_mcass = 244 if inrange(summativescalescore, 752, 753) & test_year == 2015
      & subject == "Math"
203       replace parcc_mcass = 246 if inrange(summativescalescore, 753, 754) & test_year == 2015
      & subject == "Math"
204       replace parcc_mcass = 246 if inrange(summativescalescore, 754, 755) & test_year == 2015
      & subject == "Math"
205       replace parcc mcass = 246 if inrange(summativescalescore, 755, 756) & test year == 2015
      & subject == "Math"
206       replace parcc_mcass = 248 if inrange(summativescalescore, 756, 757) & test_year == 2015
      & subject == "Math"
207       replace parcc_mcass = 248 if inrange(summativescalescore, 757, 758) & test_year == 2015
      & subject == "Math"
208       replace parcc mcass = 248 if inrange(summativescalescore, 758, 759) & test year == 2015
      & subject == "Math"
209       replace parcc_mcass = 250 if inrange(summativescalescore, 759, 760) & test_year == 2015
      & subject == "Math"
210       replace parcc_mcass = 250 if inrange(summativescalescore, 760, 761) & test_year == 2015
      & subject == "Math"
211       replace parcc_mcass = 250 if inrange(summativescalescore, 761, 762) & test_year == 2015
      & subject == "Math"
212       replace parcc_mcass = 252 if inrange(summativescalescore, 762, 763) & test_year == 2015
      & subject == "Math"
213       replace parcc_mcass = 252 if inrange(summativescalescore, 763, 764) & test_year == 2015
      & subject == "Math"
214       replace parcc_mcass = 252 if inrange(summativescalescore, 764, 765) & test_year == 2015
      & subject == "Math"
215       replace parcc_mcass = 252 if inrange(summativescalescore, 765, 766) & test_year == 2015
      & subject == "Math"
216       replace parcc_mcass = 252 if inrange(summativescalescore, 766, 767) & test_year == 2015
      & subject == "Math"
217       replace parcc_mcass = 252 if inrange(summativescalescore, 767, 768) & test_year == 2015
      & subject == "Math"
218       replace parcc_mcass = 252 if inrange(summativescalescore, 768, 769) & test_year == 2015
      & subject == "Math"
219       replace parcc_mcass = 254 if inrange(summativescalescore, 769, 770) & test_year == 2015
      & subject == "Math"
220       replace parcc_mcass = 254 if inrange(summativescalescore, 770, 771) & test_year == 2015
      & subject == "Math"
221       replace parcc_mcass = 254 if inrange(summativescalescore, 771, 772) & test_year == 2015
      & subject == "Math"
222       replace parcc_mcass = 254 if inrange(summativescalescore, 772, 773) & test_year == 2015
      & subject == "Math"
223       replace parcc_mcass = 256 if inrange(summativescalescore, 773, 774) & test_year == 2015
      & subject == "Math"
224       replace parcc_mcass = 256 if inrange(summativescalescore, 774, 775) & test_year == 2015
      & subject == "Math"
225       replace parcc_mcass = 258 if inrange(summativescalescore, 775, 776) & test_year == 2015
      & subject == "Math"
226       replace parcc_mcass = 260 if inrange(summativescalescore, 776, 777) & test_year == 2015
      & subject == "Math"
227       replace parcc_mcass = 260 if inrange(summativescalescore, 777, 779) & test_year == 2015
      & subject == "Math"
228       replace parcc_mcass = 260 if inrange(summativescalescore, 779, 780) & test_year == 2015
      & subject == "Math"
229       replace parcc_mcass = 260 if inrange(summativescalescore, 780, 781) & test_year == 2015
      & subject == "Math"
230       replace parcc mcass = 260 if inrange(summativescalescore, 781, 782) & test year == 2015
      & subject == "Math"
231       replace parcc_mcass = 260 if inrange(summativescalescore, 782, 784) & test_year == 2015
      & subject == "Math"
232       replace parcc_mcass = 260 if inrange(summativescalescore, 784, 785) & test_year == 2015
      & subject == "Math"
233       replace parcc mcass = 262 if inrange(summativescalescore, 785, 786) & test year == 2015
      & subject == "Math"
234       replace parcc_mcass = 262 if inrange(summativescalescore, 786, 788) & test_year == 2015
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      & subject == "Math"
235       replace parcc_mcass = 262 if inrange(summativescalescore, 788, 789) & test_year == 2015
      & subject == "Math"
236       replace parcc_mcass = 262 if inrange(summativescalescore, 789, 791) & test_year == 2015
      & subject == "Math"
237       replace parcc_mcass = 264 if inrange(summativescalescore, 791, 792) & test_year == 2015
      & subject == "Math"
238       replace parcc_mcass = 264 if inrange(summativescalescore, 792, 794) & test_year == 2015
      & subject == "Math"
239       replace parcc_mcass = 264 if inrange(summativescalescore, 794, 796) & test_year == 2015
      & subject == "Math"
240       replace parcc mcass = 264 if inrange(summativescalescore, 796, 797) & test year == 2015
      & subject == "Math"
241       replace parcc_mcass = 266 if inrange(summativescalescore, 797, 800) & test_year == 2015
      & subject == "Math"
242       replace parcc_mcass = 266 if inrange(summativescalescore, 800, 802) & test_year == 2015
      & subject == "Math"
243       replace parcc mcass = 266 if inrange(summativescalescore, 802, 804) & test year == 2015
      & subject == "Math"
244       replace parcc_mcass = 266 if inrange(summativescalescore, 804, 806) & test_year == 2015
      & subject == "Math"
245       replace parcc_mcass = 268 if inrange(summativescalescore, 806, 809) & test_year == 2015
      & subject == "Math"
246       replace parcc_mcass = 268 if inrange(summativescalescore, 809, 813) & test_year == 2015
      & subject == "Math"
247       replace parcc_mcass = 270 if inrange(summativescalescore, 813, 816) & test_year == 2015
      & subject == "Math"
248       replace parcc_mcass = 272 if inrange(summativescalescore, 816, 821) & test_year == 2015
      & subject == "Math"
249       replace parcc_mcass = 272 if inrange(summativescalescore, 821, 826) & test_year == 2015
      & subject == "Math"
250       replace parcc_mcass = 274 if inrange(summativescalescore, 826, 835) & test_year == 2015
      & subject == "Math"
251       replace parcc_mcass = 276 if inrange(summativescalescore, 835, 850) & test_year == 2015
      & subject == "Math"
252       replace parcc_mcass = 278 if inrange(summativescalescore, 850, 850) & test_year == 2015
      & subject == "Math"
253       replace parcc_mcass = 208 if inrange(summativescalescore, 650, 662) & test_year == 2016
      & subject == "ELA"
254       replace parcc_mcass = 212 if inrange(summativescalescore, 662, 675) & test_year == 2016
      & subject == "ELA"
255       replace parcc_mcass = 214 if inrange(summativescalescore, 675, 683) & test_year == 2016
      & subject == "ELA"
256       replace parcc_mcass = 218 if inrange(summativescalescore, 683, 690) & test_year == 2016
      & subject == "ELA"
257       replace parcc_mcass = 218 if inrange(summativescalescore, 690, 696) & test_year == 2016
      & subject == "ELA"
258       replace parcc_mcass = 220 if inrange(summativescalescore, 696, 700) & test_year == 2016
      & subject == "ELA"
259       replace parcc_mcass = 220 if inrange(summativescalescore, 700, 703) & test_year == 2016
      & subject == "ELA"
260       replace parcc_mcass = 222 if inrange(summativescalescore, 703, 707) & test_year == 2016
      & subject == "ELA"
261       replace parcc_mcass = 226 if inrange(summativescalescore, 707, 710) & test_year == 2016
      & subject == "ELA"
262       replace parcc_mcass = 228 if inrange(summativescalescore, 710, 712) & test_year == 2016
      & subject == "ELA"
263       replace parcc_mcass = 230 if inrange(summativescalescore, 712, 715) & test_year == 2016
      & subject == "ELA"
264       replace parcc_mcass = 230 if inrange(summativescalescore, 715, 717) & test_year == 2016
      & subject == "ELA"
265       replace parcc_mcass = 232 if inrange(summativescalescore, 717, 719) & test_year == 2016
      & subject == "ELA"
266       replace parcc_mcass = 232 if inrange(summativescalescore, 719, 721) & test_year == 2016
      & subject == "ELA"
267       replace parcc_mcass = 234 if inrange(summativescalescore, 721, 723) & test_year == 2016
      & subject == "ELA"
268       replace parcc mcass = 234 if inrange(summativescalescore, 723, 724) & test year == 2016
      & subject == "ELA"
269       replace parcc_mcass = 236 if inrange(summativescalescore, 724, 726) & test_year == 2016
```

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      & subject == "ELA"
270       replace parcc_mcass = 238 if inrange(summativescalescore, 726, 728) & test_year == 2016
      & subject == "ELA"
271       replace parcc_mcass = 238 if inrange(summativescalescore, 728, 729) & test_year == 2016
      & subject == "ELA"
272       replace parcc_mcass = 240 if inrange(summativescalescore, 729, 731) & test_year == 2016
      & subject == "ELA"
273       replace parcc_mcass = 240 if inrange(summativescalescore, 731, 732) & test_year == 2016
      & subject == "ELA"
274       replace parcc_mcass = 240 if inrange(summativescalescore, 732, 734) & test_year == 2016
      & subject == "ELA"
275       replace parcc_mcass = 242 if inrange(summativescalescore, 734, 735) & test_year == 2016
      & subject == "ELA"
276       replace parcc_mcass = 242 if inrange(summativescalescore, 735, 736) & test_year == 2016
      & subject == "ELA"
277       replace parcc_mcass = 242 if inrange(summativescalescore, 736, 737) & test_year == 2016
      & subject == "ELA"
278       replace parcc_mcass = 242 if inrange(summativescalescore, 737, 738) & test_year == 2016
      & subject == "ELA"
279       replace parcc_mcass = 244 if inrange(summativescalescore, 739, 740) & test_year == 2016
      & subject == "ELA"
280       replace parcc_mcass = 244 if inrange(summativescalescore, 740, 741) & test_year == 2016
      & subject == "ELA"
281       replace parcc_mcass = 244 if inrange(summativescalescore, 741, 742) & test_year == 2016
      & subject == "ELA"
282       replace parcc_mcass = 244 if inrange(summativescalescore, 742, 743) & test_year == 2016
      & subject == "ELA"
283       replace parcc_mcass = 244 if inrange(summativescalescore, 743, 744) & test_year == 2016
      & subject == "ELA"
284       replace parcc_mcass = 244 if inrange(summativescalescore, 744, 745) & test_year == 2016
      & subject == "ELA"
285       replace parcc_mcass = 246 if inrange(summativescalescore, 745, 746) & test_year == 2016
      & subject == "ELA"
286       replace parcc_mcass = 246 if inrange(summativescalescore, 746, 747) & test_year == 2016
      & subject == "ELA"
287       replace parcc_mcass = 246 if inrange(summativescalescore, 747, 748) & test_year == 2016
      & subject == "ELA"
288       replace parcc_mcass = 248 if inrange(summativescalescore, 748, 749) & test_year == 2016
      & subject == "ELA"
289       replace parcc_mcass = 248 if inrange(summativescalescore, 749, 750) & test_year == 2016
      & subject == "ELA"
290       replace parcc_mcass = 248 if inrange(summativescalescore, 750, 751) & test_year == 2016
      & subject == "ELA"
291       replace parcc_mcass = 248 if inrange(summativescalescore, 751, 752) & test_year == 2016
      & subject == "ELA"
292       replace parcc_mcass = 248 if inrange(summativescalescore, 752, 753) & test_year == 2016
      & subject == "ELA"
293       replace parcc_mcass = 248 if inrange(summativescalescore, 753, 754) & test_year == 2016
      & subject == "ELA"
294       replace parcc_mcass = 248 if inrange(summativescalescore, 754, 755) & test_year == 2016
      & subject == "ELA"
295       replace parcc_mcass = 248 if inrange(summativescalescore, 755, 756) & test_year == 2016
      & subject == "ELA"
296       replace parcc_mcass = 248 if inrange(summativescalescore, 756, 756) & test_year == 2016
      & subject == "ELA"
297       replace parcc_mcass = 248 if inrange(summativescalescore, 756, 756) & test_year == 2016
      & subject == "ELA"
298       replace parcc_mcass = 250 if inrange(summativescalescore, 756, 758) & test_year == 2016
      & subject == "ELA"
299       replace parcc_mcass = 250 if inrange(summativescalescore, 758, 759) & test_year == 2016
      & subject == "ELA"
300       replace parcc_mcass = 250 if inrange(summativescalescore, 759, 760) & test_year == 2016
      & subject == "ELA"
301       replace parcc_mcass = 250 if inrange(summativescalescore, 760, 761) & test_year == 2016
      & subject == "ELA"
302       replace parcc_mcass = 250 if inrange(summativescalescore, 761, 762) & test_year == 2016
      & subject == "ELA"
303       replace parcc_mcass = 250 if inrange(summativescalescore, 762, 762) & test_year == 2016
      & subject == "ELA"
304       replace parcc_mcass = 250 if inrange(summativescalescore, 762, 763) & test_year == 2016
```

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      & subject == "ELA"
305       replace parcc_mcass = 252 if inrange(summativescalescore, 763, 764) & test_year == 2016
      & subject == "ELA"
306       replace parcc_mcass = 252 if inrange(summativescalescore, 764, 765) & test_year == 2016
      & subject == "ELA"
307       replace parcc_mcass = 252 if inrange(summativescalescore, 765, 766) & test_year == 2016
      & subject == "ELA"
308       replace parcc_mcass = 252 if inrange(summativescalescore, 766, 766) & test_year == 2016
      & subject == "ELA"
309       replace parcc_mcass = 252 if inrange(summativescalescore, 766, 767) & test_year == 2016
      & subject == "ELA"
310       replace parcc_mcass = 252 if inrange(summativescalescore, 767, 768) & test_year == 2016
      & subject == "ELA"
311       replace parcc_mcass = 254 if inrange(summativescalescore, 768, 769) & test_year == 2016
      & subject == "ELA"
312       replace parcc_mcass = 254 if inrange(summativescalescore, 769, 770) & test_year == 2016
      & subject == "ELA"
313       replace parcc_mcass = 254 if inrange(summativescalescore, 770, 771) & test_year == 2016
      & subject == "ELA"
314       replace parcc_mcass = 254 if inrange(summativescalescore, 771, 772) & test_year == 2016
      & subject == "ELA"
315       replace parcc_mcass = 254 if inrange(summativescalescore, 772, 773) & test_year == 2016
      & subject == "ELA"
316       replace parcc_mcass = 254 if inrange(summativescalescore, 773, 773) & test_year == 2016
      & subject == "ELA"
317       replace parcc_mcass = 256 if inrange(summativescalescore, 773, 774) & test_year == 2016
      & subject == "ELA"
318       replace parcc_mcass = 256 if inrange(summativescalescore, 774, 775) & test_year == 2016
      & subject == "ELA"
319       replace parcc_mcass = 256 if inrange(summativescalescore, 775, 776) & test_year == 2016
      & subject == "ELA"
320       replace parcc_mcass = 256 if inrange(summativescalescore, 776, 777) & test_year == 2016
      & subject == "ELA"
321       replace parcc_mcass = 256 if inrange(summativescalescore, 777, 778) & test_year == 2016
      & subject == "ELA"
322       replace parcc_mcass = 256 if inrange(summativescalescore, 778, 779) & test_year == 2016
      & subject == "ELA"
323       replace parcc_mcass = 258 if inrange(summativescalescore, 779, 779) & test_year == 2016
      & subject == "ELA"
324       replace parcc_mcass = 258 if inrange(summativescalescore, 779, 780) & test_year == 2016
      & subject == "ELA"
325       replace parcc_mcass = 258 if inrange(summativescalescore, 780, 781) & test_year == 2016
      & subject == "ELA"
326       replace parcc_mcass = 258 if inrange(summativescalescore, 781, 782) & test_year == 2016
      & subject == "ELA"
327       replace parcc_mcass = 258 if inrange(summativescalescore, 782, 783) & test_year == 2016
      & subject == "ELA"
328       replace parcc_mcass = 258 if inrange(summativescalescore, 783, 784) & test_year == 2016
      & subject == "ELA"
329       replace parcc_mcass = 260 if inrange(summativescalescore, 784, 785) & test_year == 2016
      & subject == "ELA"
330       replace parcc_mcass = 260 if inrange(summativescalescore, 785, 786) & test_year == 2016
      & subject == "ELA"
331       replace parcc_mcass = 260 if inrange(summativescalescore, 786, 787) & test_year == 2016
      & subject == "ELA"
332       replace parcc_mcass = 260 if inrange(summativescalescore, 787, 788) & test_year == 2016
      & subject == "ELA"
333       replace parcc_mcass = 260 if inrange(summativescalescore, 788, 789) & test_year == 2016
      & subject == "ELA"
334       replace parcc_mcass = 260 if inrange(summativescalescore, 789, 791) & test_year == 2016
      & subject == "ELA"
335       replace parcc_mcass = 260 if inrange(summativescalescore, 791, 792) & test_year == 2016
      & subject == "ELA"
336       replace parcc_mcass = 262 if inrange(summativescalescore, 792, 793) & test_year == 2016
      & subject == "ELA"
337       replace parcc_mcass = 262 if inrange(summativescalescore, 793, 794) & test_year == 2016
      & subject == "ELA"
338       replace parcc_mcass = 262 if inrange(summativescalescore, 794, 796) & test_year == 2016
      & subject == "ELA"
339       replace parcc_mcass = 262 if inrange(summativescalescore, 796, 797) & test_year == 2016
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      & subject == "ELA"
340       replace parcc_mcass = 262 if inrange(summativescalescore, 797, 798) & test_year == 2016
      & subject == "ELA"
341       replace parcc_mcass = 262 if inrange(summativescalescore, 798, 800) & test_year == 2016
      & subject == "ELA"
342       replace parcc_mcass = 264 if inrange(summativescalescore, 800, 802) & test_year == 2016
      & subject == "ELA"
343       replace parcc_mcass = 264 if inrange(summativescalescore, 802, 803) & test_year == 2016
      & subject == "ELA"
344       replace parcc_mcass = 264 if inrange(summativescalescore, 803, 805) & test_year == 2016
      & subject == "ELA"
345       replace parcc_mcass = 268 if inrange(summativescalescore, 805, 807) & test_year == 2016
      & subject == "ELA"
346       replace parcc_mcass = 268 if inrange(summativescalescore, 807, 810) & test_year == 2016
      & subject == "ELA"
347       replace parcc_mcass = 268 if inrange(summativescalescore, 810, 812) & test_year == 2016
      & subject == "ELA"
348       replace parcc_mcass = 268 if inrange(summativescalescore, 812, 815) & test_year == 2016
      & subject == "ELA"
349       replace parcc_mcass = 272 if inrange(summativescalescore, 815, 819) & test_year == 2016
      & subject == "ELA"
350       replace parcc_mcass = 274 if inrange(summativescalescore, 819, 823) & test_year == 2016
      & subject == "ELA"
351       replace parcc_mcass = 278 if inrange(summativescalescore, 823, 830) & test_year == 2016
      & subject == "ELA"
352       replace parcc_mcass = 280 if inrange(summativescalescore, 830, 843) & test_year == 2016
      & subject == "ELA"
353       replace parcc_mcass = 280 if inrange(summativescalescore, 843, 850) & test_year == 2016
      & subject == "ELA"
354       replace parcc_mcass = 204 if inrange(summativescalescore, 650, 655) & test_year == 2016
      & subject == "Math"
355       replace parcc_mcass = 208 if inrange(summativescalescore, 655, 669) & test_year == 2016
      & subject == "Math"
356       replace parcc_mcass = 212 if inrange(summativescalescore, 669, 676) & test_year == 2016
      & subject == "Math"
357       replace parcc_mcass = 212 if inrange(summativescalescore, 676, 681) & test_year == 2016
      & subject == "Math"
358       replace parcc_mcass = 214 if inrange(summativescalescore, 682, 685) & test_year == 2016
      & subject == "Math"
359       replace parcc_mcass = 214 if inrange(summativescalescore, 685, 688) & test_year == 2016
      & subject == "Math"
360       replace parcc_mcass = 216 if inrange(summativescalescore, 688, 692) & test_year == 2016
      & subject == "Math"
361       replace parcc_mcass = 216 if inrange(summativescalescore, 692, 694) & test_year == 2016
      & subject == "Math"
362       replace parcc_mcass = 216 if inrange(summativescalescore, 694, 697) & test_year == 2016
      & subject == "Math"
363       replace parcc_mcass = 216 if inrange(summativescalescore, 697, 699) & test_year == 2016
      & subject == "Math"
364       replace parcc_mcass = 216 if inrange(summativescalescore, 699, 701) & test_year == 2016
      & subject == "Math"
365       replace parcc_mcass = 218 if inrange(summativescalescore, 701, 704) & test_year == 2016
      & subject == "Math"
366       replace parcc_mcass = 218 if inrange(summativescalescore, 704, 705) & test_year == 2016
      & subject == "Math"
367       replace parcc_mcass = 218 if inrange(summativescalescore, 705, 707) & test_year == 2016
      & subject == "Math"
368       replace parcc_mcass = 218 if inrange(summativescalescore, 708, 709) & test_year == 2016
      & subject == "Math"
369       replace parcc_mcass = 218 if inrange(summativescalescore, 709, 711) & test_year == 2016
      & subject == "Math"
370       replace parcc_mcass = 218 if inrange(summativescalescore, 711, 712) & test_year == 2016
      & subject == "Math"
371       replace parcc_mcass = 220 if inrange(summativescalescore, 712, 713) & test_year == 2016
      & subject == "Math"
372       replace parcc_mcass = 220 if inrange(summativescalescore, 713, 715) & test_year == 2016
      & subject == "Math"
373       replace parcc_mcass = 220 if inrange(summativescalescore, 715, 717) & test_year == 2016
      & subject == "Math"
374       replace parcc_mcass = 220 if inrange(summativescalescore, 717, 718) & test_year == 2016
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```
      & subject == "Math"
375       replace parcc_mcass = 220 if inrange(summativescalescore, 718, 720) & test_year == 2016
      & subject == "Math"
376       replace parcc_mcass = 222 if inrange(summativescalescore, 720, 721) & test_year == 2016
      & subject == "Math"
377       replace parcc_mcass = 222 if inrange(summativescalescore, 721, 722) & test_year == 2016
      & subject == "Math"
378       replace parcc_mcass = 224 if inrange(summativescalescore, 722, 724) & test_year == 2016
      & subject == "Math"
379       replace parcc_mcass = 224 if inrange(summativescalescore, 724, 725) & test_year == 2016
      & subject == "Math"
380       replace parcc mcass = 226 if inrange(summativescalescore, 725, 726) & test year == 2016
      & subject == "Math"
381       replace parcc_mcass = 226 if inrange(summativescalescore, 726, 728) & test_year == 2016
      & subject == "Math"
382       replace parcc_mcass = 228 if inrange(summativescalescore, 728, 729) & test_year == 2016
      & subject == "Math"
383       replace parcc mcass = 230 if inrange(summativescalescore, 729, 730) & test year == 2016
      & subject == "Math"
384       replace parcc_mcass = 230 if inrange(summativescalescore, 730, 731) & test_year == 2016
      & subject == "Math"
385       replace parcc_mcass = 230 if inrange(summativescalescore, 731, 733) & test_year == 2016
      & subject == "Math"
386       replace parcc_mcass = 232 if inrange(summativescalescore, 733, 734) & test_year == 2016
      & subject == "Math"
387       replace parcc_mcass = 232 if inrange(summativescalescore, 734, 734) & test_year == 2016
      & subject == "Math"
388       replace parcc_mcass = 234 if inrange(summativescalescore, 734, 736) & test_year == 2016
      & subject == "Math"
389       replace parcc_mcass = 234 if inrange(summativescalescore, 736, 737) & test_year == 2016
      & subject == "Math"
390       replace parcc_mcass = 236 if inrange(summativescalescore, 737, 738) & test_year == 2016
      & subject == "Math"
391       replace parcc_mcass = 236 if inrange(summativescalescore, 738, 739) & test_year == 2016
      & subject == "Math"
392       replace parcc_mcass = 238 if inrange(summativescalescore, 739, 740) & test_year == 2016
      & subject == "Math"
393       replace parcc_mcass = 238 if inrange(summativescalescore, 740, 742) & test_year == 2016
      & subject == "Math"
394       replace parcc_mcass = 240 if inrange(summativescalescore, 742, 742) & test_year == 2016
      & subject == "Math"
395       replace parcc_mcass = 240 if inrange(summativescalescore, 743, 744) & test_year == 2016
      & subject == "Math"
396       replace parcc_mcass = 240 if inrange(summativescalescore, 744, 745) & test_year == 2016
      & subject == "Math"
397       replace parcc_mcass = 240 if inrange(summativescalescore, 745, 746) & test_year == 2016
      & subject == "Math"
398       replace parcc_mcass = 240 if inrange(summativescalescore, 746, 747) & test_year == 2016
      & subject == "Math"
399       replace parcc_mcass = 242 if inrange(summativescalescore, 747, 748) & test_year == 2016
      & subject == "Math"
400       replace parcc_mcass = 242 if inrange(summativescalescore, 748, 749) & test_year == 2016
      & subject == "Math"
401       replace parcc_mcass = 242 if inrange(summativescalescore, 749, 750) & test_year == 2016
      & subject == "Math"
402       replace parcc_mcass = 244 if inrange(summativescalescore, 750, 751) & test_year == 2016
      & subject == "Math"
403       replace parcc_mcass = 244 if inrange(summativescalescore, 751, 752) & test_year == 2016
      & subject == "Math"
404       replace parcc_mcass = 246 if inrange(summativescalescore, 752, 753) & test_year == 2016
      & subject == "Math"
405       replace parcc_mcass = 246 if inrange(summativescalescore, 753, 754) & test_year == 2016
      & subject == "Math"
406       replace parcc_mcass = 246 if inrange(summativescalescore, 754, 755) & test_year == 2016
      & subject == "Math"
407       replace parcc_mcass = 248 if inrange(summativescalescore, 755, 756) & test_year == 2016
      & subject == "Math"
408       replace parcc mcass = 248 if inrange(summativescalescore, 756, 757) & test year == 2016
      & subject == "Math"
409       replace parcc_mcass = 248 if inrange(summativescalescore, 757, 758) & test_year == 2016
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```
      & subject == "Math"
410       replace parcc_mcass = 250 if inrange(summativescalescore, 758, 759) & test_year == 2016
      & subject == "Math"
411       replace parcc_mcass = 250 if inrange(summativescalescore, 759, 760) & test_year == 2016
      & subject == "Math"
412       replace parcc_mcass = 250 if inrange(summativescalescore, 760, 761) & test_year == 2016
      & subject == "Math"
413       replace parcc_mcass = 252 if inrange(summativescalescore, 761, 762) & test_year == 2016
      & subject == "Math"
414       replace parcc_mcass = 252 if inrange(summativescalescore, 762, 763) & test_year == 2016
      & subject == "Math"
415       replace parcc mcass = 252 if inrange(summativescalescore, 763, 764) & test year == 2016
      & subject == "Math"
416       replace parcc_mcass = 252 if inrange(summativescalescore, 764, 765) & test_year == 2016
      & subject == "Math"
417       replace parcc_mcass = 252 if inrange(summativescalescore, 765, 766) & test_year == 2016
      & subject == "Math"
418       replace parcc mcass = 252 if inrange(summativescalescore, 766, 767) & test year == 2016
      & subject == "Math"
419       replace parcc_mcass = 254 if inrange(summativescalescore, 767, 768) & test_year == 2016
      & subject == "Math"
420       replace parcc_mcass = 254 if inrange(summativescalescore, 768, 769) & test_year == 2016
      & subject == "Math"
421       replace parcc_mcass = 254 if inrange(summativescalescore, 769, 770) & test_year == 2016
      & subject == "Math"
422       replace parcc_mcass = 256 if inrange(summativescalescore, 770, 771) & test_year == 2016
      & subject == "Math"
423       replace parcc_mcass = 256 if inrange(summativescalescore, 771, 772) & test_year == 2016
      & subject == "Math"
424       replace parcc_mcass = 256 if inrange(summativescalescore, 772, 773) & test_year == 2016
      & subject == "Math"
425       replace parcc_mcass = 258 if inrange(summativescalescore, 773, 774) & test_year == 2016
      & subject == "Math"
426       replace parcc_mcass = 258 if inrange(summativescalescore, 774, 775) & test_year == 2016
      & subject == "Math"
427       replace parcc_mcass = 260 if inrange(summativescalescore, 775, 776) & test_year == 2016
      & subject == "Math"
428       replace parcc_mcass = 260 if inrange(summativescalescore, 776, 778) & test_year == 2016
      & subject == "Math"
429       replace parcc_mcass = 260 if inrange(summativescalescore, 778, 779) & test_year == 2016
      & subject == "Math"
430       replace parcc_mcass = 260 if inrange(summativescalescore, 779, 780) & test_year == 2016
      & subject == "Math"
431       replace parcc_mcass = 260 if inrange(summativescalescore, 780, 781) & test_year == 2016
      & subject == "Math"
432       replace parcc_mcass = 260 if inrange(summativescalescore, 781, 782) & test_year == 2016
      & subject == "Math"
433       replace parcc_mcass = 260 if inrange(summativescalescore, 782, 784) & test_year == 2016
      & subject == "Math"
434       replace parcc_mcass = 262 if inrange(summativescalescore, 784, 785) & test_year == 2016
      & subject == "Math"
435       replace parcc_mcass = 262 if inrange(summativescalescore, 785, 786) & test_year == 2016
      & subject == "Math"
436       replace parcc_mcass = 262 if inrange(summativescalescore, 786, 788) & test_year == 2016
      & subject == "Math"
437       replace parcc_mcass = 262 if inrange(summativescalescore, 788, 789) & test_year == 2016
      & subject == "Math"
438       replace parcc_mcass = 264 if inrange(summativescalescore, 789, 791) & test_year == 2016
      & subject == "Math"
439       replace parcc_mcass = 264 if inrange(summativescalescore, 791, 792) & test_year == 2016
      & subject == "Math"
440       replace parcc_mcass = 264 if inrange(summativescalescore, 792, 794) & test_year == 2016
      & subject == "Math"
441       replace parcc_mcass = 266 if inrange(summativescalescore, 794, 796) & test_year == 2016
      & subject == "Math"
442       replace parcc_mcass = 266 if inrange(summativescalescore, 796, 797) & test_year == 2016
      & subject == "Math"
443       replace parcc mcass = 268 if inrange(summativescalescore, 798, 800) & test year == 2016
      & subject == "Math"
444       replace parcc_mcass = 268 if inrange(summativescalescore, 800, 802) & test_year == 2016
```

```
    & subject == "Math"
445     replace parcc_mcass = 268 if inrange(summativescalescore, 802, 804) & test_year == 2016
    & subject == "Math"
446     replace parcc_mcass = 270 if inrange(summativescalescore, 804, 807) & test_year == 2016
    & subject == "Math"
447     replace parcc_mcass = 270 if inrange(summativescalescore, 807, 809) & test_year == 2016
    & subject == "Math"
448     replace parcc_mcass = 272 if inrange(summativescalescore, 809, 813) & test_year == 2016
    & subject == "Math"
449     replace parcc_mcass = 274 if inrange(summativescalescore, 813, 816) & test_year == 2016
    & subject == "Math"
450     replace parcc mcass = 274 if inrange(summativescalescore, 816, 821) & test year == 2016
    & subject == "Math"
451     replace parcc_mcass = 276 if inrange(summativescalescore, 821, 826) & test_year == 2016
    & subject == "Math"
452     replace parcc_mcass = 276 if inrange(summativescalescore, 826, 836) & test_year == 2016
    & subject == "Math"
453     replace parcc mcass = 278 if inrange(summativescalescore, 836, 850) & test year == 2016
    & subject == "Math"
454     replace parcc_mcass = 280 if inrange(summativescalescore, 850, 850) & test_year == 2016
    & subject == "Math"
455     assert !mi(parcc_mcass)
456
457     //reshape the file
458     keep sasid subject parcc_mcass test_year
459     reshape wide parcc_mcass, i(sasid test_year) j(subject) string
460
461     //save the file
462     isid sasid
463     save "$intermediate\parcc_mcass_conversion_`year'.dta", replace
464
465 }
466
467 //load the legacy mcas files
468 forval year=13/16 {
469     use adminyear grade sasid escaleds mscaleds using "${mcas_`year'}" ///
470         if grade == "08" & !mi(sasid) & adminyear == "20`year'", clear
471
472     //keep or generate needed variables
473     rename adminyear test_year
474     destring test_year, replace
475     keep sasid test_year escaleds mscaleds
476     if inrange(test year, 2015, 2016) {
477         //merge with
478         merge 1:1 sasid test_year using "$intermediate\parcc_mcass_conversion_`year'.dta"
479
480         //replace the missing scores
481         replace escaleds = parcc_mcassELA  if mi(escaleds)
482         replace mscaleds = parcc_mcassMath if mi(mscaleds)
483     }
484
485     //drop if missing both ELA and Math
486     keep sasid escaleds mscaleds test_year
487     drop if mi(escaleds) & mi(mscaleds)
488
489     //save the file
490     isid sasid
491     save "$intermediate\test_scores_`year'.dta", replace
492 }
493
494 //load the next gen mcas files
495 forval year=17/19 {
496     use adminyear sasid grade escaleds mscaleds using "${mcas_`year'}" ///
497         if grade == "08" & !mi(sasid) & adminyear == "20`year'", clear
498
499     //rename and numerize school year
500     rename adminyear test_year
501     destring test year, replace
502     keep sasid test_year escaleds mscaleds
503
```

```
504         //drop if missing both ELA and Math
505         drop if mi(escaleds) & mi(mscaleds)
506
507         //save the file
508         isid sasid
509         save "$intermediate\test_scores_`year'.dta", replace
510     }
511
512     //append the years
513     use "$intermediate\test_scores_13.dta",clear
514     append using "$intermediate\test_scores_14.dta"
515     append using "$intermediate\test_scores_15.dta"
516     append using "$intermediate\test_scores_16.dta"
517     append using "$intermediate\test_scores_17.dta"
518     append using "$intermediate\test_scores_18.dta"
519     append using "$intermediate\test_scores_19.dta"
520
521
522     //replace missing scores with score from non-missing year
523     // bys sasid (escaleds): replace escaleds = escaleds[1] if escaleds[_N] == .
524     // bys sasid (mscaleds): replace mscaleds = mscaleds[1] if mscaleds[_N] == .
525     duplicates drop
526
527     //keep first test
528     bys sasid (test_year): keep if test_year== test_year[1]
529
530     //keep necessary variables
531     keep sasid test_year escaleds mscaleds
532
533
534     //rename the variables
535     rename (escaleds  mscaleds) (ela math)
536
537     //confirm next gen starts in 2017
538     foreach subject in ela math {
539         assert inrange(`subject', 200, 280) if test_year < 2017 & !mi(`subject')
540         assert inrange(`subject', 440, 560) if test_year > 2016 & !mi(`subject')
541
542     }
543
544     //create separate fields for legacy and next generation MCAS
545     foreach subject in ela math {
546     gen legacy `subject' = .
547     replace legacy_`subject' = `subject' if inrange(`subject', 200, 280)
548     gen next_gen_`subject' = .
549     replace next_gen_`subject' = `subject' if inrange(`subject', 440, 560)
550     }
551     bys test_year: sum next_gen*
552     bys test_year: sum legacy*
553
554     //gen subject stratas
555     foreach var of varlist ela math {
556         gen `var'_strata = .
557         replace `var'_strata = 0 if mi(`var')
558         replace `var'_strata = 1 if inrange(`var', 200, 218) | inrange(`var', 440, 469)
559         replace `var'_strata = 2 if inrange(`var', 220, 238) | inrange(`var', 470, 499)
560         replace `var'_strata = 3 if inrange(`var', 240, 258) | inrange(`var', 500, 529)
561         replace `var'_strata = 4 if inrange(`var', 260, 280) | inrange(`var', 530, 560)
562
563         //gen proficient dumies
564         gen missing_`var' = (`var'_strata == 0)
565         gen failing_`var' = (`var'_strata == 1)
566         gen needing_`var' = (`var'_strata == 2)
567         gen meeting_`var' = (`var'_strata == 3)
568         gen exceeding_`var' = (`var'_strata == 4)
569
570     }
571
572     //label subject strata
573     label define ela_strata ///
```

```
574         0 "Missing ELA Test" ///
575         1 "Not Meeting ELA" ///
576         2 "Partially Meeting ELA" ///
577         3 "Meeting ELA" ///
578         4 "Exceeding ELA"
579     label values ela_strata ela_strata
580
581     label define math_strata ///
582         0 "Missing Math Test" ///
583         1 "Not Meeting Math" ///
584         2 "Partially Meeting Math" ///
585         3 "Meeting Math" ///
586         4 "Exceeding Math"
587     label values math_strata math_strata
588
589     //save the file
590     isid sasid
591     save "$clean\5. dese 8th grade mcas scores.dta", replace
592
```

```
/*******************************************************************************
File Name: dese_8th_grade_attendance_suspensions
Author: Pierre M. Lucien
Purpose: creates a clean 8th grade attendance and suspension file for students
*******************************************************************************/

//top matter
clear all
cap log close
set more off

//globals
global clean "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\clean_data"
global intermediate "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\intermediate_data"
global raw "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese data\raw data"

//create loops for each year
forval year =15/19{
    //load attendance data
    use SASID ATTEND MEMBER GRADE ENSTAT using "$raw\sims_`year'.dta" ///
        if GRADE == "08" & ATTEND != 555 & inlist(ENSTAT, "01", "04", "10", "11"), clear

    //lower case the variables
    rename *, lower

    //confirm variables are not missing values
    foreach var of varlist sasid member attend {
        assert !mi(`var')
    }

    //generate days absent and absence rate
    gen eighth_days_absent = member-attend
    gen eighth_abs_rate = eighth_days_absent/member

    //confirm uniqueness
    isid sasid

    //temporarily save the
    tempfile attendance_`year'
    save `attendance `year''

    //load suspension data
    use SASID DAT_DESC GRADE DAYS_MISSED using "$raw\ssdr_`year'.dta" if GRADE == "08" & ///
        regexm(DAT_DESC, "suspension"), clear

    //lower case the variables
    rename *, lower

    //collapse suspensdions
    collapse eighth_days_suspended=days_missed, by(sasid)

    //confirm uniqueness
    isid sasid

    //merge attendance and suspensions
    merge 1:1 sasid using `attendance_`year'', keep(2 3) nogen

    //replace missing days suspended to 0
    replace eighth_days_suspended = 0 if mi(eighth_days_suspended)

    //generate days suspended
    gen eighth_susp_rate = eighth_days_suspended/member

    //generate attendance and suspension variables for research
    gen eighth chronic absentee = ((eighth abs rate >= .10) & (!mi(eighth abs rate)))
    gen eighth_ever_suspended = ((eighth_days_suspended > 0) & (!mi(eighth_days_suspended)))

```

```
68        //generate school year
69        gen school_year = 20`year'
70
71        //keep necessary variables
72        keep sasid school_year eighth_*
73
74        //temporarily save each year
75        save "$intermediate\attendance_suspensions_`year'.dta", replace
76    }
77
78    //append all the files together
79    use "$intermediate\attendance suspensions 15.dta"
80    append using "$intermediate\attendance_suspensions_16.dta"
81    append using "$intermediate\attendance_suspensions_17.dta"
82    append using "$intermediate\attendance_suspensions_18.dta"
83    append using "$intermediate\attendance_suspensions_19.dta"
84
85    //keep latest 8th grade record for students who show up more than 1 year
86    bys sasid (school_year): keep if school_year == school_year[_N]
87
88    //assure not missing values
89    foreach var of varlist _all {
90        assert !mi(`var')
91    }
92
93    //save the file
94    isid sasid
95    save "$clean\6. dese_8th_grade_attendance_suspensions.dta", replace
96
97
```

```
/*******************************************************************************
File Name: dese_ec_icp_treatment_assignments
Author: Pierre M. Lucien
Purpose: creates a clean treatment assignment file for EC and ICP participants
*******************************************************************************/

//top matter
clear all
cap log close
set more off

//globals
global clean "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\clean_data"
global intermediate "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\intermediate_data"
global raw "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese data\raw data"

global sims_19 "$raw\sims_19.dta"
global sims_20 "$raw\sims_20.dta"
global sims_21 "$raw\sims_21.dta"
global sims_22 "$raw\sims_22.dta"
global sims_23 "$raw\sims_23.dta"
global sims_24 "$raw\sims_24.dta"

//loop all the years
forval year=19/24 {

    //load the needed variables from SIMS files
    use SASID SCHOOL ATTEND GRADE ENSTAT HQCPP_TYPE_CODE HQCPP_PARTICIPATION_CODE PERIOD_NAME using "${sims_`year'}" if ///
        inlist(GRADE, "09", "10", "11", "12") & inlist(ENSTAT, "01", "04", "10", "11") & ATTEND != 555, clear

    //rename the variables to lower case
    rename *, lower

    //keep needed variables
    keep sasid hqcpp_type_code hqcpp_participation_code period_name school grade

    //rename the school code variable
    rename school school code

    //explore early college participation indicators
    tab hqcpp_type_code

    //drop duplicates
    duplicates drop

    //generate school year
    tab period_name
    gen school_year = substr(period_name, strpos(period_name,"F") + 2, 4)
    destring school_year, replace
    drop period_name

    //generate EC flags
    gen ec_participant = (hqcpp_type_code == "02") ///
        if !mi(hqcpp_type_code)
    bys school_code: egen ec_school = max(ec_participant) ///
        if !mi(ec_participant)
    gen ec_school_mate = (ec_school & !ec_participant)
    gen ec_state_peer = (!ec_school)

    // label EC values
    label define ec_participant ///
        0 "Non-EC" ///
        1 "EC"
    label values ec_participant ec_participant

```

```
66        //generate IP flags
67        gen ip_participant = (hqcpp_type_code == "01") ///
68            if !mi(hqcpp_type_code)
69        bys school_code: egen ip_school = max(ip_participant) ///
70            if !mi(ip_participant)
71        gen ip_school_mate = (ip_school & !ip_participant)
72        gen ip_state_peer = (!ip_school)
73
74        // label IP values
75        label define ip_participant ///
76            0 "Non-ICP" ///
77            1 "ICP"
78        label values ip_participant ip_participant
79
80        //generate first EC comparison group
81        gen ec_comparison_group_1 = ""
82        replace ec_comparison_group_1 = "EC" if ec_participant
83        replace ec comparison group 1 = "School Peer" if ec school mate
84        replace ec_comparison_group_1 = "State" if ec_state_peer
85
86        //generate first IP comparison group
87        gen ip_comparison_group_1 = ""
88        replace ip_comparison_group_1 = "ICP" if ip_participant
89        replace ip_comparison_group_1 = "School Peer" if ip_school_mate
90        replace ip_comparison_group_1 = "State" if ip_state_peer
91
92        //drop excess variables and records
93        drop hqcpp_type_code school_code
94        duplicates drop
95
96        //temporarily save the different years
97        isid sasid
98        save "$intermediate\ec_icp_treatment_assignment_`year'.dta", replace
99    }
100
101   // append the years
102   use "$intermediate\ec_icp_treatment_assignment_19.dta"
103   append using "$intermediate\ec_icp_treatment_assignment_20.dta"
104   append using "$intermediate\ec_icp_treatment_assignment_21.dta"
105   append using "$intermediate\ec_icp_treatment_assignment_22.dta"
106   append using "$intermediate\ec_icp_treatment_assignment_23.dta"
107   append using "$intermediate\ec_icp_treatment_assignment_24.dta"
108
109   //generrate various participation indicators
110   destring grade, gen(grade_num)
111   foreach x in ec ip {
112       forval y =9/12 {
113           gen `x'_participant_`y' = (`x'_participant == 1 & grade_num == `y')
114           bys sasid (`x'_participant_`y'): replace `x'_participant_`y' = `x'_participant_`y'[
      _N]
115       }
116
117       gen ever_`x' = (`x'_participant_9 == 1 | `x'_participant_10 == 1 | ///
118           `x'_participant_11 == 1 | `x'_participant_12 == 1)
119   }
120
121   drop grade_num
122
123   //save the file
124   isid sasid school_year
125   save "$clean\7. dese_ec_icp_treatment_assignments.dta", replace
126
```

```
/*******************************************************************************
File Name: dese_nsc_college_enrollment_persistence
Author: Pierre M. Lucien
Purpose: creates a file indicating if a student enrolled and persisted in college
*******************************************************************************/

//top matter
clear all
cap log close
set more off

//globals
global clean "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\clean_data"
global intermediate "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\intermediate_data"
global raw "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese data\raw data"
global nsc "$raw\nsc_grad_22.dta"


//load the file
use "${nsc}", clear
rename *, lower

//gen sasid
cap confirm variable sasid
if _rc {
    gen sasid = substr(your_unique_identifier, 1, 10)
    order sasid
}

else {
    tostring sasid, replace
}


//keep proper enrollment records
cap rename recordfoundyn recordfound
keep if recordfound == "Y"

//fix enrollment start
cap confirm variable enrollmentbegin
    if _rc {
        rename enrollment_begin enrollmentbegin
    }

tostring enrollmentbegin, replace
gen begin = date(enrollmentbegin, "YMD")
format begin %td

//fix enrollment end
cap confirm variable enrollmentend
    if _rc {
        rename enrollment_end enrollmentend
    }

tostring enrollmentend, replace
gen end = date(enrollmentend, "YMD")
format end %td

//fix enrollment status
cap confirm variable enrollment_status
    if _rc {
        rename enrollmentstatus enrollment_status
    }
replace enrollment_status = trim(itrim(enrollment_status))
replace enrollment_status = "Full-time" if enrollment_status == "F"
replace enrollment_status = "Three-quarter time" if enrollment_status == "Q"
replace enrollment_status = "Half-time" if enrollment_status == "H"
```

```
replace enrollment_status = "Less than half-time" if enrollment_status == "L"
replace enrollment_status = "Leave of absence" if enrollment_status == "A"
replace enrollment_status = "Withdrawn" if enrollment_status == "W"
replace enrollment_status = "Deceased" if enrollment_status == "D"
replace enrollment_status = "Undefined" if mi(enrollment_status)

//generate school year
gen school_year = 2016 if begin >= date("20160701", "YMD") ///
    & end < date("20170701", "YMD")
replace school_year = 2017 if begin >= date("20170701", "YMD") ///
    & end < date("20180701", "YMD")
replace school_year = 2018 if begin >= date("20180701", "YMD") ///
    & end < date("20190701", "YMD")
replace school_year = 2019 if begin >= date("20190701", "YMD") ///
    & end < date("20200701", "YMD")
replace school_year = 2020 if begin >= date("20200701", "YMD") ///
    & end < date("20210701", "YMD")
replace school_year = 2021 if begin >= date("20210701", "YMD") ///
    & end < date("20220701", "YMD")
replace school_year = 2022 if begin >= date("20220701", "YMD") ///
    & end < date("20230701", "YMD")
replace school_year = 2023 if begin >= date("20230701", "YMD") ///
    & end < date("20240701", "YMD")
tab school_year
drop if mi(school_year)

//generate enrollment length
gen length = end-begin

//generate enrolled in college
gen enrolled_college = (recordfound == "Y")
drop if recordfound == "N"

//fix classification
cap confirm variable twoyearfouryear
    if _rc {
        cap rename _2year4year twoyearfouryear
        cap rename year4year twoyearfouryear
    }
destring twoyearfouryear, force replace
gen two_year = (twoyearfouryear == 2) if !mi(twoyearfouryear)
gen four_year = (twoyearfouryear == 4) if !mi(twoyearfouryear)

//fix public variable
assert inlist(publicprivate, "Public", "Private") if !mi(publicprivate)
gen public = (publicprivate == "Public") if !mi(publicprivate)
gen private = (publicprivate == "Private") if !mi(publicprivate)

//gen in-state variable
cap confirm variable collegestate
    if _rc {
        rename college_state collegestate
    }
gen in_state = (collegestate == "MA") if !mi(collegestate)

//generate nsc appearance
bys sasid school_year (begin): gen nsc_appearance = _n
keep if nsc_appearance == 1 //keep first appearance per year

//remove branch campus subcode
cap confirm variable collegecode
    if _rc {
        rename college_codebranch collegecode
    }
replace collegecode = substr(collegecode, 1, strpos(collegecode, "-")-1)
rename collegecode college_code
//fix college name
cap confirm variable college name
    if _rc {
        rename collegename college_name
```

```
    }
replace college_name = proper(college_name)
replace college_name = "Southern New Hampshire University" if ///
    regexm(college_name, "Southern New Hampshire")
//  replace college_name = "University Of Massachusetts" if ///
//      regexm(college_name, "University Of Massachusetts")
replace college_name = "Yale University" if ///
    regexm(college_name, "Yale University")
replace college_name = "Tulane University" if ///
    regexm(college_name, "Tulane University")
replace college_name = "Harvard University" if ///
    regexm(college name, "Harvard University")
replace college_name = "University Of Maine" if ///
    regexm(college_name, "University Of Maine")

//keep needed variables
keep sasid enrolled_college school_year enrollment_status college_name ///
    college code public private two year four year in state

//keep needed observations
keep if inrange(school_year, 2016, 2023)

//generate persistence flags
destring sasid, replace
tsset sasid school_year
gen second_year_enrollment = f.school_year
gen second_year_persistence = (school_year + 1 == second_year_enrollment)
gen third_year_enrollment = f2.school_year
replace third_year_enrollment = . if mi(second_year_enrollment)
gen third_year_persistence = (second_year_enrollment + 1 == third_year_enrollment) ///
if !mi(second_year_enrollment)
drop second_year_enrollment third_year_enrollment
tostring sasid, replace

//save the file
isid sasid school_year
save "$clean\8. dese nsc college enrollment persistence.dta", replace
```

```
/*******************************************************************************
File Name: hs_analysis_file
Author: Pierre M. Lucien
Purpose: creates a mega file for analysis and research
*******************************************************************************/

//top matter
clear all
cap log close
set more off

//globals
global clean "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\clean_data"
global time_invariant_demographics "$clean\1. dese_hs_time_invariant_demographics.dta"
global time_variant_demographics "$clean\2. dese_hs_time_variant_demographics.dta"
global high_schools "$clean\3. dese_high_schools.dta"
global school_enrollment "$clean\4. dese school enrollment attendance.dta"
global test_scores "$clean\5. dese_8th_grade_mcas_scores.dta"
global attendance_suspensions "$clean\6. dese_8th_grade_attendance_suspensions.dta"
global treatment_assignments "$clean\7. dese_ec_icp_treatment_assignments.dta"
global college_enrollment_persistence "$clean\8. dese_nsc_college_enrollment_persistence.dta  "

//1. load the time invariant demographics
use "$time_invariant_demographics", clear

//2. merge on the time variant demographics
merge 1:m sasid using "$time_variant_demographics", assert(3) ///
    keep(3) nogen

//3. merge on school enrollment information
merge 1:1 sasid school_year using "$school_enrollment", ///
    keepusing(sasid school* graduated completed*) ///
    keep(3) nogen

//4. merge on schools
merge m:1 school_code school_year using "$high_schools", keep(1 3) ///
    keepusing(school_code school_year school_name) nogen

//5. merge on baseline test scores
merge m:1 sasid using "$test_scores", keep(1 3) nogen ///
    keepusing(sasid next gen ela next gen math ///
    legacy_ela legacy_math ela_strata math_strata)

//6. merge on baseline attendance and suspensions
merge m:1 sasid using "$attendance_suspensions", keep(1 3) nogen ///
    keepusing(sasid eighth_ever_suspended eighth_chronic_absentee)
rename (eighth_ever_suspended eighth_chronic_absentee) ///
    (eighth_ever_sus eighth_chronic)

//7. merge on treatment assignments
merge 1:1 sasid school_year using "$treatment_assignments", ///
    keepusing(sasid school_year ec_comparison_group_1 ip_comparison_group_1 ///
    ec_school ip_school ec_participant ip_participant) ///
    keep(1 3) nogen
foreach x in ec ip {
    replace `x'_comparison_group_1 = "State" if ///
        mi(`x'_comparison_group_1) & `x'_school == 0
    replace `x'_comparison_group_1 = "School Peer" if ///
        mi(`x'_comparison_group_1) & `x'_school == 1
}

//8. merge on college enrollment and persistence data
merge 1:1 sasid school_year using "$college_enrollment_persistence", keep(1 3) ///
        keepusing(sasid school_year college_name college_code enrolled_college ///
        second_year_persistence third_year_persistence ///
        enrollment status four year in state public) ///
        nogen
foreach var of varlist enrolled_college second_year_persistence third_year_persistence {
```

```
69          replace `var' = 0 if mi(`var')
70      }
71
72      //9. label variables
73      label var enrolled_college "Enrolled in College"
74      label var ec_participant "EC"
75      label var ip_participant "ICP"
76      label var ip_comparison_group_1 "Comparison Group"
77      label var ec_comparison_group_1 "Comparison Group"
78      label var eco_dis_low_inc "Low-Income"
79      label var el "English Learner"
80      label var male "Male"
81      label var sped "Disability"
82      label var eighth_chronic "Chronically Absent G8"
83      label var eighth_ever_sus "Suspended G8"
84      label var next_gen_ela "Next Gen ELA Test"
85      label var next_gen_math "Next Gen Math Test"
86
87      //10. save the file
88      save "$clean\9. dese_hs_analysis_file.dta", replace
89
```

```
/*******************************************************************************
File Name: dese_adjusted_hs_analysis_file
Author: Pierre M. Lucien
Purpose: makes adjustment to analysis file based on feedback from DESE
*******************************************************************************/

//top matter
clear all
cap log close
set more off

//globals
global clean "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\clean_data"

//load the analysis file
use "$clean\9. dese_hs_analysis_file.dta", clear

//exlusions
replace ec_comparison_group_1 = "State" if ///
    (school_year == 2020 & regexm(school_name, "Leominster Center for Excellence|Putnam|Milford")) ///
    | (school_year == 2021 & regexm(school_name, "Fecteau|Somerville|North Central|Leominster Center for Excellence|Putnam|Center For Technical Education Innovation|Whittier")) ///
    | (school_year == 2021 & regexm(school_name, "Lowell") & grade_level == 9) ///
    | (school_year == 2019 & regexm(school_name, "Plymouth|Boston Day and Evening")) ///
    | (school_year == 2023 & regexm(school_name, "Putnam")) ///
    | (school_year == 2023 & regexm(school_name, "Mount Everett Regional"))

replace ec_participant = 0 if ///
    (school_year == 2020 & regexm(school_name, "Leominster Center for Excellence|Putnam|Milford")) ///
    | (school_year == 2021 & regexm(school_name, "Fecteau|Somerville|North Central|Leominster Center for Excellence|Putnam|Center For Technical Education Innovation|Whittier")) ///
    | (school_year == 2021 & regexm(school_name, "Lowell") & grade_level == 9) ///
    | (school_year == 2019 & regexm(school_name, "Plymouth|Boston Day and Evening")) ///
    | (school_year == 2023 & regexm(school_name, "Putnam")) ///
    | (school_year == 2023 & regexm(school_name, "Mount Everett Regional"))

replace ec_school = 0 if ///
    (school_year == 2020 & regexm(school_name, "Leominster Center for Excellence|Putnam|Milford")) ///
    | (school_year == 2021 & regexm(school_name, "Fecteau|Somerville|North Central|Leominster Center for Excellence|Putnam|Center For Technical Education Innovation|Whittier")) ///
    | (school_year == 2021 & regexm(school_name, "Lowell") & grade_level == 9) ///
    | (school_year == 2019 & regexm(school_name, "Plymouth|Boston Day and Evening")) ///
    | (school_year == 2023 & regexm(school_name, "Putnam")) ///
    | (school_year == 2023 & regexm(school_name, "Mount Everett Regional"))

//Additions
replace ec_comparison_group_1 = "EC" if ///
    school_year == 2022 & regexm(school_name, "New Heights Charter")
replace ec_school = 1 if ///
    school_year == 2022 & regexm(school_name, "New Heights Charter")
replace ec_participant = 1 if ///
    school_year == 2022 & regexm(school_name, "New Heights Charter")

//fix school peers for Lynn Vocational after EY discovery
replace ec_comparison_group_1 = "School Peer" if ///
(school_year == 2023 & ec_comparison_group_1 != "EC" ///
& regexm(school_name, "Lynn Vocational Tech"))

//save
save "$clean\10. dese_adjusted_hs_analysis_file.dta", replace
```

```
/*******************************************************************************
File Name: dese_ec_untabulated_counts
Author: Pierre M. Lucien
Purpose: confirms counts and rates referenced before descriptive tables
*******************************************************************************/

//top matter
clear all
cap log close
set more off

//globals
global analysis "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\clean_data\10. dese_adjusted_hs_analysis_file.dta"
global clean "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\clean_data"

/*PRE-TABLES COUNTS*/

//2022 school counts
use "$analysis" if school_year == 2022 & grade_level == 12 ///
    & ec_school == 1, clear
gen enrollment = 1
collapse (sum) enrollment ec_participant, by(school_name)
drop if ec_participant == 0
gen percent_ec = ec_participant/enrollment
sum ec_participant percent_ec, detail

//icp students at ec_schools
use "$analysis" if inrange(school_year, 2019, 2022) ///
    & ec_school == 1, clear
tab ip_comparison_group_1 if grade_level == 12

//total 12th grade EC participants
tab ec_comparison_group_1 if grade == 12 & school_year <= 2022

//count of matched participants
use "$clean\13. dese_ec_ps_calculation_match.dta", clear
tab ec_comparison_group_1

//match rate
sum ec_participant
local a = r(sum)
use "$analysis" if inrange(school_year, 2019, 2022) ///
    & ec_participant == 1 & grade_level == 12, clear
sum ec_participant
local b = r(sum)
dis `a'/`b'

//total school counts
use "$analysis" if inrange(school_year, 2019, 2022) ///
    & ec_school == 1 & grade_level == 12, clear
qui tab school_name
dis "Total School Count `r(r)'"

// 2019 school count
qui tab school_name if school_year == 2019
dis "2019 School Count `r(r)'"

// 2020 school count
qui tab school_name if school_year == 2020
dis "2020 School Count `r(r)'"

// 2021 school count
qui tab school_name if school_year == 2021
dis "2021 School Count `r(r)'"

// 2022 school count
qui tab school_name if school_year == 2022
dis "2022 School Count `r(r)'"
```

```
69
70  // count and share of ec students per year
71  table school_year, c(sum ec_participant mean ec_participant)
72
73  // count and share of ec students in ec_schools
74  table ec_school, c(sum ec_participant mean ec_participant)
75
76  // count and share of ec students across the state
77  use "$analysis" if inrange(school_year, 2019, 2022) ///
78      & grade_level == 12, clear
79  tab ec_participant
80
81
82
```

```
/*******************************************************************************
File Name: dese_ec_pre_match_descriptive_tables
Author: Pierre M. Lucien
Purpose: Produces pre-match descriptive tables for Early College
*******************************************************************************/

//top matter
clear all
cap log close
set more off

//globals
global clean "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\clean_data"
global intermediate "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\intermediate_data"
global raw "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese data\raw data"
global tables "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\tables_figures"

//load the data for series of tables
use "$clean\10. dese_adjusted_hs_analysis_file.dta" , clear
replace ec_comparison_group = "Rest of State" if ///
    regexm(ec_comparison_group, "State")
replace ec_comparison_group = "Rest of School" if ///
    regexm(ec_comparison_group, "School")

//EC enrollment by year table
tab school_year ec_comparison_group if grade_level == 12 ///
    & inrange(school_year, 2019, 2022)
cd "$tables"
asdoc tab school_year ec_comparison_group if grade_level == 12 ///
    & inrange(school_year, 2019, 2022), ///
    save(ec_enrollment_by_year) ///
    replace title(\i)

//EC enrollment by race
gen low_income  = (eco_dis == 1)
gen black = (race == 2)
gen latinx = (race == 7)
table ec_comparison if grade_level == 12 ///
    & inrange(school_year, 2019, 2022), ///
    c(mean black mean latinx mean low_income)
cd "$tables"
asdoc table ec_comparison if grade_level == 12 ///
    & inrange(school_year, 2019, 2022), ///
    c(mean black mean latinx mean low_income) ///
    save(ec_enrollment_by_race_and_income) ///
    replace title(\i)

//EC math and ELA proficiency
foreach x in math ela {
    gen meeting_`x' = `x'_strata == 3
    gen exceeding_`x' = `x'_strata == 4
}
table ec_comparison_group if grade_level == 12 & ///
    inrange(school_year, 2019, 2022), ///
    c(mean meeting_math mean meeting_ela  ///
    mean exceeding_math mean exceeding_ela)
cd "$tables"
asdoc table ec_comparison_group if grade_level == 12 & school_year < 2023, ///
    c(mean meeting_math mean meeting_ela  ///
    mean exceeding_math mean exceeding_ela) ///
    save(ec_enrollment_by_mcas_level) ///
    replace title(\i)
```

```
/*******************************************************************************
File Name: dese_ec_ps_calculation_match
Author: Pierre M. Lucien
Purpose: matches EC participants to similar non-participants in their schools
*******************************************************************************/

//top matter
clear all
cap log close
set more off

//globals
global clean "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\clean_data"
global intermediate "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\intermediate_data"
global raw "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese data\raw data"
global tables "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\tables_figures"
global analysis  "$clean\10. dese_adjusted_hs_analysis_file.dta"


//load 12th grade records from analysis file
use "$analysis" if grade_level == 12 & inrange(school_year, 2019, 2022), clear

//confirm only 12th graders are loaded
assert grade_level == 12

//generate proper comparison group
keep if inlist(ec_comparison_group_1, "EC", "School Peer") ///
    & ip_comparison_group_1 != "ICP"

//adjust race variable
replace race = 6 if inrange(race, 3, 5)
label define race 6 "Other" 7 "Latinx", modify

// conduct the match
logit ec_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year, or
predict p
sum p
local caliper = .2*r(sd)

//match the treatment with non-treatment observation of the same propensity score
psmatch2 ec_participant, out(enrolled_college) pscore(p) n(1) noreplacement caliper(`caliper')
gen pair = _id if _treated==0
replace pair = _n1 if _treated==1

//delete non-treatment observations that do not match to a treatment one
sort pair
order pair
keep if pair == pair[_n+1] | pair == pair[_n-1]
drop if mi(_treated)
// bys pair: gen match_number = _N
// order match_number

//check the balance between the two groups
pstest i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    i.ela_strata i.math_strata i.school_year, or

//drop treatment records missing a pair
assert ec_comparison_group_1 == "EC" if mi(pair)
drop if mi(pair)
replace ec comparison group 1 = "Comparison Group" if ///
    ec_comparison_group_1 == "School Peer"

```

```
66   //create school variable for fixed effects
67   destring(school_code), gen(school)
68
69   //save the matched file
70   save "$clean\13. dese_ec_ps_calculation_match.dta", replace
71
```

```
/*******************************************************************************
File Name: dese_ec_post_match_diagnostic_tests
Author: Pierre M. Lucien
Purpose: Produces post-match descriptive tables for Early College
*******************************************************************************/

//top matter
clear all
cap log close
set more off

//globals
global clean "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\clean_data"
global intermediate "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\intermediate_data"
global raw "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese data\raw data"
global tables "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\tables_figures"

/*POST MATCH TABLES AND FIGURES*/
use "$clean\13. dese_ec_ps_calculation_match.dta", clear


//prepapre gender for balance table
gen Female = (male == 0)

//balance table
cd "$tables"
asdoc pstest i.race Female eco_dis_low_inc el sped  ///
    ib1.ela_strata ib1.math_strata ///
    eighth_chronic eighth_ever_sus, ///
    label save(ec_post_match_balance_table) ///
    replace title(\i)

//conduct sensitivity test
use "$clean\13. dese_ec_ps_calculation_match.dta", clear
drop if ec_comparison_group_1 == "EC Unmatched"
gen delta = enrolled_college - _enrolled_college if _treat==1 & _support==1
rbounds delta, gamma(1.25 (.05) 1.75) // sigonly
cd "$tables"
asdoc rbounds delta, gamma(1.25 (.05) 1.75) sigonly ///
    save(ec_post_match_sensitivity) replace

//Distribution of Propensity Score across Treatment and Comparison
use "$clean\13. dese_ec_ps_calculation_match.dta", clear
drop if ec_comparison_group_1 == "EC Unmatched"
psgraph, treated (_treated) pscore(_pscore) ///
    title("Distribution of Propensity Scores") ///
    ytitle("Density") ylabel(-.2 ".2" -.1 ".1" 0 .1 .2)
graph export "$tables\ec_ps_distribution_by_treatment.pdf", replace


/*MATCHED VS UNMATCHED*/
global matched "$clean\13. dese_ec_ps_calculation_match.dta"
global analysis "$clean\10. dese_adjusted_hs_analysis_file.dta"

//load the matched file
use "$matched", clear

//drop treatment records missing a pair
drop if mi(pair)

//keep matched EC students
keep if ec_comparison_group_1 == "EC"
keep sasid grade_level school_year

//temporarily save the file
tempfile matched
```

```
67  save `matched'
68
69  //load 12th grade records from analysis file
70  use "$analysis" if grade_level == 12 & ec_comparison_group_1 == "EC" & ///
71      inrange(school_year, 2019, 2022), clear
72
73  //merge matched to unmatched
74  merge 1:1 sasid grade_level school_year using `matched', assert(1 3) ///
75      gen(matched)
76  recode matched (1=0) (3=1)
77  label drop _merge
78
79  //prepapre gender for balance table
80  gen Female = (male == 0)
81
82  //adjust race variable
83  replace race = 6 if inrange(race, 3, 5)
84  label define race 6 "Other" 7 "Latinx", modify
85
86  //balance table
87  cd "$tables"
88  asdoc pstest i.race Female eco_dis_low_inc el sped  ///
89      ib1.ela_strata ib1.math_strata ///
90      eighth_chronic eighth_ever_sus, ///
91      raw treated(matched) label ///
92      save(ec_matched_vs_unmatched_balance)
93
94
95
96
97
```

```
/*******************************************************************************
File Name: dese_ec_regression_tables_interaction_graphs
Author: Pierre M. Lucien
Purpose: Produces regression tables and interaction graphs for Early College
*******************************************************************************/

//top matter
clear all
cap log close
set more off

//globals
global clean "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\clean_data"
global intermediate "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\intermediate_data"
global raw "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese data\raw data"
global tables "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\tables_figures"
global analysis  "$clean\10. dese_adjusted_hs_analysis_file.dta"
global matched_data "$clean\13. dese_ec_ps_calculation_match.dta"

/*PS REGRESSION*/
eststo clear

//load 12th grade records from analysis file
use "$analysis" if grade_level == 12 & inrange(school_year, 2019, 2022), clear

//confirm only 12th graders are loaded
assert grade_level == 12

//generate proper comparison group
keep if inlist(ec_comparison_group_1, "EC", "School Peer") ///
    & ip_comparison_group_1 != "ICP"

//adjust race variable
replace race = 6 if inrange(race, 3, 5)
label define race 6 "Other" 7 "Latinx", modify

// conduct the match
logit ec_participant i.race eco_dis male ///
    sped el eighth chronic eighth ever sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year
eststo: qui logit ec_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year

//output tables
esttab using "$tables\ec_ps_calculation_regression.rtf", ///
    eform varwidth(20) nobaselevels mtitle("Logistic Regression Odds Ratios") title("PS Calculation Model") ///
    nonumbers eqlabels(none) collabels(none) modelwidth(10) se label compress ///
    not wide replace b(2) se(2)

/*COLLEGE READINESS REGRESSION OUPUTS*/
eststo clear

//load matched data
use "$matched_data", clear

// treatment with covariates
logit completed_mass_core ec_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year, ///
    or vce(cluster school)
eststo: quietly logit completed_mass_core ec_participant i.race eco_dis male ///
    sped el eighth chronic eighth ever sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year, ///
    or vce(cluster school)
```

```
66
67  // treatment with covariates and school fixed effects
68  logit completed_mass_core ec_participant i.race eco_dis male ///
69      sped el eighth_chronic eighth_ever_sus ///
70      ib1.ela_strata ib1.math_strata ib2020.school_year i.school, ///
71      or vce(cluster school)
72  eststo: quietly logit completed_mass_core ec_participant i.race eco_dis male ///
73      sped el eighth_chronic eighth_ever_sus ///
74      ib1.ela_strata ib1.math_strata ib2020.school_year i.school, ///
75      or vce(cluster school)
76
77  // treatment with covariates and school fixed effects and interactions
78  logit completed_mass_core ec_participant##i.race ///
79      ec_participant##eco_dis male ///
80      sped el eighth_chronic eighth_ever_sus ///
81      ib1.ela_strata ib1.math_strata ib2020.school_year i.school, ///
82      or vce(cluster school)
83  eststo: quietly logit completed mass core ec participant##i.race ///
84      ec_participant##eco_dis male ///
85      sped el eighth_chronic eighth_ever_sus ///
86      ib1.ela_strata ib1.math_strata ib2020.school_year i.school, ///
87      or vce(cluster school)
88
89  //output
90  esttab using "$tables\ec_psm_readiness_regressions.rtf", ///
91      eform drop(*school) varwidth(20) nobaselevels ///
92      mtitle("Treatment with Covariates" ///
93      "Treatment with Covariates and School Fixed-Effects" ///
94      "Treatment with Covariates, School Fixed-Effects, and Interactions") ///
95      title("Effects on MassCore Completion/College Readiness") ///
96      nonumbers eqlabels(none) collabels(none) modelwidth(10) se label ///
97      compress not wide replace b(2) se(2)
98
99  /*COLLEGE ACCESS REGRESSION OUPUTS*/
100 eststo clear
101
102 // treatment with covariates
103 logit enrolled_college ec_participant i.race eco_dis male ///
104     sped el eighth_chronic eighth_ever_sus ///
105     ib1.ela_strata ib1.math_strata ib2020.school_year, ///
106     or vce(cluster school)
107 eststo: quietly logit enrolled_college ec_participant i.race eco_dis male ///
108     sped el eighth chronic eighth ever sus ///
109     ib1.ela_strata ib1.math_strata ib2020.school_year, ///
110     or vce(cluster school)
111
112 // treatment with covariates and school fixed effects
113 logit enrolled_college ec_participant i.race eco_dis male ///
114     sped el eighth_chronic eighth_ever_sus ///
115     ib1.ela_strata ib1.math_strata ib2020.school_year i.school, ///
116     or vce(cluster school)
117 eststo: quietly logit enrolled_college ec_participant i.race eco_dis male ///
118     sped el eighth_chronic eighth_ever_sus ///
119     ib1.ela_strata ib1.math_strata ib2020.school_year i.school, ///
120     or vce(cluster school)
121
122 // treatment with covariates, school fixed effects, and interactions
123 logit enrolled_college ec_participant##i.race ///
124     ec_participant##eco_dis male ///
125     sped el eighth_chronic eighth_ever_sus ///
126     ib1.ela_strata ib1.math_strata ib2020.school_year i.school, ///
127     or vce(cluster school)
128 eststo: quietly logit enrolled_college ec_participant##i.race ///
129     ec_participant##eco_dis male ///
130     sped el eighth_chronic eighth_ever_sus ///
131     ib1.ela_strata ib1.math_strata ib2020.school_year i.school, ///
132     or vce(cluster school)
133 margins ec participant#eco dis
134 marginsplot, noci title("Predictive Margins of EC and Income Interaction with School FE") ///
135     ytitle("Probability of Enrolling in College") ///
```

```
136       note("*EC participation is binary, not continous. Lines between points are for
      illustrative purposes.")
137   graph export "$tables\ec_psm_accesss_income_interaction.pdf", replace
138
139
140   //output
141   esttab using "$tables\ec_psm_access_regressions.rtf", ///
142       eform drop(*school) varwidth(20) nobaselevels ///
143       mtitle("Treatment with Covariates" ///
144       "Treatment with Covariates and School Fixed Effects" ///
145       "Treatment with Covariates, School Fixed Effects, and Interactions") ///
146       title("Effects on College Enrollment") ///
147       nonumbers eqlabels(none) collabels(none) modelwidth(10) se label ///
148       compress not wide replace b(2) se(2)
149
150   /*COLLEGE PERSISTENCE REGRESSION OUPUTS*/
151   eststo clear
152
153   // treatment with covariates
154   logit second_year_persistence ec_participant i.race eco_dis male ///
155       sped el eighth_chronic eighth_ever_sus ///
156       ib1.ela_strata ib1.math_strata ib2020.school_year, ///
157       or vce(cluster school)
158   eststo: quietly logit second_year_persistence ec_participant i.race eco_dis male ///
159       sped el eighth_chronic eighth_ever_sus ///
160       ib1.ela_strata ib1.math_strata ib2020.school_year, ///
161       or vce(cluster school)
162
163   // treatment with covariates and school fixed effects
164   logit second_year_persistence ec_participant i.race eco_dis male ///
165       sped el eighth_chronic eighth_ever_sus ///
166       ib1.ela_strata ib1.math_strata ib2020.school_year i.school, ///
167       or vce(cluster school)
168   eststo: quietly logit second_year_persistence ec_participant i.race eco_dis male ///
169       sped el eighth_chronic eighth_ever_sus ///
170       ib1.ela_strata ib1.math_strata ib2020.school_year i.school, ///
171       or vce(cluster school)
172
173   // treatment with covariates and school fixed effects and interactions
174   logit second_year_persistence ec_participant##i.race ///
175       ec_participant##eco_dis male ///
176       sped el eighth_chronic eighth_ever_sus ///
177       ib1.ela strata ib1.math strata ib2020.school year i.school, ///
178       or vce(cluster school)
179   eststo: quietly logit second_year_persistence ec_participant##i.race ///
180       ec_participant##eco_dis male ///
181       sped el eighth_chronic eighth_ever_sus ///
182       ib1.ela_strata ib1.math_strata ib2020.school_year i.school, ///
183       or vce(cluster school)
184
185   //output
186   esttab using "$tables\ec_psm_success_regressions.rtf", ///
187       eform drop(*school) varwidth(20) nobaselevels ///
188       mtitle("Treatment with Covariates" ///
189       "Treatment with Covariates and School Fixed-Effects Model" ///
190       "Treatment with Covariates, School Fixed-Effects Model, and Interactions") ///
191       title("Effects on College Persistence") ///
192       nonumbers eqlabels(none) collabels(none) modelwidth(10) se label ///
193       compress not wide replace b(2) se(2)
194
```

```
/*******************************************************************************
File Name: dese_ec_robustness_check_regression_tables
Author: Pierre M. Lucien
Purpose: Performs robustness checks for regressions
*******************************************************************************/

//top matter
clear all
cap log close
set more off

//globals
global clean "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\clean_data"
global intermediate "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\intermediate_data"
global raw "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese data\raw data"
global tables "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\tables_figures"
global analysis  "$clean\10. dese_adjusted_hs_analysis_file.dta"
global matched_data "$clean\13. dese_ec_ps_calculation_match.dta"

/* NEXT GEN MCAS YEARS REGRESSION OUPUTs*/
eststo clear

//load 12th grade records from analysis file
use "$analysis" if grade_level == 12 & inrange(school_year, 2021, 2022) ///
    & !mi(next_gen_ela) & !mi(next_gen_math), clear

//confirm only 12th graders are loaded
assert grade_level == 12

//generate proper comparison group
keep if inlist(ec_comparison_group_1, "EC", "School Peer") ///
    & ip_comparison_group_1 != "ICP"

//adjust race variable
replace race = 6 if inrange(race, 3, 5)
label define race 6 "Other" 7 "Latinx", modify

// conduct the match
logit ec participant i.race eco dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    next_gen_ela next_gen_math ib2021.school_year
predict p
sum p
local caliper = .2*r(sd)

//match the treatment with non-treatment observation of the same propensity score
psmatch2 ec_participant, out(enrolled_college) pscore(p) n(1) noreplacement caliper(`caliper')
gen pair = _id if _treated==0
replace pair = _n1 if _treated==1

//delete non-treatment observations that do not match to a treatment one
sort pair
order pair
keep if pair == pair[_n+1] | pair == pair[_n-1]
drop if mi(_treated)
// bys pair: gen match_number = _N
// order match_number

//check the balance between the two groups
pstest i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    next_gen_ela next_gen_math i.school_year, or

//drop treatment records missing a pair
assert ec_comparison_group_1 == "EC" if mi(pair)
```

```
drop if mi(pair)
replace ec_comparison_group_1 = "Comparison Group" if ///
    ec_comparison_group_1 == "School Peer"

//fix school variable for fixed effects regression
destring(school_code), gen(school)

// college readiness
logit completed_mass_core ec_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    next_gen_ela next_gen_math ib2021.school_year i.school, ///
    or vce(cluster school)
eststo: quietly logit completed_mass_core ec_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    next_gen_ela next_gen_math ib2021.school_year i.school, ///
    or vce(cluster school)

// college access
logit enrolled_college ec_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    next_gen_ela next_gen_math ib2021.school_year i.school, ///
    or vce(cluster school)
eststo: quietly logit enrolled_college ec_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    next_gen_ela next_gen_math ib2021.school_year i.school, ///
    or vce(cluster school)

// college success
logit second_year_persistence ec_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    next_gen_ela next_gen_math ib2021.school_year i.school, ///
    or vce(cluster school)
eststo: quietly logit second_year_persistence ec_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    next_gen_ela next_gen_math ib2021.school_year i.school, ///
    or vce(cluster school)

//output
esttab using "$tables\ec_robustness_check_regression_logit.rtf", ///
    eform drop(*school) varwidth(20) nobaselevels mtitle("Effects on College Readiness" ///
    "Effects on College Access" "Effects on College Success") ///
    title("Robustness Checks") nonumbers eqlabels(none) collabels(none) ///
    modelwidth(10) se label compress not wide replace b(2) se(2)

/* LINEAR PROBABILITY MODELS */
eststo clear

//load matched data
use "$matched_data", clear

// college readiness
regress completed_mass_core ec_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year i.school, ///
    vce(cluster school)
eststo: quietly regress completed_mass_core ec_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year i.school, ///
    vce(cluster school)

// college access
regress enrolled_college ec_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year i.school, ///
    vce(cluster school)
eststo: quietly regress enrolled_college ec_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela strata ib1.math strata ib2020.school year i.school, ///
    vce(cluster school)

```

```
136   // college success
137   regress second_year_persistence ec_participant i.race eco_dis male ///
138       sped el eighth_chronic eighth_ever_sus ///
139       ib1.ela_strata ib1.math_strata ib2020.school_year i.school, ///
140       vce(cluster school)
141   eststo: quietly regress second_year_persistence ec_participant i.race eco_dis male ///
142       sped el eighth_chronic eighth_ever_sus ///
143       ib1.ela_strata ib1.math_strata ib2020.school_year i.school, ///
144       vce(cluster school)
145
146   //output
147   esttab using "$tables\ec robustness check regression lpm.rtf", ///
148       drop(*school) varwidth(20) nobaselevels mtitle("Effects on College Readiness" ///
149       "Effects on College Access" "Effects on College Success") ///
150       title("Robustness Checks") nonumbers eqlabels(none) collabels(none) ///
151       modelwidth(10) se label compress not wide replace b(2) se(2)
152
```

```
/*******************************************************************************
File Name: dese_ec_psm_appendix_regression_tables
Author: Pierre M. Lucien
Purpose: creates appendices of regresssion tables not in paper
*******************************************************************************/

//top matter
clear all
cap log close
set more off

//globals
global clean "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\clean_data"
global intermediate "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\intermediate_data"
global raw "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese data\raw data"
global tables "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\tables_figures"
global analysis  "$clean\10. dese_adjusted_hs_analysis_file.dta"
global matched_data "$clean\13. dese_ec_ps_calculation_match.dta"

//load matched data
eststo clear
use "$matched_data", clear

// readiness interactions without school fixed effects
logit completed_mass_core ec_participant##i.race ///
    ec_participant##eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year, ///
    or vce(cluster school)
eststo: quietly logit completed_mass_core ec_participant##i.race ///
    ec_participant##eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year, ///
    or vce(cluster school)

// access interactions without school fixed effects
logit enrolled_college ec_participant##i.race ///
    ec_participant##eco_dis male ///
    sped el eighth chronic eighth ever sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year, ///
    or vce(cluster school)
eststo: quietly logit enrolled_college ec_participant##i.race ///
    ec_participant##eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year, ///
    or vce(cluster school)

// success interactions without school fixed effects
logit second_year_persistence ec_participant##i.race ///
    ec_participant##eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year, ///
    or vce(cluster school)
eststo: quietly logit second_year_persistence ec_participant##i.race ///
    ec_participant##eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year, ///
    or vce(cluster school)

//output
esttab using "$tables\ec_psm_appendix.rtf", ///
    eform varwidth(20) nobaselevels mtitle( ///
    "Readiness Interactions without School Fixed effects"  ///
    "Access Interactions without School Fixed effects" ///
    "Success Interactions without School Fixed effects") ///
    title("Race and Income Interactions wihtout School Fixed Effects") ///
```

```
67        nonumbers eqlabels(none) collabels(none) modelwidth(10) se label ///
68        compress not wide replace b(2) se(2)
69
70
```

```
/*******************************************************************************
File Name: dese_icp_untabulated_counts
Author: Pierre M. Lucien
Purpose: confirms counts and rates referenced before descriptive tables
*******************************************************************************/

//top matter
clear all
cap log close
set more off

//globals
global analysis "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\clean_data\10. dese_adjusted_hs_analysis_file.dta"
global clean "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\clean_data"

/*PRE-TABLES COUNTS*/

//2022 school counts
use "$analysis" if school_year == 2022 & grade_level == 12 ///
    & ip_school == 1, clear
gen enrollment = 1
collapse (sum) enrollment ip_participant, by(school_name)
drop if ip_participant == 0
gen percent_icp = ip_participant/enrollment
sum ip_participant percent_icp, detail

//ec students at icp_schools
use "$analysis" if inrange(school_year, 2019, 2022) ///
    & ip_school == 1, clear
tab ec_comparison_group_1 if grade_level == 12

//total 12th grade ICP participants
tab ip_comparison_group_1 if grade == 12 & school_year <= 2022

//total school counts
use "$analysis" if inrange(school_year, 2019, 2022) ///
    & ip_school == 1 & grade_level == 12, clear
qui tab school_name
dis "Total School Count `r(r)'"

// 2019 school count
qui tab school_name if school_year == 2019
dis "2019 School Count `r(r)'"

// 2020 school count
qui tab school_name if school_year == 2020
dis "2020 School Count `r(r)'"

// 2021 school count
qui tab school_name if school_year == 2021
dis "2021 School Count `r(r)'"

// 2022 school count
qui tab school_name if school_year == 2022
dis "2022 School Count `r(r)'"

// count and share of icp students per year
table school_year, c(sum ip_participant mean ip_participant)

// count and share of ec students in total
table ip_school, c(sum ip_participant mean ip_participant)

```

```
/*******************************************************************************
File Name: dese_icp_pre_weight_descriptive_tables
Author: Pierre M. Lucien
Purpose: Produces pre-weight descriptive tables for Innovation Career Pathways
*******************************************************************************/

//top matter
clear all
cap log close
set more off

//globals
global clean "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\clean_data"
global intermediate "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\intermediate_data"
global raw "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese data\raw data"
global tables "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\tables_figures"
global analysis  "$clean\10. dese_adjusted_hs_analysis_file.dta"

//load data for series of tables
use "$analysis", clear
replace ip_comparison_group = "Rest of State" if ///
    regexm(ip_comparison_group, "State")
replace ip_comparison_group = "Rest of School" if ///
    regexm(ip_comparison_group, "School")

//IP enrollment by year table
tab school_year ip_comparison_group if grade_level == 12 ///
    & inrange(school_year, 2019, 2022)
cd "$tables"
asdoc tab school_year ip_comparison_group if grade_level == 12 ///
    & inrange(school_year, 2019, 2022), ///
    save(icp_enrollment_by_year) ///
    replace title(\i)

//IP enrollment by race
gen low_income  = (eco_dis == 1)
gen black = (race == 2)
gen latinx = (race == 7)
table ip comparison if grade level == 12 ///
    & inrange(school_year, 2019, 2022), ///
    c(mean black mean latinx mean low_income)
cd "$tables"
asdoc table ip_comparison if grade_level == 12 ///
    & inrange(school_year, 2019, 2022), ///
    c(mean black mean latinx mean low_income) ///
    save(icp_enrollment_by_race_and_income) ///
    replace title(\i)

//IP math and ELA proficiency
foreach x in math ela {
    gen meeting_`x' = `x'_strata == 3
    gen exceeding_`x' = `x'_strata == 4
}
table ip_comparison_group if grade_level == 12 & inrange(school_year, 2019, 2022), ///
    c(mean meeting_math mean meeting_ela  ///
    mean exceeding_math mean exceeding_ela)
cd "$tables"
asdoc table ip_comparison_group if grade_level == 12 & inrange(school_year, 2019, 2022), ///
    c(mean meeting_math mean meeting_ela  ///
    mean exceeding_math mean exceeding_ela) ///
    save(icp_enrollment_by_mcas_level) ///
    replace title(\i)
```

```
/*******************************************************************************
File Name: dese_icp_ps_calculation_weight
Author: Pierre M. Lucien
Purpose: creates weights for ICP participants based on propensity scores
*******************************************************************************/

//top matter
clear all
cap log close
set more off

//globals
global clean "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\clean_data"
global intermediate "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\intermediate_data"
global raw "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese data\raw data"
global tables "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\tables_figures"
global analysis  "$clean\10. dese_adjusted_hs_analysis_file.dta"

//load 12th grade records from analysis file
use "$analysis" if grade_level == 12 & inrange(school_year, 2019, 2022), clear

//confirm only 12th graders are loaded
assert grade_level == 12

//generate proper comparison group
keep if inlist(ip_comparison_group_1, "ICP", "School Peer") ///
    & ec_comparison_group_1 != "EC"

//adjust race variable
replace race = 6 if inrange(race, 3, 5)
label define race 6 "Other" 7 "Latinx", modify

// calculate propensity score
logit ip_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus  ///
    ib1.ela_strata ib1.math_strata ib2020.school_year, or
predict p, pr
sum p

//calculate weights
gen ate_weight = .
replace ate_weight = 1/p if ip_participant == 1
replace ate_weight = 1/(1-p) if ip_participant == 0

gen att_weight = .
replace att_weight = 1 if ip_participant == 1
replace att_weight = p/(1-p) if ip_participant == 0

//create school variable for fixed effects
destring(school_code), gen(school)

//save the weighted file
save "$clean\20. dese_icp_ps_calculation_weight.dta", replace

```

```
/*******************************************************************************
File Name: dese_icp_post_weight_diagnostic_tests
Author: Pierre M. Lucien
Purpose: Produces post-weight diagnostic graphs and tables for Early College
*******************************************************************************/

//top matter
clear all
cap log close
set more off

//globals
global clean "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\clean_data"
global intermediate "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\intermediate_data"
global raw "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese data\raw data"
global tables "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\tables_figures"
global analysis  "$clean\10. dese_adjusted_hs_analysis_file.dta"
global weighted_data "$clean\20. dese_icp_ps_calculation_weight.dta"

/*CONFIRM PSM IS NO GOOD*/

//load 12th grade records from analysis file
use "$analysis" if grade_level == 12 & inrange(school_year, 2019, 2022), clear

//confirm only 12th graders are loaded
assert grade_level == 12

//generate proper comparison group
keep if inlist(ip_comparison_group_1, "ICP", "School Peer") ///
    & ec_comparison_group_1 != "EC"

//adjust race variable
replace race = 6 if inrange(race, 3, 5)
label define race 6 "Other" 7 "Latinx", modify

// conduct the match
logit ip_participant i.race eco_dis el sped male ///
    eighth_chronic eighth_ever_sus ///
    ib1.ela strata ib1.math strata ib2020.school year, or
predict p
sum p
local caliper = .2*r(sd)

//match the treatment with non-treatment observation of the same propensity score
psmatch2 ip_participant, out(enrolled_college) pscore(p) n(1) noreplacement caliper(`caliper')
gen pair = _id if _treated==0
replace pair = _n1 if _treated==1

//delete non-treatment observations that do not match to a treatment one
sort pair
order pair
keep if pair == pair[_n+1] | pair == pair[_n-1]
drop if mi(_treated)

gen delta = enrolled_college - _enrolled_college if _treat==1 & _support==1
rbounds delta, gamma(1 (.1) 2) // sigonly
cd "$tables"
asdoc rbounds delta, gamma(1 (.1) 2) sigonly ///
    save(icp_post_match_sensitivity) replace

/*POST WEIGHT TABLES AND FIGURES*/
use "$weighted_data", clear

//balance table
teffects ipw (enrolled_college) (ip_participant i.race eco_dis male ///
```

```
66          sped el eighth_chronic eighth_ever_sus ///
67          ib1.ela_strata ib1.math_strata ib2020.school_year), pomeans //to confirm
68      tebalance summarize
69      cd "$tables"
70      asdoc tebalance summarize, ///
71          save(icp_post_weight_balance_table) replace
72
73      //over identification test
74      tebalance overid
75      cd "$tables"
76      asdoc tebalance overid, ///
77          save(icp post weight over identification) replace
78
79      // histogram of propensity scores
80      cd "$tables"
81      hist p, by(ip_comparison_group_1) xtitle("Propensity Score")
82      graph export "$tables\icp_ps_distribution_by_treatment.pdf", replace
83
84
```

```
/*******************************************************************************
File Name: dese_icp_regression_tables_interaction_graphs
Author: Pierre M. Lucien
Purpose: Produces regression tables and interaction graphs for ICP
*******************************************************************************/

//top matter
clear all
cap log close
set more off

//globals
global clean "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\clean_data"
global intermediate "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\intermediate_data"
global raw "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese data\raw data"
global tables "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\tables_figures"
global analysis  "$clean\10. dese_adjusted_hs_analysis_file.dta"
global weighted_data "$clean\20. dese_icp_ps_calculation_weight.dta"

//load the data
use "$analysis" if grade_level == 12 &  inrange(school_year, 2019, 2022), clear

//generate proper comparison group
keep if inlist(ip_comparison_group_1, "ICP", "School Peer") ///
    & ec_comparison_group_1 != "EC"

//adjust race variable
replace race = 6 if inrange(race, 3, 5)
label define race 6 "Other" 7 "Latinx", modify

/*PS REGRESSION*/
eststo clear

// calculate propensity score
logit ip_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year, or
eststo: quietly // calculate propensity score
logit ip participant i.race eco dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year, or

//output tables
esttab using "$tables\icp_ps_calculation_regression.rtf", ///
    eform varwidth(20) nobaselevels mtitle("Logistic Regression Odds Ratios") title("PS Calculation Model") ///
    nonumbers eqlabels(none) collabels(none) modelwidth(10) se ///
    label compress not wide replace b(2) se(2)


/*COLLEGE READINESS REGRESSIONS*/
use "$weighted_data", clear
eststo clear

// treatment with covariates
logit completed_mass_core ip_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year [pweight=ate_weight], ///
    or vce(cluster school)
eststo: quietly logit completed_mass_core ip_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year [pweight=ate_weight], ///
    or vce(cluster school)

// treatment with covariates and school fixed effects
logit completed_mass_core ip_participant i.race eco_dis male ///
```

```
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year i.school [pweight=ate_weight], ///
    or vce(cluster school)
eststo: quietly logit completed_mass_core ip_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year i.school [pweight=ate_weight], ///
    or vce(cluster school)

// treatment with covariates, school fixed effects, and interactions
logit completed_mass_core ip_participant##i.race ///
    ip_participant##eco_dis male ///
    sped el eighth chronic eighth ever sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year i.school [pweight=ate_weight], ///
    or vce(cluster school)
eststo: quietly logit completed_mass_core ip_participant##i.race ///
    ip_participant##eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela strata ib1.math strata ib2020.school year i.school [pweight=ate weight], ///
    or vce(cluster school)

//output
esttab using "$tables\icp_iptw_readiness_regressions.rtf", ///
    eform drop(*school) varwidth(20) nobaselevels ///
    mtitle("Treatment with Covariates" ///
    "Treatment with Covariates and School Fixed Effects" ///
    "Treatment with Covariates, School Fixed Effects, and Interactions") ///
    title("Effects on MassCore Completion/College Readiness") ///
    nonumbers eqlabels(none) collabels(none) modelwidth(10) se label ///
    compress not wide replace b(2) se(2)

/*COLLEGE ACCESS REGRESSION OUPUTS*/
eststo clear

// treatment with covariates
logit enrolled_college ip_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year [pweight=ate_weight], ///
    or vce(cluster school)
eststo: quietly logit enrolled_college ip_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year [pweight=ate_weight], ///
    or vce(cluster school)

// treatment with covariates and school fixed effects
logit enrolled_college ip_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year i.school [pweight=ate_weight], ///
    or vce(cluster school)
eststo: quietly logit enrolled_college ip_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year i.school [pweight=ate_weight], ///
    or vce(cluster school)

// treatment with covariates, school fixed effects, and interactions
logit enrolled_college ip_participant##i.race ///
    ip_participant##eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year i.school [pweight=ate_weight], ///
    or vce(cluster school)
eststo: quietly logit enrolled_college ip_participant##i.race ///
    ip_participant##eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year i.school [pweight=ate_weight], ///
    or vce(cluster school)
margins ip_participant#eco_dis
marginsplot, noci title("Predictive Margins of ICP and Income Interaction with School FE")
///
    ytitle("Probability of Enrolling in College") ///
    note("*EC participation is binary, not continous. Lines between points are for
illustrative purposes.")
```

```
graph export "$tables\icp_iptw_accesss_income_interaction.pdf", replace


//output
esttab using "$tables\icp_iptw_access_regressions.rtf", ///
    eform drop(*school) varwidth(20) nobaselevels ///
    mtitle("Treatment with Covariates" ///
    "Treatment with Covariates and School Fixed Effects" ///
    "Treatment with Covariates, School Fixed Effects, and Interactions") ///
    title("Effects on College Enrollment") ///
    nonumbers eqlabels(none) collabels(none) modelwidth(10) se label ///
    compress not wide replace b(2) se(2)

/*COLLEGE PERSISTENCE REGRESSION OUPUTS*/
eststo clear

// treatment with covariates
logit second year persistence ip participant i.race eco dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year [pweight=ate_weight], ///
    or vce(cluster school)
eststo: quietly logit second_year_persistence ip_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year [pweight=ate_weight], ///
    or vce(cluster school)

// treatment with covariates and school fixed effects
logit second_year_persistence ip_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year i.school [pweight=ate_weight], ///
    or vce(cluster school)
eststo: quietly logit second_year_persistence ip_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year i.school [pweight=ate_weight], ///
    or vce(cluster school)

// treatment with covariates, school fixed effects, and interactions
logit second_year_persistence ip_participant##i.race ///
    ip_participant##eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year i.school [pweight=ate_weight], ///
    or vce(cluster school)
eststo: quietly logit second year persistence ip participant##i.race ///
    ip_participant##eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year i.school [pweight=ate_weight], ///
    or vce(cluster school)

//output
esttab using "$tables\icp_iptw_success_regressions.rtf", ///
    eform drop(*school) varwidth(20) nobaselevels ///
    mtitle("Treatment with Covariates" ///
    "Treatment with Covariates and School Fixed Effects Model" ///
    "Treatment with Covariates, School Fixed Effects Model, and Interactions") ///
    title("Effects on College Persistence") ///
    nonumbers eqlabels(none) collabels(none) modelwidth(10) se label ///
    compress not wide replace b(2) se(2)


```

```
/*******************************************************************************
File Name: dese_icp_robustness_check_regression_tables
Author: Pierre M. Lucien
Purpose: Performs robustness checks for ICP weighted regressions
*******************************************************************************/

//top matter
clear all
cap log close
set more off

//globals
global clean "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\clean_data"
global intermediate "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\intermediate_data"
global raw "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese data\raw data"
global tables "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\tables_figures"
global analysis  "$clean\10. dese_adjusted_hs_analysis_file.dta"
global weighted_data "$clean\20. dese_icp_ps_calculation_weight.dta"

//load 12th grade records from analysis file
eststo clear
use "$analysis" if grade_level == 12 & inrange(school_year, 2021, 2022) ///
    & !mi(next_gen_ela) & !mi(next_gen_math), clear

//generate proper comparison group
keep if inlist(ip_comparison_group_1, "ICP", "School Peer") ///
    & ec_comparison_group_1 != "EC"

//adjust race variable
replace race = 6 if inrange(race, 3, 5)
label define race 6 "Other" 7 "Latinx", modify

/*PS Regression*/

// calculate propensity score
logit ip_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    next_gen_ela next_gen_math ib2021.school_year
predict p, pr
sum p

//calculate weights
gen ate_weight = .
replace ate_weight = 1/p if ip_participant == 1
replace ate_weight = 1/(1-p) if ip_participant == 0

gen att_weight = .
replace att_weight = 1 if ip_participant == 1
replace att_weight = p/(1-p) if ip_participant == 0

/* NEXT GEN MCAS YEARS REGRESSION OUPUTs*/

//fix school variable for fixed effects regression
destring(school_code), gen(school)

// college readiness
logit completed_mass_core ip_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus next_gen_ela next_gen_math ///
    ib2021.school_year i.school [pweight=ate_weight], ///
    or vce(cluster school)
eststo: logit completed_mass_core ip_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus next_gen_ela next_gen_math ///
    ib2021.school_year i.school [pweight=ate_weight], ///
    or vce(cluster school)

// college access
```

```
logit enrolled_college ip_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus next_gen_ela next_gen_math ///
    ib2021.school_year i.school [pweight=ate_weight], ///
    or vce(cluster school)
eststo: logit enrolled_college ip_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus next_gen_ela next_gen_math ///
    ib2021.school_year i.school [pweight=ate_weight], ///
    or vce(cluster school)

// college success
logit second_year_persistence ip_participant i.race eco_dis male ///
    sped el eighth chronic eighth ever sus next gen ela next gen math ///
    ib2021.school_year i.school [pweight=ate_weight], ///
    or vce(cluster school)
eststo: logit second_year_persistence ip_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus next_gen_ela next_gen_math ///
    ib2021.school_year i.school [pweight=ate_weight], ///
    or vce(cluster school)

//output
esttab using "$tables\icp_robustness_check_regression_logit.rtf", ///
    eform drop(*school) varwidth(20) nobaselevels mtitle("Effects on College Readiness" ///
    "Effects on College Access" "Effects on College Success") ///
    title("Robustness Checks") nonumbers eqlabels(none) collabels(none) ///
    modelwidth(10) se label compress not wide replace b(2) se(2)

/* LINEAR PROBABILITY MODELS */
eststo clear

//load matched data
use "$weighted_data", clear

// college readiness
regress completed_mass_core ip_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year i.school [pweight=ate_weight], ///
    vce(cluster school)
eststo: quietly regress completed_mass_core ip_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year i.school [pweight=ate_weight], ///
    vce(cluster school)

// college access
regress enrolled_college ip_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year i.school [pweight=ate_weight], ///
    vce(cluster school)
eststo: quietly regress enrolled_college ip_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year i.school [pweight=ate_weight], ///
    vce(cluster school)

// college success
regress second_year_persistence ip_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year i.school [pweight=ate_weight], ///
    vce(cluster school)
eststo: quietly regress second_year_persistence ip_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year i.school [pweight=ate_weight], ///
    vce(cluster school)

//output
esttab using "$tables\icp_robustness_check_regression_lpm.rtf", ///
    drop(*school) varwidth(20) nobaselevels mtitle("Effects on College Readiness" ///
    "Effects on College Access" "Effects on College Success") ///
    title("Robustness Checks") nonumbers eqlabels(none) collabels(none) ///
    modelwidth(10) se label compress not wide replace b(2) se(2)
```

```
/*******************************************************************************
File Name: dese_icp_iptw_appendix_regression_tables
Author: Pierre M. Lucien
Purpose: creates appendices of regresssion tables not in paper
*******************************************************************************/

//top matter
clear all
cap log close
set more off

//globals
global clean "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\clean_data"
global intermediate "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\intermediate_data"
global raw "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese data\raw data"
global tables "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\tables_figures"
global analysis  "$clean\10. dese_adjusted_hs_analysis_file.dta"
global weighted_data "$clean\20. dese_icp_ps_calculation_weight.dta"

// TRIMMING WEIGHTS
eststo clear

// load the data
use "$weighted_data", clear
sum ate_weight, detail
keep if inrange(ate_weight, r(p1), r(p99))

// college readiness
logit completed_mass_core ip_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year i.school [pweight=ate_weight], ///
    or vce(cluster school)
eststo: quietly logit completed_mass_core ip_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year i.school [pweight=ate_weight], ///
    or vce(cluster school)

// college access
logit enrolled college ip participant i.race eco dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year i.school [pweight=ate_weight], ///
    or vce(cluster school)
eststo: quietly logit enrolled_college ip_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year i.school [pweight=ate_weight], ///
    or vce(cluster school)

// treatment with covariates and school fixed effects
logit second_year_persistence ip_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year i.school [pweight=ate_weight], ///
    or vce(cluster school)
eststo: quietly logit second_year_persistence ip_participant i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year i.school [pweight=ate_weight], ///
    or vce(cluster school)

//output
esttab using "$tables\icp_iptw_trimmed_data_appendix.rtf", ///
    eform drop(*school) varwidth(20) nobaselevels mtitle( ///
    "Effects of Treatment on College Readiness with School Fixed effects"  ///
    "Effects of Treatment on College Access with School Fixed effects" ///
    "Effects of Treatment on College Success with School Fixed effects") ///
    title("Trimmed Weights ICP IPTW Regressions") ///
    nonumbers eqlabels(none) collabels(none) modelwidth(10) se label ///
    compress not wide replace b(2) se(2)
```

```
/*******************************************************************************
File Name: dese_ec_vs_icp_untabulated_counts
Author: Pierre M. Lucien
Purpose: confirms counts and rates referenced before descriptive tables
*******************************************************************************/

//top matter
clear all
cap log close
set more off

//globals
global analysis "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\clean_data\10. dese_adjusted_hs_analysis_file.dta"
global clean "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\clean_data"

/*PRE-TABLES COUNTS*/

//icp students at ec_schools
use "$analysis" if inrange(school_year, 2019, 2022) ///
    & ec_school == 1, clear
qui sum ip_participant if grade_level == 12
dis "ICP Students at EC Schools: `r(sum)'"
local a = r(sum)

//total 12th grade ICP participants
use "$analysis" if inrange(school_year, 2019, 2022) ///
    & ip_school == 1, clear
qui sum ip_participant if grade == 12 & school_year <= 2022
dis "Total 12th grade ICP students: `r(sum)'"
local b = r(sum)

//percent of IP students who attend EC schools
dis "Percent of IP students who attend EC schools:"
dis `a'/`b'

// total number of EC or IP schools
use "$analysis" if inrange(school_year, 2019, 2022) ///
    & (ip_school == 1 | ec_school == 1) & grade_level == 12, clear
qui tab school_name
dis "Total EC or ICP School Count `r(r)'"

//total EC school counts
use "$analysis" if inrange(school_year, 2019, 2022) ///
    & ec_school == 1 & grade_level == 12, clear
qui tab school_name
dis "Total EC School Count `r(r)'"

//total IP school counts
use "$analysis" if inrange(school_year, 2019, 2022) ///
    & ip_school == 1 & grade_level == 12, clear
qui tab school_name
dis "Total ICP School Count `r(r)'"

// total number of EC and IP schools
use "$analysis" if inrange(school_year, 2019, 2022) ///
    & ip_school == 1 & ec_school == 1 & grade_level == 12, clear
qui tab school_name
dis "Total EC and ICP School Count `r(r)'"

//total student count
use "$analysis" if inrange(school_year, 2019, 2022) ///
    & (ec_school == 1 | ip_school == 1) & grade_level == 12, clear
qui tab school_name
dis "Total Student Count `r(N)'"

```

```
/*******************************************************************************
File Name: dese_ec_vs_icp_pre_weight_descriptive_tables
Author: Pierre M. Lucien
Purpose: Produces pre-weight descriptive tables for EC and ICP participants
*******************************************************************************/

//top matter
clear all
cap log close
set more off

//globals
global clean "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\clean_data"
global intermediate "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\intermediate_data"
global raw "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese data\raw data"
global tables "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\tables_figures"
global analysis  "$clean\10. dese_adjusted_hs_analysis_file.dta"

//load the file
use "$analysis" if inrange(school_year, 2019, 2022) ///
    & grade_level == 12 & (ec_school== 1 | ip_school == 1), clear

//gen treatment variable
assert ec_participant == 0 if ip_participant == 1
gen treatment_type = ""
replace treatment_type = "EC" if ec_comparison_group_1 == "EC"
replace treatment_type = "ICP" if ip_comparison_group_1 == "ICP"
replace treatment_type = "None" if mi(treatment_type)
gen no_treatment = (treatment_type == "None")


//tabulate enrollment by year
tab treatment_type, mi
table school_year, c(sum ec_participant sum ip_participant sum no_treatment)
cd "$tables"
asdoc table school_year, c(sum ec_participant sum ip_participant sum no_treatment) ///
    save(ec_vs_icp_enrollment_by_year) replace title(\i)

//gen test score
foreach x in ela math {
    gen proficient_meeting_`x' = (`x'_strata == 3)
    gen advanced_exceeding_`x' = (`x'_strata == 4)
    drop `x'_strata
}

//ELA and Math proficiency
table treatment_type, c(mean proficient_meeting_math mean proficient_meeting_ela  ///
    mean advanced_exceeding_math mean advanced_exceeding_ela)
cd "$tables"
asdoc table treatment_type, c(mean proficient_meeting_math mean proficient_meeting_ela  ///
    mean advanced_exceeding_math mean advanced_exceeding_ela) ///
    save(ec_vs_icp_enrollment_by_mcas_level) replace title(\i)

//create race dummies
gen black = (race == 2)
gen latinx = (race == 7)

//Minority and low income representation
table treatment_type, c(mean black mean latinx mean eco_dis)
cd "$tables"
asdoc table treatment_type, c(mean black mean latinx mean eco_dis) ///
    save(ec_vs_icp_enrollment_by_race_and_income) replace title(\i)


```

```
/*******************************************************************************
File Name: dese_ec_vs_icp_ps_calculation_weight
Author: Pierre M. Lucien
Purpose: creates weights for EC and ICP participants based on generalized propensity scores
*******************************************************************************/

//top matter
clear all
cap log close
set more off

//globals
global clean "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\clean_data"
global intermediate "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\intermediate_data"
global raw "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese data\raw data"
global tables "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\tables_figures"
global analysis  "$clean\10. dese_adjusted_hs_analysis_file.dta"

//load the data with relevant years
use "$analysis" if grade_level == 12 & inrange(school_year, 2019, 2022), clear

//keep EC and IP schools
keep if ec_school == 1 | ip_school == 1

//adjust race variable
replace race = 6 if inrange(race, 3, 5)
label define race 6 "Other" 7 "Latinx", modify

//gen treatment variables
gen treatment = 1
replace treatment = 2 if ec_comparison_group_1 == "EC"
replace treatment = 3 if ip_comparison_group_1 == "ICP"
label define treatment 1 "None" 2 "EC" 3 "ICP"
label values treatment treatment
tab treatment

//calculate propensity scores
mlogit treatment i.race eco_dis_low_inc male el sped ///
    eighth chronic eighth ever sus ///
    ib1.ela_strata ib1.math_strata  ib2020.school_year, rrr
predict gps_*, scores
summarize gps_*


//calculate the weights
gen ate_weight = .
replace ate_weight = 1/gps_3 if treatment == 3
replace ate_weight = 1/(1-gps_3) if treatment != 3
gen att_weight = .
replace att_weight = 1 if treatment == 3
replace att_weight = gps_3/(1-gps_3) if treatment != 3

//create school variable for fixed effects
destring(school_code), gen(school)

//save the weighted file
save "$clean\27. dese_ec_vs_icp_ps_calculation_weight.dta", replace

```

```
/*******************************************************************************
File Name: dese_ec_vs_icp_post_weight_diagnostic_tests
Author: Pierre M. Lucien
Purpose: Produces post-weight diagnostic graphs and tables for EC and ICP
*******************************************************************************/

//top matter
clear all
cap log close
set more off

//globals
global clean "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\clean_data"
global intermediate "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\intermediate_data"
global raw "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese data\raw data"
global tables "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\tables_figures"
global analysis  "$clean\10. dese_adjusted_hs_analysis_file.dta"
global weighted_data "$clean\27. dese_ec_vs_icp_ps_calculation_weight.dta"

/*POST WEIGHT TABLES AND FIGURES*/
use "$weighted_data", clear

//balance table
teffects aipw (enrolled_college i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year, logit) ///
    (treatment i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year, mlogit), pomeans //to confirm
tebalance summarize
cd "$tables"
asdoc tebalance summarize, ///
    save(ec_vs_icp_post_weight_balance_table) ///
    replace title(\i)

//propensity score overlap graph
use "$weighted_data", clear
label define treatment 1 "Untreated Subjects" 2 "EC Subjects" 3 "ICP subjects", modify
graph box gps 2, over(treatment) ///
    title("Distribution of Generalized Propensity Scores for EC Treatment") ///
    ytitle("Log Odds Propensity Scores") name(graph1, replace)
graph box gps_3, over(treatment) ///
    title("Distribution of Generalized Propensity Scores for ICP Treatment") ///
    ytitle("Log Odds of Propensity Scores") name(graph2, replace)
graph combine graph1 graph2, row(2)
graph export "$tables\ec_vs_icp_ps_distribution_by_treatment.pdf", replace
```

```
/*******************************************************************************
File Name: dese_ec_vs_icp_regression_tables_interaction_graphs
Author: Pierre M. Lucien
Purpose: Produces regression tables and interaction graphs for ICP
*******************************************************************************/

//top matter
clear all
cap log close
set more off

//globals
global clean "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\clean_data"
global intermediate "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\intermediate_data"
global raw "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese data\raw data"
global tables "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\tables_figures"
global analysis  "$clean\10. dese_adjusted_hs_analysis_file.dta"
global weighted_data "$clean\27. dese_ec_vs_icp_ps_calculation_weight.dta"

/*PS REGRESSION*/
eststo clear

// calculate propensity score
use "$analysis" if grade_level == 12 & inrange(school_year, 2019, 2022), clear

//keep needed records
keep if ec_school == 1 | ip_school == 1

//adjust race variable
replace race = 6 if inrange(race, 3, 5)
label define race 6 "Other" 7 "Latinx", modify

//generate treatment
gen treatment = 1
replace treatment = 2 if ec_comparison_group_1 == "EC"
replace treatment = 3 if ip_comparison_group_1 == "ICP"
label define treatment 1 "None" 2 "EC" 3 "ICP"
label values treatment treatment
tab treatment

//calculate propensity scores
mlogit treatment i.race eco_dis_low_inc male el sped ///
    eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata  ib2020.school_year, rrr
eststo: quietly mlogit treatment i.race eco_dis_low_inc male el sped ///
    eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata  ib2020.school_year, rrr

//output table
esttab using "$tables\ec_vs_icp_gps_calculation_regression.rtf", ///
    eform varwidth(20) nobaselevels mtitle("Logistic Regression Odd Ratios") title("PS Calculation Model") ///
    nonumbers eqlabels(none) collabels(none) modelwidth(10) se ///
    label compress not wide replace

/*COLLEGE READINESS*/
eststo clear

// load the data
use "$weighted_data", clear

// treatment with covariates
logit completed_mass_core i.treatment i.race eco_dis_low_inc male el sped ///
    eighth chronic eighth ever sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year ///
    [pweight= ate_weight], or vce(cluster school)
```

```
   eststo: quietly logit completed_mass_core i.treatment i.race eco_dis_low_inc male el sped ///
       eighth_chronic eighth_ever_sus ///
       ib1.ela_strata ib1.math_strata ib2020.school_year ///
       [pweight= ate_weight], or vce(cluster school)

   // treatment with covariates and school fixed effects
   logit completed_mass_core i.treatment i.race eco_dis_low_inc male el sped ///
       eighth_chronic eighth_ever_sus ///
       ib1.ela_strata ib1.math_strata ib2020.school_year i.school ///
       [pweight= ate_weight], or vce(cluster school)
   eststo: quietly logit completed_mass_core i.treatment i.race eco_dis_low_inc male el sped ///
       eighth chronic eighth ever sus ///
       ib1.ela_strata ib1.math_strata ib2020.school_year i.school ///
       [pweight= ate_weight], or vce(cluster school)

   // treatment with covariates, school fixed effects, and interactions
   logit completed_mass_core i.treatment##i.race ///
       i.treatment##eco dis low inc male el sped ///
       eighth_chronic eighth_ever_sus ///
       ib1.ela_strata ib1.math_strata ib2020.school_year i.school ///
       [pweight= ate_weight], or vce(cluster school)
   eststo: quietly logit completed_mass_core i.treatment##i.race ///
       i.treatment##eco_dis_low_inc male el sped ///
       eighth_chronic eighth_ever_sus ///
       ib1.ela_strata ib1.math_strata ib2020.school_year i.school ///
       [pweight= ate_weight], or vce(cluster school)

   //output table
   esttab using "$tables\ec_vs_icp_iptw_readiness_regressions.rtf", ///
       eform drop(*school) varwidth(20) nobaselevels ///
       mtitle("Treatment with Covariates" ///
       "Treatment with Covariates and School Fixed Effects" ///
       "Treatment with Covariates, School Fixed Effects, and Interactions") ///
       title("Effects on MassCore Completion/College Readiness") ///
       nonumbers eqlabels(none) collabels(none) modelwidth(10) se label ///
       compress not wide replace b(2) se(2)

   /*COLLEGE ACCESS*/
   eststo clear

   // treatment with covariates
   logit enrolled_college i.treatment i.race eco_dis_low_inc male el sped ///
       eighth chronic eighth ever sus ///
       ib1.ela_strata ib1.math_strata ib2020.school_year ///
       [pweight= ate_weight], or vce(cluster school)
   eststo: quietly logit enrolled_college i.treatment i.race eco_dis_low_inc male el sped ///
       eighth_chronic eighth_ever_sus ///
       ib1.ela_strata ib1.math_strata ib2020.school_year ///
       [pweight= ate_weight], or vce(cluster school)

   // treatment with covariates and school fixed effects
   logit enrolled_college i.treatment i.race eco_dis_low_inc male el sped ///
       eighth_chronic eighth_ever_sus ///
       ib1.ela_strata ib1.math_strata ib2020.school_year i.school ///
       [pweight= ate_weight], or vce(cluster school)
   eststo: quietly logit enrolled_college i.treatment i.race eco_dis_low_inc male el sped ///
       eighth_chronic eighth_ever_sus ///
       ib1.ela_strata ib1.math_strata ib2020.school_year i.school ///
       [pweight= ate_weight], or vce(cluster school)

   // treatment with covariates, school fixed effects, and interactions
   logit enrolled_college i.treatment##i.race ///
       i.treatment##eco_dis_low_inc male el sped ///
       eighth_chronic eighth_ever_sus ///
       ib1.ela_strata ib1.math_strata ib2020.school_year i.school ///
       [pweight= ate_weight], or vce(cluster school)
   eststo: quietly logit enrolled_college i.treatment##i.race ///
       i.treatment##eco dis low inc male el sped ///
       eighth_chronic eighth_ever_sus ///
       ib1.ela_strata ib1.math_strata ib2020.school_year i.school ///
```

```
136       [pweight= ate_weight], or vce(cluster school)
137   margins i.treatment#eco_dis_low_inc if treatment != 3
138   marginsplot, noci title("Predictive Margins of EC and Income Interaction") ///
139       ytitle("Probability of Enrolling in College") ///
140       note("*EC participation is binary, not continous. Lines between points are for
      illustrative purposes.")
141   graph export "$tables\ec_vs_icp_iptw_accesss_income_interaction.pdf", replace
142   margins i.treatment#i.race if treatment != 3
143   marginsplot, noci title("Predictive Margins of EC and Race Interaction") ///
144       ytitle("Probability of Enrolling in College") ///
145       note("*EC participation is binary, not continous. Lines between points are for
      illustrative purposes.")
146   graph export "$tables\ec_vs_icp_iptw_accesss_race_interaction.pdf", replace
147
148
149   //output table
150   esttab using "$tables\ec_vs_icp_iptw_access_regressions.rtf", ///
151       eform drop(*school) varwidth(20) nobaselevels ///
152       mtitle("Treatment with Covariates" ///
153       "Treatment with Covariates and School Fixed Effects" ///
154       "Treatment with Covariates, School Fixed Effects, and Interactions") ///
155       title("Effects on College Enrollment") ///
156       nonumbers eqlabels(none) collabels(none) modelwidth(10) se label ///
157       compress not wide replace b(2) se(2)
158
159   /*COLLEGE SUCCESS*/
160   eststo clear
161
162   // treatment with covariates
163   logit second_year_persistence i.treatment i.race eco_dis_low_inc male el sped ///
164       eighth_chronic eighth_ever_sus ///
165       ib1.ela_strata ib1.math_strata ib2020.school_year ///
166       [pweight= ate_weight], or vce(cluster school)
167   eststo: quietly logit second_year_persistence i.treatment i.race eco_dis_low_inc male el
      sped ///
168       eighth_chronic eighth_ever_sus ///
169       ib1.ela_strata ib1.math_strata ib2020.school_year ///
170       [pweight= ate_weight], or vce(cluster school)
171
172   // treatment with covariates and school fixed effects
173   logit second_year_persistence i.treatment i.race eco_dis_low_inc male el sped ///
174       eighth_chronic eighth_ever_sus ///
175       ib1.ela strata ib1.math strata ib2020.school year i.school ///
176       [pweight= ate_weight], or vce(cluster school)
177   eststo: quietly logit second_year_persistence i.treatment i.race eco_dis_low_inc male el
      sped ///
178       eighth_chronic eighth_ever_sus ///
179       ib1.ela_strata ib1.math_strata ib2020.school_year i.school ///
180       [pweight= ate_weight], or vce(cluster school)
181
182   // treatment with covariates, school fixed effects, and interactions
183   logit second_year_persistence i.treatment##i.race ///
184       i.treatment##eco_dis_low_inc male el sped ///
185       eighth_chronic eighth_ever_sus ///
186       ib1.ela_strata ib1.math_strata ib2020.school_year i.school ///
187       [pweight= ate_weight], or vce(cluster school)
188   eststo: quietly logit second_year_persistence i.treatment##i.race ///
189       i.treatment##eco_dis_low_inc male el sped ///
190       eighth_chronic eighth_ever_sus ///
191       ib1.ela_strata ib1.math_strata ib2020.school_year i.school ///
192       [pweight= ate_weight], or vce(cluster school)
193   margins i.treatment#eco_dis_low_inc if treatment != 3
194   marginsplot, noci title("Predictive Margins of EC and Income Interaction") ///
195       ytitle("Probability of Persisting in College") ///
196       note("*EC participation is binary, not continous. Lines between points are for
      illustrative purposes.")
197   graph export "$tables\ec_vs_icp_iptw_successs_income_interaction.pdf", replace
198
199
200   //output table
```

```
201   esttab using "$tables\ec_vs_icp_iptw_success_regressions.rtf", ///
202       eform drop(*school) varwidth(20) nobaselevels ///
203       mtitle("Treatment with Covariates" ///
204       "Treatment with Covariates and School Fixed Effects" ///
205       "Treatment with Covariates, School Fixed Effects, and Interactions") ///
206       title("Effects on College Persistence") ///
207       nonumbers eqlabels(none) collabels(none) modelwidth(10) se label ///
208       compress not wide replace b(2) se(2)
209
210
211
212
213
214
```

```
/*******************************************************************************
File Name: dese_ec_vs_icp_robustness_check_regression_tables
Author: Pierre M. Lucien
Purpose: Performs robustness checks for EC vs ICP GPS weighted regressions
*******************************************************************************/

//top matter
clear all
cap log close
set more off

//globals
global clean "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\clean_data"
global intermediate "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\intermediate_data"
global raw "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese data\raw data"
global tables "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\tables_figures"
global analysis  "$clean\10. dese_adjusted_hs_analysis_file.dta"
global weighted_data "$clean\27. dese_ec_vs_icp_ps_calculation_weight.dta"

/*PS Regression*/
eststo clear

// calculate propensity score
use "$analysis" if grade_level == 12 & inrange(school_year, 2021, 2022) ///
    & !mi(next_gen_ela) & !mi(next_gen_math), clear

//keep needed records
keep if ec_school == 1 | ip_school == 1

//adjust race variable
replace race = 6 if inrange(race, 3, 5)
label define race 6 "Other" 7 "Latinx", modify

//generate treatment
gen treatment = 1
replace treatment = 2 if ec_comparison_group_1 == "EC"
replace treatment = 3 if ip_comparison_group_1 == "ICP"
label define treatment 1 "None" 2 "EC" 3 "ICP"
label values treatment treatment
tab treatment

//calculate propensity scores
mlogit treatment i.race eco_dis_low_inc male el sped ///
    eighth_chronic eighth_ever_sus ///
    next_gen_ela next_gen_math ib2021.school_year, rrr
predict gps_*, scores
summarize gps_*

//calculate the weights
gen ate_weight = .
replace ate_weight = 1/gps_3 if treatment == 3
replace ate_weight = 1/(1-gps_3) if treatment != 3
gen att_weight = .
replace att_weight = 1 if treatment == 3
replace att_weight = gps_3/(1-gps_3) if treatment != 3

/* NEXT GEN MCAS YEARS REGRESSION OUPUTs*/

//fix school variable for fixed effects regression
destring(school_code), gen(school)

// college readiness
logit completed_mass_core i.treatment i.race eco_dis_low_inc male el sped ///
    eighth chronic eighth ever sus ///
    next_gen_ela next_gen_math ib2021.school_year i.school ///
    [pweight= ate_weight], or vce(cluster school)
```

```
eststo: quietly logit completed_mass_core i.treatment i.race eco_dis_low_inc male el sped ///
    eighth_chronic eighth_ever_sus ///
    next_gen_ela next_gen_math ib2021.school_year i.school ///
    [pweight= ate_weight], or vce(cluster school)

/// college access
logit enrolled_college i.treatment i.race eco_dis_low_inc male el sped ///
    eighth_chronic eighth_ever_sus ///
    next_gen_ela next_gen_math ib2021.school_year i.school ///
    [pweight= ate_weight], or vce(cluster school)
eststo: quietly logit enrolled_college i.treatment i.race eco_dis_low_inc male el sped ///
    eighth chronic eighth ever sus ///
    next_gen_ela next_gen_math ib2021.school_year i.school ///
    [pweight= ate_weight], or vce(cluster school)

// college success
logit second_year_persistence i.treatment i.race eco_dis_low_inc male el sped ///
    eighth chronic eighth ever sus ///
    next_gen_ela next_gen_math ib2021.school_year i.school ///
    [pweight= ate_weight], or vce(cluster school)
eststo: quietly logit second_year_persistence i.treatment i.race eco_dis_low_inc male el
sped ///
    eighth_chronic eighth_ever_sus ///
    next_gen_ela next_gen_math ib2021.school_year i.school ///
    [pweight= ate_weight], or vce(cluster school)

//output table
esttab using "$tables\ec_vs_icp_robustness_check_regression_logit.rtf", ///
    eform drop(*school) varwidth(20) nobaselevels mtitle("Effects on College Readiness" ///
    "Effects on College Access" "Effects on College Success") ///
    title("Robustness Checks") nonumbers eqlabels(none) collabels(none) ///
    modelwidth(10) se label compress not wide replace b(2) se(2)

/* LINEAR PROBABILITY MODELS */
eststo clear

//load matched data
use "$weighted_data", clear

// college readiness
regress completed_mass_core i.treatment i.race eco_dis_low_inc male el sped ///
    eighth_chronic eighth_ever_sus ///
    ib1.ela strata ib1.math strata ib2020.school year i.school ///
    [pweight= ate_weight], vce(cluster school)
eststo: quietly regress completed_mass_core i.treatment i.race eco_dis_low_inc male el sped
///
    eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year i.school ///
    [pweight= ate_weight], vce(cluster school)

// college access
regress enrolled_college i.treatment i.race eco_dis_low_inc male el sped ///
    eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year i.school ///
    [pweight= ate_weight], vce(cluster school)
eststo: quietly regress enrolled_college i.treatment i.race eco_dis_low_inc male el sped ///
    eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year i.school ///
    [pweight= ate_weight], vce(cluster school)

// college success
regress second_year_persistence i.treatment i.race eco_dis_low_inc male el sped ///
    eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year i.school ///
    [pweight= ate_weight], vce(cluster school)
eststo: quietly regress second_year_persistence i.treatment i.race eco_dis_low_inc male el
sped ///
    eighth chronic eighth ever sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year i.school ///
    [pweight= ate_weight], vce(cluster school)
```

```
134
135   //output
136   esttab using "$tables\ec_vs_icp_robustness_check_regression_lpm.rtf", ///
137       drop(*school) varwidth(20) nobaselevels mtitle("Effects on College Readiness" ///
138       "Effects on College Access" "Effects on College Success") ///
139       title("Robustness Checks") nonumbers eqlabels(none) collabels(none) ///
140       modelwidth(10) se label compress not wide replace b(2) se(2)
141
142
143
144
145
146
147
```

```
/*******************************************************************************
File Name: dese_ec_vs_icp_iptw_appendix_regression_tables
Author: Pierre M. Lucien
Purpose: creates appendices of regresssion tables not in paper
*******************************************************************************/

//top matter
clear all
cap log close
set more off

//globals
global clean "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\clean_data"
global intermediate "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\intermediate_data"
global raw "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese data\raw data"
global tables "C:\Users\pierre.lucien\OneDrive - Commonwealth of Massachusetts\Desktop\dese_data\tables_figures"
global analysis  "$clean\10. dese_adjusted_hs_analysis_file.dta"
global weighted_data "$clean\27. dese_ec_vs_icp_ps_calculation_weight.dta"

// TRIMMING WEIGHTS
eststo clear

// load the data
use "$weighted_data", clear
sum ate_weight, detail
keep if inrange(ate_weight, r(p1), r(p99))

// college readiness
logit completed_mass_core i.treatment i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year i.school [pweight=ate_weight], ///
    or vce(cluster school)
eststo: quietly logit completed_mass_core i.treatment i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year i.school [pweight=ate_weight], ///
    or vce(cluster school)

// college access
logit enrolled college i.treatment i.race eco dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year i.school [pweight=ate_weight], ///
    or vce(cluster school)
eststo: quietly logit enrolled_college i.treatment i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year i.school [pweight=ate_weight], ///
    or vce(cluster school)

// treatment with covariates and school fixed effects
logit second_year_persistence i.treatment i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year i.school [pweight=ate_weight], ///
    or vce(cluster school)
eststo: quietly logit second_year_persistence i.treatment i.race eco_dis male ///
    sped el eighth_chronic eighth_ever_sus ///
    ib1.ela_strata ib1.math_strata ib2020.school_year i.school [pweight=ate_weight], ///
    or vce(cluster school)

//output
esttab using "$tables\ec_vs_icp_iptw_trimmed_data_appendix.rtf", ///
    eform drop(*school) varwidth(20) nobaselevels mtitle( ///
    "Effects of Treatment on College Readiness with School Fixed effects"  ///
    "Effects of Treatment on College Access with School Fixed effects" ///
    "Effects of Treatment on College Success with School Fixed effects") ///
    title("Trimmed Weights EC vs. ICP IPTW Regressions") ///
    nonumbers eqlabels(none) collabels(none) modelwidth(10) se label ///
    compress not wide replace b(2) se(2)
```