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Preparing for the STEM Pathways? Dual Enrollment and College Major Choice in STEM

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ABSTRACT

Guided by the STEM pathway model, our study hypothesizes that dual enrollment can serve as an effective strategy to improve and equalize college students' access to STEM programs. We analyzed a nationally representative dataset to disaggregate the influence of dual enrollment course-taking (i.e. participation, dual credits in Math/Science, number of dual credits) on students' STEM major selection, with a focus on traditionally underrepresented students in STEM. We found that taking dual enrollment courses in general is positively associated with the probability of majoring in STEM, especially at the baccalaureate level. However, taking dual enrollment courses in Math/Science is not associated with the probability of majoring in STEM when compared with students with no dual enrollment courses in Math/Science. The relationship between dual enrollment course-taking and STEM outcomes varies across different student background groups: It is consistently positive for students of higher household income to major in STEM but not statistically significant for low-income students. We discussed practical implications and future research with a focus on the role dual enrollment plays in advancing postsecondary STEM access.

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Dual enrollment; STEM; college major choice; sociodemographic background; High School Longitudinal Study

Introduction

A critical problem in U.S. postsecondary education is that colleges and universities do not produce enough graduates in science, technology, engineering, and mathematics (STEM) to meet the workforce demand (National Science Foundation [NSF], 2010; Sithole et al., 2017). The number of STEM graduates is especially low for traditionally underrepresented college students, which are defined as women, students of color, low-income, and first-generation students in the current study. Traditionally underrepresented students are often less likely to enroll in STEM programs at the postsecondary level, largely due to systemic barriers which prevent them from realizing their full potential in STEM (Grossman & Porche, 2014; Hardy & Katsinas, 2010; Pierszalowski et al., 2021; Wang, 2013b, 2016). For example, Hazari et al. (2013) noted that STEM students of different gender and race/ethnicity indicated varying

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levels of science identity, and Byars-Winston (2014) emphasized the STEM equity imperative in career planning for traditionally underrepresented students. National research and policy have put priority to broaden and equalize STEM participation for traditionally underrepresented students and support their STEM success in postsecondary education (Fayer et al., 2017).

To realize educational success and equity in STEM, feasible and effective interventions in the secondary-postsecondary nexus are a must. Dual enrollment (DE), which allows high school students to take college-level courses and earn college credits while in high school, is a potential strategy to improve and equalize college students' access to STEM programs. As of 2022, 48 states and the District of Columbia have state-level DE policies, but only 31 states mandate every high school to participate (Education Commission of the States [ECS], 2022). On average and across states, 82% of public schools offer DE opportunities for students, and about a third of high school students have been dually enrolled at some point during high school (U.S. Department of Education [ED], 2019, 2020). For the development of students' interest and success in STEM in particular, DE programs not only support high school students with early access to college-level STEM resources, but they also serve traditionally underrepresented students by developing a STEM identity early, accessing postsecondary STEM education while enrolled in high school, and accumulating course credits and skillsets toward a STEM degree and career (Barnett, 2018; Ozmun, 2013; Zinth, 2018).

While previous studies have indicated that DE participation has a generally positive impact on students' high school graduation, college matriculation, and college readiness (e.g., An, 2013; An & Taylor, 2015; Cowan & Goldhaber, 2015), these studies often simplify DE participation as a binary indicator which obscures students' varying DE course-taking patterns. The multifaceted DE participation (e.g., subject area of DE credits, number of DE credits) needs to be specifically identified and studied to examine *if* and *how* DE course-taking contributes to students' STEM major selection in postsecondary education. Given the prevalence of DE programs and the large number of high school students in the nation that are dually enrolled, the current study uses a nationally representative longitudinal dataset to disaggregate the influence of DE course-taking (i.e., participation, subject areas, number of credits earned) on students' STEM major selection in college. Guided by the STEM pathway model (Cannady et al., 2014; Fealing et al., 2015), this study addresses the following research questions:

(1) *To what extent does DE course-taking (i.e., participation, subject areas, number of credits earned) influence college students' major choice in STEM?*
(2) *Does the relationship vary across college student groups, in terms of sex, student-of-color status, low-income status, and first-generation status?*

Literature review

Sociodemographic disparities in college and major choice

Individuals' sociodemographic backgrounds play a significant role in college and major choice among STEM-aspiring students (Crisp et al., 2009; Hughes et al., 2019). Out of the 429,298 bachelor's degrees conferred in STEM fields in 2019–20 academic year, 62.6% were conferred to men students and 37.4% were conferred to women students (U.S. Department of Education [ED], 2021), continuing to contribute to the long-standing employment and compensation inequity (Michelmore & Sassler, 2016). Similarly, of all the bachelor's degrees conferred to students of a certain race/ethnicity, the percentage of bachelor's degrees in STEM varies. Only 14% of Black bachelor's degree holders, 17% of Hispanic/Latinx bachelor's degree holders, and 14% of American Indian and Alaska Native bachelor's degree holders received their degrees in STEM, and these numbers are constantly lower than the national average of 21%. In comparison, 37% of Asian American bachelor's degree holders are in STEM fields (National Center of Educational Statistics, 2022). In STEM occupations, 26% of STEM workers were women and 74% were men, and Hispanic/Latinx and Black populations are substantially underrepresented in most STEM occupations (Funk & Parker, 2018; Landivar, 2013).

When discussing its mechanisms, sociological and economic perspectives argue that individuals' background situates themselves in a social and cultural system (i.e., habitus) that informs their perceived value of education and prior experience with college, which eventually influences their decision of college attendance and choice of major (Paulsen, 2001; Perna, 2006). Students who are sensitive to the cost and benefit of different types of postsecondary degree programs because of financial needs may choose the more affordable sub-baccalaureate pathway (e.g., two-year colleges; Wickersham, 2020). Additionally, social cognitive and behavioral perspectives posit that individuals of varying socioeconomic background accumulate different learning and career experience and expectation (Weeden et al., 2020), which in turn guides their educational and academic choice and action (Lent & Brown, 2013; Parker et al., 2012).

Empirical research largely resonates with prominent theories that women, students of color, students from low-income families, and first-generation students in STEM disciplines face multiple obstacles in their pathway to college. Due to a lack of resources for college preparation and other systemic barriers, traditionally underrepresented students may be exposed to limited knowledge of postsecondary education and its benefit even when holding academic readiness constant (Cook et al., 2021; Lindstrom et al., 2022; Majors, 2019; Perez-Felkner, 2015). Given the commitment of time and monetary resources to postsecondary education, the cost may direct students to choose sub-baccalaureate programs and prioritize the expected economic return over intrinsic academic or career interest (Wickersham, 2020).

Following the social cognitive approach, accumulating learning experiences is one viable way to combat the negative effect of sociodemographic background on students' educational pathways, particularly for STEM-aspiring students (Lent et al., 2015). Taking advanced courses, dual enrollment, and even out-of-school-time activities have all been found to promote the likelihood of attending college and choosing a STEM major (An & Taylor, 2019; Kim et al., 2015; Trusty, 2002; Wang et al., 2015). Moreover, beyond the general positive effect on academic outcomes, gaining extra learning experiences appears to benefit students of minoritized sociodemographic backgrounds more (Beyer, 2014; Wang et al., 2017). DE course-taking, as an additional educational opportunity, holds great promise for more positive STEM outcomes for students from traditionally underrepresented backgrounds.

DE course-taking and college major in STEM

As introductory STEM courses follow relatively strict course sequences, they can be considered as obstacles to student access and success in STEM fields (Dunbar, 2006, U.S. Department of Education [ED], 2018; Xu & Dadgar, 2017). Among the academic factors of the STEM achievement gap, the long math course sequence remains a major barrier for traditionally underrepresented students to enter and stay on a STEM track (Fouad et al., 2010). A student's course-taking pattern, such as the number of advanced math and science courses, is a predictor for major selection in STEM (Card & Payne, 2017; Kim et al., 2015). For example, taking DE course(s) in math induces students to take more advanced math courses and reduces their likelihood of enrolling in developmental mathematics (Hemelt et al., 2020). DE courses in the core academic subjects (e.g., English, science, math), as opposed to vocational-focused courses, have a larger effect on promoting students' baccalaureate success in general (Giani et al., 2014).

In particular, DE programs provide an additional access point for traditionally underrepresented students to college-level courses. In general, DE courses are more accessible for traditionally underrepresented students than other programs that allow high school students to earn college credits (Barnett, 2018; Zinth & Barnett, 2018). Unlike Advanced Placement (AP) and International Baccalaureate (IB) programs, DE courses are not limited to the most advanced high school students. Minaya (2021) also found that taking dual enrollment courses on STEM subjects motivates high school students in Florida to major in STEM in college and increases college retention for Black and Hispanic students. Moreover, DE participation can greatly increase a student's rating of their abilities in math and science and support them to transition to college (Karp, 2012; Ozmun, 2013; Robinson et al., 2019), particularly familiarizing traditionally underrepresented students with a college environment and academic expectations from college faculty (Giani et al., 2014). Earning DE credits has the potential to build an academic foundation for traditionally underrepresented students and improve college students' STEM access (Zinth, 2018).

Conceptual framework

This study uses the STEM pathway model to explain the logic of how the DE intervention may influence students' college major choice in STEM and how the influence may differ by students' sociodemographic characteristics (Cannady et al., 2014; Fealing et al., 2015). The STEM pathway model builds upon prior work on STEM identity (Holland et al., 1998), academic momentum in STEM (Adelman, 1999, 2006; Wang, 2016), and the social cognitive career theory for traditionally underrepresented students (Fouad & Santana, 2017). Specifically, the model illustrates how a potential intervention (i.e., DE course-taking and its various forms) can *alter* or *accelerate* a student's diverse academic trajectories in STEM, particularly for traditionally underrepresented students. Figure 1 presents a visual representation of the STEM pathway model explaining the mechanism of DE programs on students' diverse pathways toward STEM majors in college.

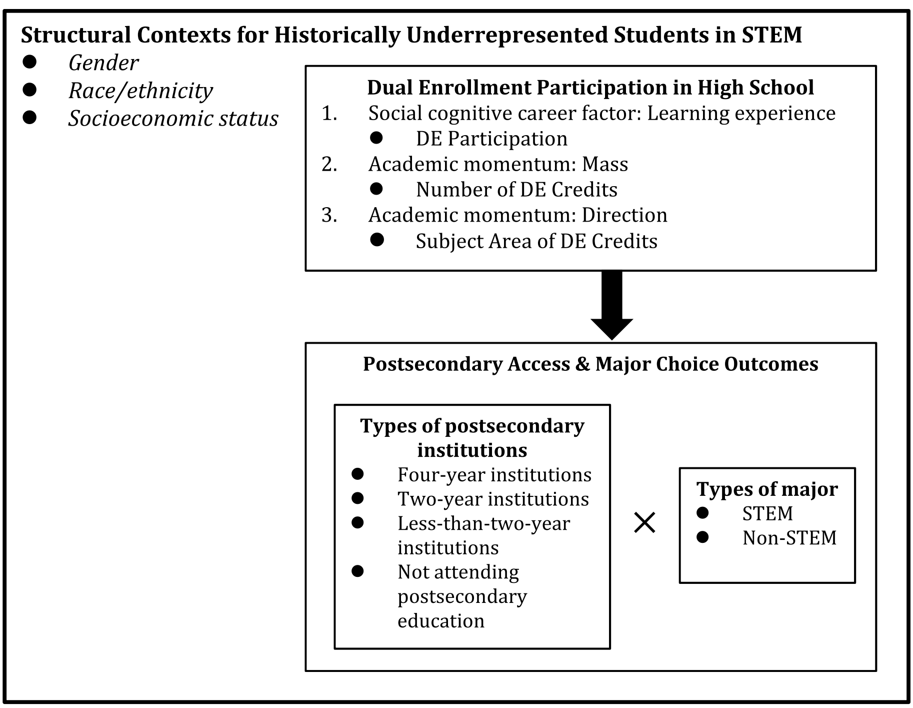

Figure 1. The influence of dual enrollment on STEM access from the lens of the STEM pathway model.

First and foremost, the pathway framework acknowledges that a student's access to STEM fields can be a result of structural barriers and contextual factors (Grossman & Porche, 2014; Hardy & Katsinas, 2010; Pierszalowski et al., 2021; Wang, 2013b). Though DE programs provide relatively broader access to college-level courses than similar programs (e.g., AP, IB programs; Barnett, 2018; Zinth & Barnett, 2018), students do not have equal eligibility to access (the same number and subject area) DE course due to preexisting differences, such as academic performance and program offering in high schools (Zinth & Barnett, 2018). Despite 82% of public high schools offering access to DE courses, variations exist across the urbanicity of high schools and the percentage of students in a school who were approved for free or reduced-price lunch (FRPL). Compared with the national average of 82%, only 72% of city schools and 71% of schools in which 75% or more of students were approved for FRPL offered dual enrollment (U.S. Department of Education [ED], 2020). For STEM DE courses and take Texas for example, all and 73.5% of the surveyed colleges and high schools, respectively, offered math DE courses in 2009–10 academic year, whereas 80% and 50% of the surveyed colleges and high schools, respectively, offered science DE courses (compared with above 90% for English and social studies; Texas Education Agency, 2011), leaving great room for improvement in equitable access to STEM DE courses. DE programs can encourage learning, career experience, and expectation in STEM and postsecondary matriculation in STEM for traditionally underrepresented students (An & Taylor, 2015; Fouad & Santana, 2017; Zinth, 2015), and the larger context (e.g., sociodemographic characteristics) should be empirically accounted for in examining the effect of DE course-taking on STEM access and equity.

A key significance of the pathway framework is that it umbrellas STEM trajectories in multiple sectors, including students that followed college attendance patterns other than a baccalaureate academic program (Wang, 2016). In fact, traditionally underrepresented students often attend a community college, take developmental courses, choose a career and technical education (CTE) program, or transfer upwardly, in order to pursue an advanced degree or a career in STEM (Fealing et al., 2015; Wang, 2020; Wyatt et al., 2015). While recent state data show that DE particularly benefits students of color, first-generation students, and students of low SES background more than their counterparts in terms of choosing four- over two-year college (Lee et al., 2022), this study further unpacks STEM major at both the sub-baccalaureate and baccalaureate levels.

Finally, disaggregating the concept of DE participation by subject area and number of DE credits can identify specific aspects of DE programs that are meaningful for equitable STEM access. Among the dual-enrolled students, some students can be more likely to earn more DE credits (i.e., the mass in academic momentum) and/or take more DE courses in math and science (i.e., the direction in academic momentum). Because each additional DE course accumulates to the likelihood of postsecondary persistence and completion (Giani et al., 2014), the disparities within DE course-taking patterns (e.g., earning 3 versus 15 DE credits, taking advanced math courses versus non-essential STEM courses) can have different influences on a student's progress toward STEM major choice in college, thus altering their STEM trajectories in the long term. In sum, the STEM pathway model accentuates the focus on STEM success and equity for individual students in their situated contexts with tangible progress toward their educational goals, without excluding the conventional baccalaureate degree path for students to choose a STEM major.

Methods

Data sources and sample

To answer the set of research questions, we analyzed observational data of a nationally representative dataset provided by the National Center of Educational Statistics (NCES). Conducted by ED, the High School Longitudinal Study of 2009 (HSLS:09) firstly surveyed over 23,500 9th graders from 944 schools in 2009 and followed up in their 11th grade and 12th grade, and three years and four years after high school graduation, respectively. Though not highly detailed, HSLS:09 includes students' DE course-taking information (e.g., DE course-taking in Math/Science, number of DE credits earned) based on students' self-report surveys. The sample includes 11,560 college students with valid major choice records as of February 2016. We addressed the missing values of predictors using multiple imputation with sampling weight to generate five imputed datasets.[1]

Variables

We examined the influence of DE course-taking on major selection in STEM. Specifically, the first outcome was a binary indicator of major choice in STEM as of February 2016, based on the definition used by the Department of Defense's Science, Mathematics, and Research for Transformation (SMART) grant. The second outcome was categorical representing if the major is STEM or not at the baccalaureate level or sub-baccalaureate level, respectively.

The treatments were defined differently depending on the average treatment effect of interest. First, it was defined as a binary indicator of overall DE *participation* to understand the aggregated influence of DE course-taking on the outcomes, with the treatment group being students who have taken at least one DE course and the control group being students who have never taken a DE course. Additionally, DE *subject area* was defined as binary, indicating whether the DE course taken was in the subject of Math/Science or not. Finally, to examine the specific impact of the *number* of DE credits earned, treatment was defined in a continuous manner based on the number of DE credits earned in STEM sequence and non-STEM sequence, respectively.

Pre-treatment covariates were selected based on prior research and the conceptual framework to predict the likelihood of a certain DE course-taking pattern for individual students (Caliendo & Kopeinig, 2008). These variables included students' sociodemographic characteristics (i.e., sex,[2] race/ethnicity, socioeconomic status quintile, whether at least one parent working in STEM occupation), academic measures in the 9th grade in high school (i.e., grade point average [GPA], educational expectations, the highest level of math course), and high school characteristics (i.e., whether provide DE opportunities, location, control). The outcome model specifications also accounted for additional post-treatment covariates. Based on how these variables may influence students' STEM major selection (e.g., Wang, 2020), we also included students' intent to major in STEM and the number of AP/IB credits earned as post-treatment covariates in all outcome models. Detailed operationalizations of these variables are also presented in Appendix A.

Addressing selection bias

Students' DE course-taking depends on students' pre-college characteristics (e.g., race/ethnicity, family income, academic performance) and high school characteristics (e.g., whether the high school provides DE opportunities). Thus, we employed propensity score models (PSMs) to ensure overlap and comparability between the treatment group and the control group to reduce selection bias (Guo & Fraser, 2015). PSM as a quasi-experimental research design has been widely applied in educational research because it can substantively reduce the potential self-selection bias to arrive at findings that are as close as possible to causal inference (Powell et al., 2019). We selected a set of pre-treatment covariates as mentioned above to predict the likelihood of a certain DE course-taking for individual students (Caliendo & Kopeinig, 2008).

Using logistic regression, we estimated propensity score p for each observation, controlling for students' pre-treatment characteristics. The resulting propensity score p represents a student's probability of receiving treatment while enrolled in high school. For the binary treatments (i.e., whether took DE courses, whether took DE in Math/Science), the average treatment effect on the treated (ATT) reveals what the outcomes would have been for DE students had they not received the treatment in the respective model specifications. We calculated the ATT weights as the inverse of the resulting propensity score p. In this example, students in the treatment group (i.e., DE participation) receive a weight of 1, and students in the control group (i.e., no DE participation) receive a weight of $p/(1 - p)$. The final weight for each observation included in the post-weighting estimation will be normalized as a product term between the ATT weight and the sampling weight, divided by the mean of such product term to ensure generalization (Leite, 2017). For the full sample and each subsample categorized by sex, student-of-color status,[3] low-income status, and first-generation status, we repeated this procedure to estimate different sets of propensity scores due to students' varying probability of DE participation in individual subgroups. As indicated in Table 1 and Figure 2, the standardized mean differences before and after weighting indicated the data met the balancing property of PSM (Rubin, 2001; Shadish et al., 2008). The characteristics of all covariates pre- and post-weighting are presented in Appendix B.

Table 1. Standardized differences between treated and control groups by treatment.

	DE Course-Taking		Math/Science DE Course-Taking	
	Pre-weighting	Post-weighting	Pre-weighting	Post-weighting
Female	0.107	−0.016	0.136	−0.009
Race/Ethnicity				
Black/African American	−0.064	0.017	−0.165	−0.005
Hispanic/Latinx	−0.023	−0.019	−0.137	−0.003
Asian American, Native Hawaiian/Pacific Islander	0.013	−0.057	0.044	0.069
American Indian/Alaska Native	−0.010	0.024	−0.022	0.013
More than one race	−0.016	0.039	−0.028	−0.011
Socioeconomic Status Quintile				
Second quintile	0.016	0.035	−0.063	−0.024
Third quintile	0.004	0.020	−0.030	0.000
Fourth quintile	0.041	0.019	0.023	0.076
Highest quintile	−0.018	−0.040	0.119	−0.033
At least one parent working in a STEM occupation	−0.016	−0.040	0.070	0.005
Highest degree expected				
Associate degree	−0.048	0.039	−0.132	0.047
Bachelor's degree	−0.012	−0.006	−0.028	−0.047
Master's degree	0.066	0.064	0.109	0.033
Doctoral degree or Professional degree	0.104	−0.055	0.155	0.006
Don't know	−0.091	−0.024	−0.124	−0.041
Highest level of mathematics				
Basic math	−0.035	0.013	−0.037	−0.019
Other math	−0.050	0.017	−0.059	0.061
Pre-algebra	−0.041	−0.010	−0.131	0.016
Algebra I	−0.100	0.023	−0.293	0.009
Geometry	0.133	−0.024	0.242	−0.073
Algebra II	0.043	−0.021	0.143	0.024
Trigonometry	0.044	0.003	0.127	0.031
Other advanced math	−0.012	−0.004	0.042	0.056
9th Grade GPA	0.340	−0.045	0.674	−0.044
High school provides dual enrollment opportunities	0.178	0.050	0.228	0.045
High school location				
Suburb	−0.041	0.018	−0.076	0.009
Town	0.105	0.048	0.165	0.003
Rural	0.073	−0.069	0.067	0.012
High school control				
Private	−0.142	0.081	−0.111	0.010

Note. Sampling weights are applied to pre-weighting calculation. The weight for each observation included in the post-weighting estimation was a product term between the inverse probability treatment weight and the sampling weight, divided by the mean of such product terms.

SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009. Base Year, First Follow-Up, High School Transcript Study, and Postsecondary Education Transcript Study and Student Financial Aid Records Data Collection.

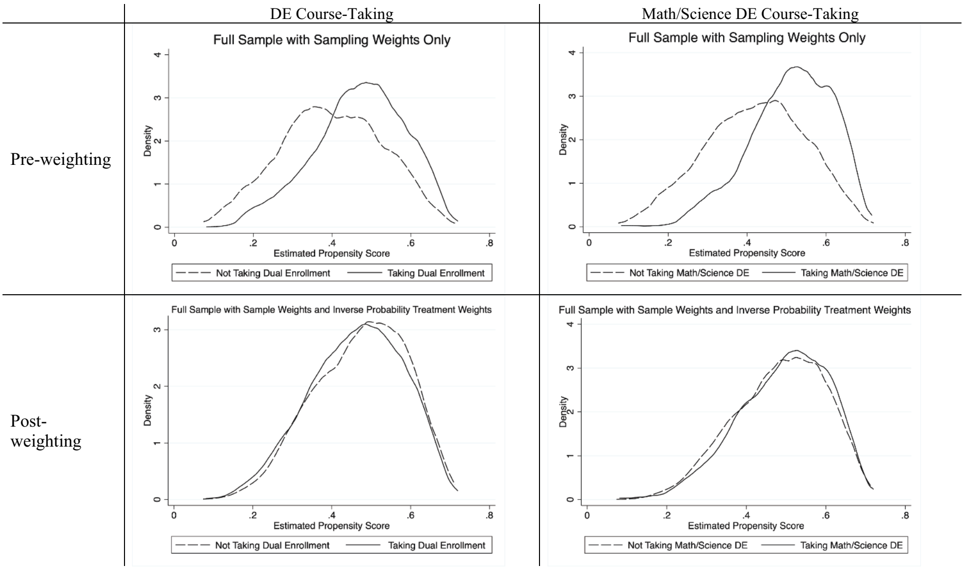

Figure 2. Estimated propensity scores between treated and control groups (pre- and post-weighting).
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009. Selected years 2009, 2012, 2013, and 2016

To further unpack the relationship between the number of DE credit-earning and STEM major choices, we estimated the unit-level dose-response function to measure the influence of various doses of the treatment on the outcomes (Hirano & Imbens, 2004). The goal of this procedure is to reduce selection bias within strata with the same density of the treatment, so the probability of receiving a given treatment level does not depend on the value of the pre-treatment covariates for DE students. Particularly, we followed Bia and Mattei (2008) to estimate the generalized propensity scores (GPS) using Stata commands *gpscore* and *doseresponse*. However, because the treatment did not have a normal distribution conditional on the covariates, we converted the treatment using the zero-skewness log to estimate the GPS instead.[4]

Analyses of the influence of DE credits on STEM major choice

Accounting for the selection bias, we conducted both descriptive analysis and a series of logistic regression and multinomial regression analyses to examine the influence of DE course-taking (i.e., participation, subject in Math/Science, number of DE credits earned) on college students' STEM major selection. For each set of outcomes, we used the proper regression model that controlled for the pre-treatment and post-treatment variables, incorporating the series of propensity score weights, sampling weights, the primary sampling unit, and strata to ensure generalization to the national population (Ridgeway et al., 2015). Analyses for each subsample of students by sex, student-of-color status, low-income status, and first-generation status were also conducted. The effect size of the treatment was also calculated if the treatment was statistically significant (Sullivan & Feinn, 2012).

Lastly, we performed sensitivity analyses to examine whether the treatment effect would become statistically nonsignificant due to hidden unobservables increases since unmeasured confounding variables can bias estimates of the treatment effect on outcomes (Linden et al., 2020; VanderWeele & Ding, 2017). By calculating the E-value, which handles both binary and multi-level categorical outcomes incorporating ATT weights, we examined the minimum strength of association that "an unmeasured confounder would need to have with both the treatment and the outcome to fully explain away a specific treatment — outcome association" (VanderWeele & Ding, 2017, p. 1). More specifically, E-values for significant associations ranged from 1.57 to 2.22, depending on the specified outcome variable and sample. For example, in the main analysis, the E-value associated with an odds ratio of 1.38 is 1.63, meaning the risk ratio of 1.38 could be explained away by an unmeasured confounder that was associated with both the treatment (i.e., DE course-taking) and the outcome (i.e., STEM major choice) by an odds ratio of 1.63-fold each, but weaker confounders could not. The relatively small E-value suggests that our study could not fully exclude the possibility of unmeasured confounding that the evidence for causality between DE course-taking and students' STEM major choice might be weak.

Limitations

Under the constraint of a secondary dataset, readers should be cautious when interpreting our findings. First of all, since the subject treatment variable was self-reported, students might not be aware that they were taking DE at all or mistaking an advanced course (e.g., AP) for a DE course. Second, since traditionally underrepresented students often attend a community college or choose a CTE program before moving onto more advanced degree programs (Fealing et al., 2015), CTE-based STEM DE may be of particular interest for these students. As such, separating CTE and non-CTE DE courses may further shed light on the motivating coursework among traditionally underrepresented students and correspond to our research interest. However, though we had access to the transcript data, it was not readily available to devise a way to clearly differentiate STEM coursework from CTE credits. Instead, given the Perkins Act of 2006 and Common Core policy and practice, STEM and CTE curricula are being integrated to help train students' STEM skills occupationally (Sublett & Plasman, 2017). It is thus highly likely that the STEM DE coursework coded in the current study intersected with CTE credits. When such information is available, future research can further examine the relationship between DE CTE courses and students' major choice in CTE- or non-CTE-based STEM, particularly for underrepresented student population.

Third, we observed missing data in some variables and conducted multiple imputations to retain as many participants as possible. Multiple imputation is found to be a better choice than listwise deletion (Baraldi & Enders, 2010) and the missing value indicator method (Groenwold et al., 2012) given the large sample size, the nature of survey data, and the uncertainty to ascertain missing completely at random (Little, 1988), but it is likely that multiple imputation resulted in a higher correlation between variables and thus a higher statistical power. Hence, we generated only five imputed datasets to avoid inflating the statistical power (Graham, 2009), addressed all the complex sampling features inherent in HSLS:09, and reported pooled results (Horton & Lipsitz, 2001) to counterbalance the potential inflation of intercorrelation between variables. Finally, whereas we strived to clear potential bias inherent in the data through statistical methods (e.g., multiple imputation for handling missing data) and adhered to the complex sampling design, the propensity score-based technique precludes strong causal inferences in the relationship between DE course-taking and college students' STEM major choice.

Results

Descriptive summary

Table 2 presents the descriptive results for the outcomes in the treatment and control groups. Before applying propensity score weights, a larger proportion of DE students (23.43%) majored in a STEM field than non-DE students (18.89%), and the difference was even larger between students who took a DE course in the subject of Math/Science (27.78%) and students without taking a DE course in Math/Science (19.93%). On average, a larger proportion of DE students majored in a non-STEM field (52.53%) and STEM field (19.13%) at the baccalaureate level relative to non-DE students (46.21% in non-STEM and 13.47% in STEM at the baccalaureate level). However, a smaller proportion of DE students majored in a non-STEM field (24.04%) and STEM field (4.3%) at the sub-baccalaureate level relative to non-DE students (34.91% in non-STEM and 5.41% in STEM at the sub-baccalaureate level). A similar pattern was found between students who took a DE course in the subject of Math/Science and students without taking a DE course in Math/Science. After incorporating propensity score weights, the differences between the treated group and control group considerably decreased.

Table 2. Descriptive results for STEM major choice.

	Pre-weighting			Post-weighting		
	Treated	Control	Difference	Treated	Control	Difference
Panel A: Treatment being DE Course-Taking						
STEM Major Choice	23.43%	18.89%	4.54%	26.19%	23.67%	2.52%
STEM Major Choice and Degree Level						
Sub-baccalaureate non-STEM	24.04%	34.91%	−10.87%	18.59%	20.60%	−2.01%
Sub-baccalaureate STEM	4.30%	5.41%	−1.11%	3.64%	3.32%	0.32%
Baccalaureate Non-STEM	52.53%	46.21%	6.32%	55.21%	55.73%	−0.52%
Baccalaureate STEM	19.13%	13.47%	5.66%	22.55%	20.35%	2.20%
Number of observations	4,640	6,920		4,640	6,920	
Panel B: Treatment being DE Course-Taking in Math/Science						
STEM Major Choice	27.78%	19.93%	7.85%	31.71%	24.24%	7.47%
STEM Major Choice and Degree Level						
Sub-baccalaureate non-STEM	17.45%	31.85%	−14.40%	12.76%	19.70%	−6.94%
Sub-baccalaureate STEM	3.82%	5.07%	−1.25%	3.90%	3.17%	0.73%
Baccalaureate Non-STEM	54.77%	48.21%	6.56%	55.53%	56.07%	−0.54%
Baccalaureate STEM	23.96%	14.86%	9.10%	27.81%	21.07%	6.74%
Number of observations	1,230	10,330		1,230	10,330	

Note. Sampling weights are applied to pre-weighting calculation. The weight for each observation included in the post-weighting estimation was a product term between the inverse probability treatment weight and the sampling weight, divided by the mean of such product terms.

SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009. Base Year, First Follow-Up, High School Transcript Study, and Postsecondary Education Transcript Study and Student Financial Aid Records Data Collection.

The influence of DE course-taking on STEM major choice

Controlling for pre-treatment and post-treatment covariates, the weighted model estimates of the full sample indicated that taking DE courses was positively associated with the probability of majoring in STEM (odds ratio = 1.380, $p = .002$). In other words, college students with DE course-taking records were 1.380 times more likely to major in STEM, when compared with college students without DE course-taking records (as presented in Table 3). More specifically, DE course-taking was statistically related to students' probability of STEM major choice at varying award levels. Compared with non-DE students, DE students

Table 3. Odds ratios of the effect of dual enrollment on STEM major choice.

	Pre-weighting		Post-weighting	
Outcome variable	DE course-taking	DE course-taking in Math/Science	DE course-taking	DE course-taking in Math/Science
STEM Major Choice	1.251	1.054	1.380**	1.306
	(0.203)	(0.226)	(0.145)	(0.189)
STEM Major Choice and Degree Level				
Sub-baccalaureate	1.002	0.824	1.155	1.298
STEM	(0.284)	(0.304)	(0.214)	(0.334)
Sub-baccalaureate	0.826	0.799	0.827*	0.756
non-STEM	(0.105)	(0.163)	(0.074)	(0.108)
Baccalaureate STEM	1.254	1.023	1.367**	1.230
	(0.206)	(0.226)	(0.154)	(0.184)

Note. Standard errors in parentheses. Sampling weights are applied to pre-weighting calculation. The weight for each observation included in the post-weighting estimation was a product term between the inverse probability treatment weight and the sampling weight, divided by the mean of such product terms. $n = 11540$.

***$p < .001$, **$p < .01$, *$p < .05$.

SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009. Base Year, First Follow-Up, High School Transcript Study, and Postsecondary Education Transcript Study and Student Financial Aid Records Data Collection.

were 1.367 times more likely to major in STEM at the baccalaureate level rather than non-STEM at the baccalaureate level ($p = .006$), and 0.827 times as likely to major in non-STEM at the sub-baccalaureate level than non-STEM at the baccalaureate level ($p = .035$).

No statistically significant relationship at the .05 level was detected between DE course-taking in Math/Science and STEM major choice across award levels. In supplemental analyses (as shown in Appendix C), we excluded 3,450 dually enrolled students in any non-Math/Science subject from the sample to directly compare students' STEM access between students taking DE courses in Math/Science and students with no DE course-taking at all. The weighted model specifications suggested that, compared with students with no DE course-taking, students taking DE courses in Math/Science were 1.544 times more likely to major in STEM ($p = .004$), 1.469 times more likely to major in STEM at the baccalaureate level rather than non-STEM at the baccalaureate level ($p = .015$), and 0.682 times as likely to major in non-STEM at the sub-baccalaureate level than non-STEM at the baccalaureate level ($p = .012$).

The sub-sample analyses suggested that the relationship between DE course-taking and STEM major choice may vary by students' sociodemographic characteristics (as shown in Table 4). While the positive relationship between DE course-taking and STEM major choice remained to be significantly positive for most subgroups of students, it was not statistically significant for the female and low-income subgroups as well as students of color when Asian students were excluded. DE course-taking in Math/Science was only positively related to students' STEM major choice for students of color (including Asian) and continuing-generation students but not statistically significant for other subgroup analyses. DE course-taking seemed to encourage certain student groups to major in STEM at the baccalaureate level, while discouraging some other student groups from majoring in non-STEM at the sub-baccalaureate level. It is worth noting that the odds ratio should be interpreted as comparisons between the treatment group and the control group within the subgroup; coefficients and significance tests should not be directly compared between subgroups. We discuss statistically significant findings on STEM award levels by subgroup specifically.

For the subgroup of male students (as presented in Panel A of Table 4), compared with male students who did not take DE courses, male students with DE courses were 1.431 times more likely to major in STEM ($p = .012$). For the racial subgroups (as presented in Panel B of Table 4), White students who took any DE courses were 1.321 times more likely to major in STEM ($p = .035$) and 27.1% less likely to major in non-STEM at the sub-baccalaureate level (odds ratio = 0.729, $p = .005$). For students of color (including Asian students), those who took any DE courses were 1.428 times more likely to major in STEM ($p = .035$) and 1.557 times more likely to major in STEM at the baccalaureate level ($p = .015$). Compared with

Table 4. Odds ratios of the effect of dual enrollment on STEM major choice for subgroups.

Panel A: Subgroups by sex

Outcome	Female Students		Male Students	
	DE course-taking	DE course-taking in Math/Science	DE course-taking	DE course-taking in Math/Science
STEM Major Choice	1.328	1.387	1.431*	1.243
	(0.202)	(0.285)	(0.202)	(0.258)
STEM Major Choice and Degree Level				
Sub-baccalaureate STEM	0.884	1.041	1.380	1.558
	(0.283)	(0.501)	(0.325)	(0.506)
Sub-baccalaureate Non-STEM	0.818	0.800	0.814	0.611
	(0.100)	(0.139)	(0.113)	(0.156)
Baccalaureate STEM	1.371	1.384	1.357	1.055
	(0.220)	(0.290)	(0.213)	(0.236)
Number of Observations	6,260		5,120	

Panel B: Subgroups by race

Outcome	White Students		Students of Color		Students of Color excluding Asian	
	DE course-taking	DE course-taking in Math/Science	DE course-taking	DE course-taking in Math/Science	DE course-taking	DE course-taking in Math/Science
STEM Major Choice	1.321*	1.089	1.428*	1.911**	1.389	1.233
	(0.178)	(0.195)	(0.240)	(0.456)	(0.294)	(0.396)
STEM Major Choice and Degree Level						
Sub-baccalaureate STEM	1.269	1.201	1.013	1.449	0.799	0.710
	(0.320)	(0.402)	(0.283)	(0.638)	(0.272)	(0.417)
Sub-baccalaureate Non-STEM	0.729**	0.818	0.999	0.553*	0.985	0.605
	(0.083)	(0.142)	(0.137)	(0.140)	(0.146)	(0.161)
Baccalaureate STEM	1.242	1.016	1.557*	1.782*	1.670*	1.205
	(0.174)	(0.185)	(0.283)	(0.436)	(0.389)	(0.393)
Number of Observations	6,200		5,170		3,950	

(*Continued*)

Table 4. (Continued).

Panel C: Subgroups by low-income status

Outcome	Low-Income Students		Non-Low-Income Students	
	DE course-taking	DE course-taking in Math/Science	DE course-taking	DE course-taking in Math/Science
STEM Major Choice	1.028	1.205	1.450**	1.375
	(0.241)	(0.458)	(0.170)	(0.226)
STEM Major Choice and Degree Level				
Sub-baccalaureate STEM	0.486	0.421	1.502	1.470
	(0.183)	(0.363)	(0.334)	(0.441)
Sub-baccalaureate Non-STEM	0.801	0.742	0.805*	0.718
	(0.132)	(0.173)	(0.082)	(0.121)
Baccalaureate STEM	1.156	1.335	1.384**	1.278
	(0.308)	(0.525)	(0.172)	(0.215)
Number of Observations	2,740		8,110	

Panel D: Subgroups by first-generation status

Outcome	First-Generation Students		Continuing-Generation Students	
	DE course-taking	DE course-taking in Math/Science	DE course-taking	DE course-taking in Math/Science
STEM Major Choice	1.745*	1.092	1.351*	1.403*
	(0.479)	(0.471)	(0.161)	(0.230)
STEM Major Choice and Degree Level				
Sub-baccalaureate STEM	1.242	0.969	1.302	1.397
	(0.447)	(0.496)	(0.301)	(0.472)
Sub-baccalaureate Non-STEM	0.755	0.657	0.861	0.797
	(0.116)	(0.174)	(0.092)	(0.138)
Baccalaureate STEM	1.944*	0.946	1.320*	1.346
	(0.624)	(0.483)	(0.166)	(0.221)
Number of Observations	2,760		8,070	

Notes. Sampling weights are applied to pre-weighting calculation. The weight for each observation included in the post-weighting estimation was a product term between the inverse probability treatment weight and the sampling weight, divided by the mean of such product terms. $^{**}p < .01$, $^{*}p < .05$.

SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009. Base Year, First Follow-Up, High School Transcript Study, and Postsecondary Education Transcript Study and Student Financial Aid Records Data Collection.

students of color with no DE course-taking in Math/Science, students of color with DE course-taking in Math/Science are 1.911 times more likely to major in STEM than in non-STEM ($p = .007$), 1.782 times in STEM at the baccalaureate level ($p = .019$) than non-STEM at the baccalaureate level, but only 0.553 times as likely to major in non-STEM at the sub-baccalaureate level as opposed to non-STEM at the baccalaureate level ($p = .020$). However, after excluding Asian students from the students of color subgroup, DE course-taking was only positively associated with students' probability of majoring in STEM at the baccalaureate level (odds ratio = 1.670, $p = .029$).

For the income-based subgroups (as presented in Panel C of Table 4), DE students with higher family income were 1.450 times more likely to major in STEM, when compared to non-DE students with higher family income ($p = .002$). Particularly, taking DE courses was positively associated with the probability of majoring in STEM at the baccalaureate level (odds ratio = 1.384, $p = .009$), but negatively associated with the probability of majoring in non-STEM at the sub-baccalaureate level (odds ratio = 0.805, $p = .033$), as opposed to non-STEM at the baccalaureate level for the students with higher family income. For the final set of subgroups based on first-generation status (as presented in Panel D of Table 4), DE course-taking was positively associated with students' STEM major choice regardless of their first-generation status. First-generation students with DE courses were 74.5% more likely to major in STEM when compared with first-generation students without DE courses (odds ratio = 1.745, $p = .043$). First-generation DE students were 1.944 times more likely to major in STEM at the baccalaureate level ($p = .039$) as opposed to non-STEM at the baccalaureate level. Continuing-generation students with DE courses were 35.1% more likely to major in STEM when compared with continuing-generation students without DE courses ($p = .012$), and 1.320 times more likely to major in STEM at the baccalaureate level ($p = .028$) as opposed to non-STEM at the baccalaureate level. DE course-taking in Math/Science was only significantly related to the STEM major choice in general for continuing-generation students (odds ratio = 1.403, $p = .04$). All results are summarized and presented in Appendix E.

Discussion

Using the STEM Pathways framework, this study examined the impact of DE course-taking on college students' major choice in STEM fields, providing evidence-based, generalizable implications for practices to support STEM success, especially for traditionally underrepresented students. The findings suggest that taking DE courses is positively associated with a 1.38 times probability of majoring in STEM, especially at the baccalaureate level. Like other programs offering high school students to earn college credits (e.g., AP credits), taking DE courses also supports college students' STEM success (Barnett, 2018; Smith et al., 2018; Zinth, 2018). This positive relationship may be attributed to how DE programs provide an additional access point to college-level courses and learning experiences for high school students with both a college environment and academic expectations from college faculty (Karp, 2012; Ozmun, 2013; Robinson et al., 2019; Zinth & Barnett, 2018). This finding further emphasized the importance of equal DE access to broaden STEM participation to better support traditionally underrepresented students (Taylor et al., 2022).

Focusing on students' diverse STEM pathways, the current study emphasizes the balance between broadening STEM participation and normalizing students' diverse academic trajectories beyond the conventional baccalaureate programs. Our findings indicated that not only is DE course-taking associated with an increased probability of majoring in STEM at the baccalaureate level, but it also decreases students' probability of majoring in a non-STEM field at the sub-baccalaureate level, relative to students with no DE course-taking experiences. However, we did not detect consistent evidence of the relationship between DE course-taking and majoring in STEM at the sub-baccalaureate level. This null finding aligns with earlier work on DE's overall stronger influence on students' enrollment at four-year colleges, as opposed to two-year colleges (Hemelt et al., 2020; Lee et al., 2022). It further highlights the importance to understand how DE participation influences students' STEM outcomes at both sub-baccalaureate and baccalaureate levels (Plasman et al., 2017) as well as the role sub-baccalaureate programs (e.g., CTE programs) play in closing the STEM success gap (Hamilton et al., 2015; Yoon & Strobel, 2017). Practitioners and policymakers should be aware that one way to remediate the inequity at the postsecondary level is to normalize the different academic pathways in STEM fields, such as offering stackable credentials to intentionally design sub-baccalaureate programs and provide students with multiple access points to the STEM pathways (Bohn & McConville, 2018).

The positive relationship between DE course-taking in Math/Science and STEM major choice was not statistically significant, when compared with students with no DE course or with DE courses in a non-Math/Science subject. In supplemental analyses when the control group only included students with no DE course (as shown in Appendix C), our findings on DE course-taking in Math/Science are consistent with the main analyses and prior studies on how students' course-taking in advanced math and science courses (i.e., the direction of academic momentum) may predict their major selection in STEM (Card & Payne, 2017; Hemelt et al., 2020; Kim et al., 2015; Minaya, 2021). It is possible that individuals' DE coursework in Math/Science fulfills the general education requirement but does not meet specific academic requirements of STEM majors. Take Texas for example, math DE courses ranged between general college-level math (e.g., college algebra) to calculus (Texas Education Agency, 2011; The University of Texas System, 2018). To declare a STEM major at the sub-baccalaureate level, a satisfactory performance (i.e., B or above) in DE college algebra is sufficient (Dallas College, n.d.). To declare a STEM major at the baccalaureate level, a satisfactory performance in DE college algebra is not sufficient but DE calculus is (The University of Texas at Austin, n.d.). That is, fundamental DE math courses (e.g., college algebra) can be used to fulfill the general education requirements in non-STEM disciplines, but only advanced DE math courses (e.g., calculus) count toward required math courses in STEM majors. Since it is beyond the scope of our study to examine the differences between DE courses in non-Math/Science and DE courses in Math/Science or the level of DE courses, future research can use course-level data to examine if more advanced Math/Science courses which fulfill STEM degree plan requirements have a stronger effect on students' STEM major choice. Because DE course-taking is positively related to STEM major choice, especially at the baccalaureate level, researchers in the future should explore the reasons why students take such courses, and whether and how DE in Math/Science effectively influences students' motivation, interest, or aspiration for STEM majors and career (Wang, 2013a).

Finally, the subgroup analyses revealed how the relationship between DE course-taking and STEM outcomes varies across different student groups, depicting a complex picture of serving the diverse student population with DE programs. This finding reflects concerns over the role DE plays in educational equity and social justice (Taylor et al., 2022). Specifically, DE course-taking can reinstate educational inequity by benefitting the overrepresented student population in STEM rather than certain underrepresented student groups and further exacerbates the inequities in the STEM field (Hardy & Katsinas, 2010, Wang, 2016). For instance, students with higher family income backgrounds tend to benefit more from DE course-taking with a higher likelihood of majoring in STEM at both baccalaureate and sub-baccalaureate levels and a lower likelihood of majoring in non-STEM at the sub-baccalaureate level than their counterparts without taking and DE courses. On the contrary, students with low family income backgrounds who took DE courses did not experience any significantly changed likelihood of majoring in STEM at any level. In another example, for the pooled sample, White students subsample, and non-White students subsample (including Asian students), dually enrolled students are more likely to major in STEM than their counterparts without DE experiences. However, dually enrolled students of color (excluding Asian students) and their non-DE counterparts do not differ in the probability of majoring in STEM. These findings imply the limit of DE's influence on enrolling students of all backgrounds in STEM disciplines despite the overall positive relationship with STEM major choice.

As we joined existing literature that SES is related to STEM major choice and success (Evans et al., 2020; Jefferies et al., 2020), students with lower SES backgrounds can be discouraged from majoring in STEM via a lack of sustainable resources and decreasing students' expectation of success in STEM fields, which in turn prevents them from majoring in STEM (Perez-Felkner et al., 2019). Following the STEM pathway model, the systemic barriers historically underrepresented students experience remain salient predictors for students' STEM access in postsecondary education. Future research should unpack whether and how DE learning experience can provide positive feedback to students' expectancy of success in STEM fields. To further identify the effectiveness of DE programs on postsecondary STEM success, researchers are also encouraged to focus on students' participation in DE and their pursuit of STEM majors and how it interacts with their lived experience and individual contexts facing structural barriers.

Notes

1. Specifically, the multiple imputation procedure addressed missing values in the control variables: race/ethnicity (3.8%), SES (6.8%), high school GPA (7.4%), educational expectations (7.5%), highest math level (7.2%), the number of AP/IB credits (4.4%), and intent to major in STEM (6.9%), respectively.
2. Because the HSLS data does not properly report gender identity (Marine, 2011), we use students' sex assigned at birth as a binary indicator to create the subgroups.
3. Due to the relatively small and unbalanced number of treated observations in each racial/ethnic group, we were unable to conduct subgroup analyses using propensity score models based on individual racial/ethnic groups. Thus, we had to aggregate racially minoritized groups based on their student-of-color status. We first defined students of color as students who identify as non-White. In additional analyses, we excluded Asian American students from the sub-sample given their relatively high performance in STEM fields (National Center of Educational Statistics [NCES], 2022).
4. The readers should be cautioned that, due to the treatment transformation, it is challenging to interpret the coefficients in the context of DE credits earned. Additionally, these commands are not supported by the *svy* prefix to account for complex survey data, the dose-response model only provides suggestive evidence, without generalization to the broader population. Given these methodological challenges, we present the dose-response findings as supplemental analyses in Appendix D.

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Appendix A

Characteristics of Variables in the Outcome Model

		Variables	Variable Characteristics
Outcome Variable		Major in STEM	0 = non-STEM; 1 = STEM
		Major in STEM and degree level	1 = Sub-baccalaureate non-STEM; 2 = Sub-baccalaureate STEM; 3 = Baccalaureate non-STEM; 4 = Baccalaureate STEM
Treatment		DE participation	0 = No DE course-taking; 1 = DE course-taking
		Number of total DE credits earned	Continuous
		Ever took DE math and/or science courses	0 = No DE math/science course-taking; 1 = Ever took a DE math/science course
Pre-treatment Variable	*Sociodemographic characteristics*	Sex	0 = Male; 1 = Female
		Race	1 = White; 2 = Black/African American; 3 = Hispanic/Latinx; 4 = Asian American and Native Hawaiian/Pacific Islander; 5 = American Indian/Alaska Native; 6 = More than one race
		Socioeconomic status quintile	1 = Lowest quintile; 2 = second quintile; 3 = third quintile; 4 = fourth quintile; 5 = highest quintile
		At least one parent working in STEM occupation	0 = non-STEM; 1 = STEM
	Academic measures in 9th grade high school	Highest degree expected	1 = HS and below; 2 = Associate degree; 3 = Bachelor's degree; 4 = Master's degree; 5 = Doctoral degree or Professional degree; 6 = don't know
		GPA	Continuous
		Highest level of mathematics	0 = No Math; 1 = Basic math; 2= other math; 3 = Pre-algebra; 4 = Algebra I; 5 = Geometry; 6 = Algebra II; 7 = Trigonometry; 8 = Other advanced math
	High school characteristics	Whether high school provides dual enrollment opportunities	0 = No; 1 = Yes
		Location	1 = city; 2 = suburb; 3 = town; 4 = rural
		Control	1 = Public; 2 = Private
Post-treatment Variable		Intent to choose a STEM major	0 = non-STEM; 1 = STEM
		Number of AP/IB courses taken	Continuous

Appendix B

Descriptive Results for all Variables in the Full Sample

Variable	Pre-weighting DE Course-Taking	Pre-weighting No DE Course-Taking	Post-weighting DE Course-Taking	Post-weighting No DE Course-Taking
Female	56.44%	49.69%	57.84%	59.38%
Race/Ethnicity				
White	61.90%	51.17%	63.49%	61.73%
Black/African American	9.52%	12.71%	7.61%	7.02%
Hispanic/Latinx	17.45%	21.38%	11.73%	12.44%
Asian American	4.78%	3.91%	9.14%	10.40%
Native Hawaiian/Pacific Islander	0.14%	0.38%	0.35%	0.36%
American Indian/Alaska Native	0.37%	1.17%	0.35%	0.26%
More than one race	5.84%	9.27%	7.33%	7.74%
Socioeconomic Status Quintile				
Lowest quintile	11.32%	14.35%	7.23%	7.73%
Second quintile	14.75%	15.31%	12.38%	11.09%
Third quintile	18.66%	19.28%	17.15%	17.15%
Fourth quintile	22.29%	22.50%	23.08%	23.83%
Highest quintile	32.98%	28.56%	40.15%	40.20%
At least one parent working in a STEM occupation	24.28%	21.45%	26.58%	29.01%
Highest degree expected				
High school graduation or below	5.21%	8.91%	3.22%	3.83%
Associate degree	4.83%	6.83%	4.00%	3.05%
Bachelor's degree	20.34%	17.77%	18.60%	19.07%
Master's degree	25.77%	25.24%	27.60%	26.03%
Doctoral degree or Professional degree	27.66%	22.41%	30.13%	31.72%
don't know	16.19%	18.79%	16.45%	16.31%
Highest level of mathematics				
No math	1.00%	4.95%	1.22%	0.86%
Basic math	1.18%	1.50%	0.84%	0.60%
other math	0.44%	1.07%	0.38%	0.48%
Pre-algebra	3.91%	3.28%	2.73%	2.51%
Algebra I	45.68%	48.17%	44.07%	43.30%
Geometry	34.39%	28.84%	35.70%	38.15%
Algebra II	8.00%	6.40%	9.37%	9.72%
Trigonometry	0.89%	0.52%	1.09%	0.66%
Other advanced math	4.50%	5.28%	4.60%	3.73%
9th Grade GPA	3.178	2.819	3.275	3.302
	(0.029)	(0.038)	(0.016)	(0.014)
High school provides dual enrollment opportunities	90.40%	89.55%	88.24%	86.28%
High school location				
City	27.83%	34.51%	28.32%	28.71%
Suburb	34.40%	35.41%	35.03%	31.94%
Town	11.45%	9.36%	13.20%	13.67%
Rural	26.32%	20.73%	23.46%	25.68%
High school control — Private	7.42%	11.54%	22.37%	20.08%
Intent to choose a STEM major	26.51%	22.56%	29.40%	29.45%
Number of AP/IB courses taken	1.832	1.696	1.970	2.543
	(0.102)	(0.085)	(0.071)	(0.096)
Number of observations	4,640	6,920	4,640	6,920

Standard deviation in parentheses. Sampling weights are applied to pre-weighting calculation. The weight for each observation included in the post-weighting estimation was a product term between the inverse probability treatment weight and the sampling weight, divided by the mean of such product terms.

SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009. Base Year, First Follow-Up, High School Transcript Study, and Postsecondary Education Transcript Study and Student Financial Aid Records Data Collection.

Appendix C

Odds Ratios of the Effect of Dual Enrollment in Math/Science on STEM Major Choice

	Full Sample	Female students	Male students	White students	Students of color	Students of color excluding Asians	Low-income students	Non low-income students	First-generation students	Continuing-generation students
STEM Major Choice	1.544**	1.589*	1.536*	1.337	2.025**	1.361	1.120	1.644**	1.620	1.573**
	(0.231)	(.326)	(0.330)	(0.269)	(0.480)	(0.459)	(0.427)	(0.278)	(0.675)	(0.266)
STEM Major Choice and Degree Level										
Sub-baccalaureate STEM	1.373	0.993	1.804	1.380	1.146	0.647	0.384	1.834	0.870	1.646
	(0.389)	(.524)	(0.676)	(0.510)	(0.609)	(0.475)	(0.325)	(0.587)	(0.512)	(0.560)
Sub-baccalaureate Non-STEM	.682*	0.708	0.595*	0.668*	0.587*	0.623	0.617	0.657*	0.598	0.736
	(0.104)	(.133)	(0.156)	(0.124)	(0.148)	(0.161)	(0.152)	(0.116)	(0.160)	(0.129)
Baccalaureate STEM	1.469*	1.610*	1.342	1.207	2.015**	1.385	1.169	1.511*	1.788	1.492*
	(0.231)	(.347)	(0.310)	(0.252)	(0.499)	(0.481)	(0.468)	(0.265)	(0.867)	(0.257)
Number of Observations	8,090	4,240	3,620	4,320	3,520	2,660	1,780	5,650	1,800	5,620

Standard error in parentheses. The supplementary analyses excluded students who have taken DE courses in non-Math/Science. Sampling weights are applied to pre-weighting calculation. The weight for each observation included in the post-weighting estimation was a product term between the inverse probability treatment weight and the sampling weight, divided by the mean of such product terms. ***$p < .001$, **$p < .01$, *$p < .05$.

SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009. Base Year, First Follow-Up, High School Transcript Study, and Postsecondary Education Transcript Study and Student Financial Aid Records Data Collection.

Appendix D

Supplemental Analyses of the Dose-Response Models

Following the same logic of controlling for students' likelihood of taking DE courses when the treatment is dichotomous, the dose-response model controlled for the impacts of selection bias to examine the extent to which the probability of choosing a STEM major varies with an increase in the number of DE credits earned. Though prior studies have indicated that it is important to examine the relationship between the number of dual credits and postsecondary outcomes (Giani et al., 2014; Lee et al., 2022; Miller et al., 2018), no known study has addressed the selection bias derived from students' likelihood of earning a certain number of dual credits in their modeling. As it is challenging to interpret our findings in the practical context, future studies should continue to explore other methodologically rigorous approaches to identifying the dose-response effect of dual enrollment with meaningful practical implications.

Within the sample of students who have ever earned any DE credits ($n = 2{,}130$), students earned DE credits between 1 and 126 normalized credits (mean = 12 normalized credits, mode = 9 normalized credits). Figure D1 depicts the dose-response function, representing the propensity to major in STEM for all values of DE credits earned in its zero-skewness log form, along with 95% confidence bands. Descriptively, an increase in the number of DE credits seems to be positively associated with a student's probability of majoring in STEM: The slope was steeper as students start to accumulate DE credits (i.e., the probability of majoring in STEM increased from 0.24 to 0.35 when the unit of treatment increased from 10 to 40), and it became flatter with more DE credits accumulated (i.e., the probability of majoring in STEM increased from 0.35 to 0.41 when the unit of treatment increased from 40 to 100). A similar trend was found for the probability of majoring in STEM at the baccalaureate level. Additionally, students' probability of enrolling in a non-STEM sub-baccalaureate program decreased from 0.19 to 0.15 as they start to accumulate DE credits, but the probability started to increase once students accumulated more than 20 units of DE credits in its zero-skewness log form. Finally, students' probability of enrolling in a sub-baccalaureate STEM program increased from 0.03 to 0.42 as they start to accumulate DE credits, but the probability started to decrease once they accumulated more than 30 units of zero-skewness-log-transformed DE credits. However, none of the estimates were statistically significant, suggesting that the probability of majoring in STEM with fewer units of DE credits (in its zero-skewness log form) was not more or less sensitive to DE credits than those with more units of DE credits.

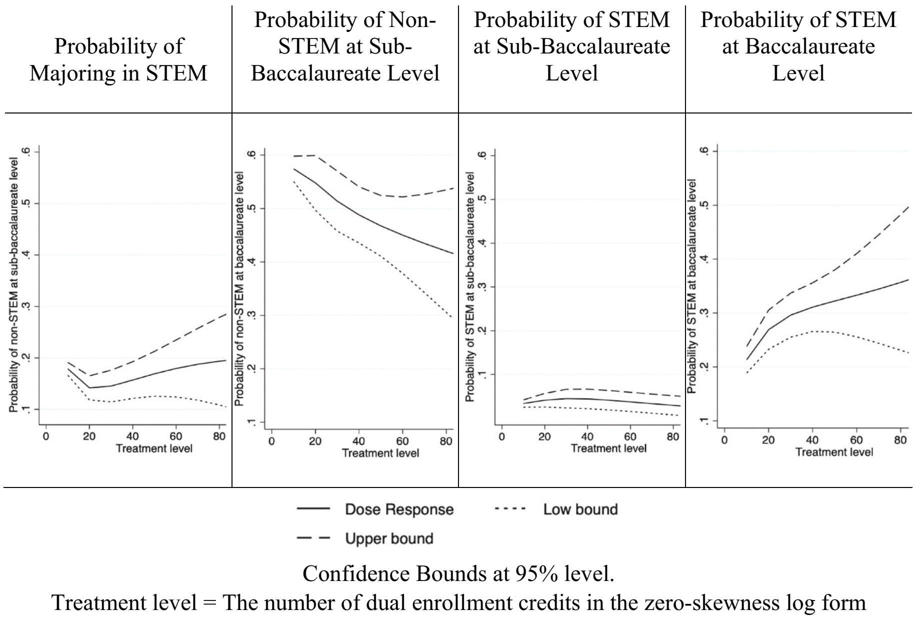

Figure D1. Estimation and 95% confidence bands of the dose-response function, confidence bounds at 95% level. SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009. Base Year, First Follow-Up, High School Transcript Study, and Postsecondary Education Transcript Study and Student Financial Aid Records Data Collection.

Building on prior work focusing on the number of DE courses on postsecondary outcomes (Giani et al., 2014), our findings indicated that the number of DE credits earned is not statistically related to college students' probability of majoring in STEM, once the impact of selection is controlled for. In other words, students that were more likely to major in STEM also tended to take more DE courses (i.e., the mass of academic momentum). This null finding can also be due to data transformation that the interpretation of changes in the outcome is based on the unit of treatment in its zero-skewness log form. This suggestive evidence indicates that high schools and colleges do not need to overly push high school students to take more DE courses solely to broaden STEM access. Even when a student considerably increased the units of DE credits earned (from 10 units to 100 units), the probability of majoring in STEM only increases by 17 percentage points on average. Especially when students may feel their major choice is limited with many earned DE credits and face potential credit loss (Taylor et al., 2022; Tobolowsky & Allen, 2016), the risk of earning a large number of DE credits in high school can outweigh the benefits. For high school students that intend to take only one DE course, one well-designed rigorous DE course, as opposed to the large quantity of DE courses, is meaningful for these students to learn both academic content and transferrable skills to meet college-level academic demands and develop their self-efficacy in STEM fields.

Appendix E

Summary of results

		Full Sample	Female	Male	White	Students of Color	Students of color exc. Asians	Low-income	Non low-income	First-gen	Continuing-gen
STEM vs. Non-STEM	DE vs. no-DE	Positive	NS	Positive	Positive	Positive	NS	NS	Positive	Positive	Positive
	DE M/S vs. no-DE M/S	NS	NS	NS	NS	Positive	NS	NS	NS	NS	Positive
	DE M/S vs. no-DE	Positive	Positive	Positive	NS	Positive	NS	NS	Positive	NS	Positive
Sub-baccalaureate STEM vs. baccalaureate non-STEM	DE vs. no-DE	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS
	DE M/S vs. no-DE M/S	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS
	DE M/S vs. no-DE	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS
Sub-baccalaureate non-STEM vs. baccalaureate non-STEM	DE vs. no-DE	Negative	NS	NS	Negative	NS	NS	NS	Negative	NS	NS
	DE M/S vs. no-DE M/S	NS	NS	NS	NS	Negative	NS	NS	NS	NS	NS
	DE M/S vs. no-DE	Negative	NS	Negative	Negative	Negative	NS	NS	Negative	NS	NS
Baccalaureate STEM vs. baccalaureate non-STEM	DE vs. no-DE	Positive	NS	NS	NS	Positive	Positive	NS	Positive	Positive	Positive
	DE M/S vs. no-DE M/S	NS	NS	NS	NS	Positive	NS	NS	NS	NS	NS
	DE M/S vs. no-DE	Positive	Positive	NS	NS	Positive	NS	NS	Positive	NS	Positive

DE = dual enrollment, DE M/S = dual enrollment in Math/Science, NS = not significant.