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EdWorkingPaper No. 26-1421

Dual-Enrollment Dosage Design: Conceptualization and Measurement of Student Profiles and School Structures

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Dual-enrollment ("DE"), in which students enroll in college-level courses and receive college credit in high school, has become one of the most prominent strategies for promoting college access and readiness. DE models range from a la carte options or "random acts of dual-enrollment" to highly structured pathways leading to associate degrees embedded in whole-school reform models. However, limited research has examined the breadth of DE models students engage in, identified students' latent DE profiles, or investigated how they relate to school structural reforms that prioritize DE. Drawing upon a sample of roughly 3.5 million students who graduated from a Texas high school between 2014-2023, 21.1% (n = 724,964) of whom completed at least one DE course, we estimate five latent profiles of DE students: 1) DE Dabblers; 2) DE Explorers; 3) DE-CTE Concentrators; 4) ECHS Non-Completers, and; 5) ECHS Completers. We then examine how these profiles relate to students' demographic and academic characteristics and school reform structures.

VERSION: March 2026

Suggested citation: Giani, Matt S., Madison E. Andrews, and Rashi Agarwal. (2026). Dual-Enrollment Dosage Design: Conceptualization and Measurement of Student Profiles and School Structures. (EdWorkingPaper: 26-1421). Retrieved from Annenberg Institute at Brown University: https://doi.org/10.26300/nbxh-9r36

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Author's Note: This research was supported by the Gates Foundation (INV#:064324) and the National Institute for Child Health and Human Development (P2CHD042849 and T32HD007081). The authors would like to thank Jacklyn Altuna Willard for her generosity, insight, and support she contributed to this study. The conclusions of this research do not necessarily reflect the opinion or official position of the Texas Education Research Center, the Texas Education Agency, the Texas Higher Education Coordinating Board, the Texas Workforce Commission, or the State of Texas.
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Introduction

Dual-enrollment[1] ("DE"), in which students can enroll in college-level courses and receive college credit in high school, has become one of the most prominent strategies for promoting college access and readiness. Data from the National Center for Education Statistics show that roughly 82% of all American public high schools offered at least one DE course in 2017-18 (NCES, 2020) and more than one-third of fall 2009 ninth-graders took one or more DE courses in high school (NCES, 2019). Texas lags somewhat behind the nation, with roughly one-quarter of high school graduates completing DE courses according to data from TEA's Texas Academic Performance Report (TAPR) system. Nevertheless, DE figures prominently into state policy. Students are considered *college, career, or military ready* (CCMR) for school accountability purposes if they successfully pass a DE course in high school, and Texas has promoted a number of college and career ready school models (CCRSM), such as early college high schools (ECHS) and pathways in technology early college high schools (P-TECH), that include substantial DE coursework as a key component of the reform model.

As DE has grown in prominence in education policy and school reform efforts, so has the literature base on DE expanded. A number of literature reviews have now been conducted summarizing what the field knows (or not) about DE coursework (An & Taylor, 2019; Taylor et al., 2022; What Works Clearinghouse, 2017). Although these reviews suggest DE coursework is positively associated with students' postsecondary outcomes on average, a key question remains insufficiently explored: What is the optimal "dosage" of DE? As An (2022) concluded in his review of DE's outcomes and impacts, only a handful of studies have examined "dosage effects" of DE,

[1] We use the term dual-enrollment to refer broadly to a set of related strategies that allow high school students to take college courses. DE courses are courses that confer high school and college credit for the same course. Dual-enrollment encompasses DE courses and related strategies, such as early college high schools, students enrolling at a community college and taking college-only courses while still in high school, the OnRamps model developed by the University of Texas at Austin where students enroll simultaneously in separate high school and college instances of the same course and potentially receive different grades for each course instance, and so forth.

tested for nonlinearities in these dosage effects, and examined how "dosage profiles" vary across student populations and postsecondary outcomes. While researchers have argued for examining DE as a continuous dosage rather than a binary treatment for years (e.g. Giani et al., 2014), a dearth of evidence regarding the optimal dosage of DE remains.

There are three reasons why research on DE dosage is particularly critical. First, at least some researchers and reformers have raised concerns about students completing *too much* DE coursework, particularly for students attending ECHS or completing a high number of DE courses. In particular, students may not be able to transfer the DEs they earned to the college they enroll in (*general credit loss*) or may not be able to apply the credits to their chosen major (*major credit loss*), phenomena recently documented in Texas (Giani, Schudde, and Sultana, 2024a, 2024b) and themes that have emerged from qualitative research on DE students' transition to college (Espinoza, 2024). And while DE courses should be just as likely to transfer and apply to a student's major compared to the same course taken in-residence, this research suggests that DE courses are less likely to be applied (Giani, Schudde, and Sultana, 2024a).

Second, a variety of policies and school reform models[2] are founded upon assumptions regarding the optimal number of DE courses students should complete, yet these assumptions have not been sufficiently examined. The ECHS model consists of students completing 60 credits and earning an associate's degree in high school. The Gates Foundation, which invested heavily in the spread of the ECHS model in Texas and across the country, recently pivoted towards an initiative known as Accelerate ED[3]. In this school reform model, students should be able to complete an associate's degree in their first year after high school, implying that students should earn roughly 30 credits before graduating. Alternatively, the P-TECH blueprint allows more flexibility in terms of the

[2] See: https://texasccrsm.org/

[3] https://www.highereddive.com/news/gates-foundation-pushes-to-scale-dual-enrollment-and-early-college/624324/

number of DE courses students complete and the percentage of high school graduates who should meet particular indicators (e.g. 40% of students earn an associate degree or certificate by graduation). Throughout the state, House Bill 8 (HB8, 2023), which reformed community college finance, made high school student attainment of 15 SCH a key outcome that financially rewards community colleges. Despite the wide variety of models and indicators of DE dosage in Texas and across the nation, we still have limited evidence regarding whether these specific dosages provide students with the optimal benefits of DE participation.

Third, dosage itself has been insufficiently conceptualized and measured in the DE space. The most simplistic approach to measuring DE dosage is to count the number of DE courses students complete or the SCH earned through DE. However, understanding the relationship between DE dosage and postsecondary outcomes likely requires more sophisticated approaches. One question that needs to be examined is how to best model the functional form of the relationship between DE coursework and postsecondary outcomes, as assuming a linear relationship (e.g. Giani et al., 2014) may not be appropriate if the benefits of DE taper off, reverse, or reemerge at particular thresholds. Additionally, research suggests that the relationship between DE coursework and postsecondary outcomes varies across characteristics of the course such as its subject, how (e.g. online vs. in-person) and where (e.g. at the high school vs. at the community college) it is taught, and who teaches it (e.g. high school teachers or college instructors) (Giani et al., 2014; Ryu et al., 2024). And perhaps most critically, courses may be combined into pathways or programs of study, and the combination of courses may be more influential than the number of credits students earn. Although structural reforms, such as ECHS and P-TECH models, are intended to promote students' completion of DE pathways, the relationship between these structural reforms and empirical patterns of students' engagement in DE coursework has been insufficiently examined.

Given these gaps in the literature, the purpose of this proposed study is to develop a conceptual framework for DE dosage by examining ways to measure DE dosage aligned with this framework. We address four key questions:

1) How much dosage of DE do students engage in during high school, and how has this changed over time?
2) How do school structures relate to the breadth and depth of DE dosage students experience?
3) What are the latent profiles of students' DE dosage?
4) How do students' DE profiles relate to their demographic and academic characteristics and school structures?

Drawing upon a sample of roughly 3.5 million students who graduated from a Texas public high school between 2014-2023, we begin by descriptively examining measures of DE dosage, such as the percentage of students who participate in DE, how much DE they typically take, and the popularity of different DE courses and subjects. We then develop a school-level typology that categorizes schools based on their DE model and the extent of DE participation in the school. This "structural" analysis is followed by a student-level empirical examination of students' DE coursetaking patterns, using latent profile analysis (LPA) to categorize students based on these patterns and examining how students' demographic and academic characteristics vary across these profiles. We then investigate the intersection between the structural and empirical approaches by examining the commonality of students' DE profiles across categories in the school-level typology.

Our study makes a number of contributions to the field. First, while school-level structures do shape students' engagement in DE coursework, our results highlight meaningful variation in DE engagement even within schools of the same structure (e.g. ECHSs). Second, our LPA analyses reveal six distinct profiles of DE students that vary in terms of the amount of DE coursework they take, the subjects of courses they complete, and the types of students who fit each profile. Third, although there is correspondence between school-level structures and the most common student DE profiles found in each school, there is even greater variability within school structures than between them in terms of students' DE profiles. Taken together, these findings suggest that examining within-school mechanisms that shape students' DE pathways, a line of research that has been infrequently examined in the literature, may be even more critical than examining how DE dosage varies across school structures. Our analyses also lay the foundation for future research examining how the intersection of school structures and DE profiles relates to students' postsecondary outcomes.

Our paper is outlined as follows. We begin by reviewing the literature on DE, with a focus on the disparate ways in which researchers have measured dosage and the implications of these varying approaches for estimates of DE's effects on students' secondary and postsecondary outcomes. Throughout this review, we discuss the various school-, course-, and student-level factors that are associated with DE participation, dosage, and benefits. In doing so, we marry a structural, between-school perspective with a course-level and student-level, within-school view of the mechanisms that shape DE dosage, thereby developing a conceptual framework for our analyses. Our methods are then described, followed by a presentation of our results. We conclude with implications for researchers who study DE, policymakers, and school and district leaders and reformers.

Dual-Enrollment Definitions and School Structures

We define DE as an array of related strategies that allow students to earn college credits in high school. We note that the various terms used to describe these approaches – dual-enrollment, concurrent enrollment, and dual-credit in particular – are sometimes used interchangeably and are used more or less frequently in different state and educational contexts. A review of state policies and programs by the Education Commission of the States (2022) suggests that DE is the most common term, although dual-credit is used frequently. Concurrent enrollment appears to be the least common term, although the National Alliance of Concurrent Enrollment Partnerships (NACEP) is arguably the largest and most influential professional association focused solely on DE. Additionally, states may "brand" their programs with names such as "head start," "running start," "OnRamps," the "Commonwealth Dual Enrollment Partnership (CDEP)," and so forth. Although the terms used to describe these programs vary, DE is distinguished from related strategies such as Advanced Placement (AP) and International Baccalaureate (IB) courses which require students to score above particular thresholds on end-of-course standardized exams, enroll in a college, and claim their test scores for credit. In contrast, students receive credit and a college transcript immediately upon successfully completing a DE course.

For the purposes of our study, we define dual-credit as a specific DE strategy in which students enroll in courses that confer both high school and college credit. In general, school districts must partner with colleges or universities – most commonly community colleges – to develop and deliver dual-credit courses that meet both K-12 standards and college-level learning objectives. Because dual-credit courses confer both high school and college credit, students tend to receive a single grade for the course that applies to both high school and college sections. However, high school students can also enroll directly in college-level courses that do not confer high school credit, particularly for more advanced high school students who have completed all of their high school graduation requirements by their junior or senior year of high school. These students are "dually enrolled" in high school and college courses, even if they are not enrolled in dual-credit courses that confer both high school and college credit. Such DE students and the college-level courses they complete are included in our study.

Finally, although DE is primarily defined by the specific courses students enroll in, some school reform models center DE as a key strategy. One of the first such approaches was Middle Colleges or Middle College High Schools (MCHS), formal partnerships between school districts and community colleges in which schools are typically located on the college campus and allow high school students to complete considerable numbers of college credits (Venezia & Jaeger, 2013). The Middle College at LaGuardia Community College in New York City, created in 1974, is generally considered to be the first instance of this school model (Wechsler, 2001). Although the Middle College model broadened, it never became widespread; data from AIR suggests fewer than 100 programs across the country (American Institutes for Research, 2025).

In contrast, ECHS emerged in the 2000s as an approach designed to allow students to complete 60 credits and earn an associate's degree in high school and subsequently grew rapidly. AIR's data suggests nearly 1,000 ECHS are operating across the country, although they are highly concentrated in some states (e.g. Michigan, North Carolina, Texas) and entirely absent from others (e.g. Idaho, Montana, Wyoming). Because ECHS tended to focus on students' completion of academic, transfer-oriented associate's degrees, Pathways in Technology Early College High (P-TECH) schools emerged as an alternative model that promotes greater career and technical education (CTE) coursetaking and weakens the requirement to complete an associate's degree compared to the traditional ECHS model.

Although DE school reform models occupy an important place in the college readiness landscape and a compelling body of literature suggests that these school models positively impact students' postsecondary outcomes (Edmunds, et al. 2024a; Song et al., 2024), two caveats are important to note. First, while Middle Colleges, ECHS, and P-TECH programs are generally referred to as school reform models, they are often implemented as *within-school programs.* AIR's data suggests that roughly 60% of ECHS and 88% of P-TECH programs are within-school rather than whole-school models. Although nearly 90% of Middle College programs are whole-school, these schools are far less common than ECHS and P-TECH. Second, while over 1,000 schools operate an ECHS or P-TECH program, this is still a small fraction of the roughly 25,000 high schools in the United States (NCES, 2023).

Prior Literature on Dual-Enrollment Dosage Effects

Research examining how students' engagement in DE coursework relates to their high school and postsecondary outcomes has taken various approaches to conceptualizing and parameterizing DE. Much of the earliest literature in this vein treated DE as a dichotomous "treatment" that students either received or didn't. For example, An's (2013a, 2013b) analyses of data from the National Education Longitudinal Study of 1988 (NELS:88) dichotomized DE participation and used propensity score matching (PSM) to compare the college outcomes of DE students to observably equivalent students who did not participate in DE. Indeed, in their systematic review and meta-analysis of DE research, Schaller et al. (2025) note that the vast majority of studies estimating the impact of DE dichotomize the independent variable, meaning they estimate the impact of any DE participation, rather than varying dosages. Of the 162 effect sizes of DE included in their review, nearly 90% parameterized DE as a dichotomous treatment. Although data limitations often make this approach the only viable option for identifying DE students and estimating impacts of participation, it masks considerable variation in students' DE experiences.

An improvement is to count the number of courses completed or credits earned through DE. Eighteen of the 162 effect sizes included in Schaller et al.'s (2025) review were drawn from studies that measured the amount of DE courses students completed. Taken together, these studies suggest that each DE course students complete increases their likelihood of earning any postsecondary credential by 6 percentage points (pp) and earning a bachelor's degree by roughly 2pp. However, whether it is reasonable to assume a linear relationship between the number of DE courses students completed and their postsecondary outcomes is unclear. Karp et al. (2007) estimated that the benefits of DE increased with the number of DE courses students completed for some outcomes, but not others. For example, students were estimated to earn better GPAs the more DE courses they completed in Florida, but the estimated impact of DE on baccalaureate attainment in New York was roughly equivalent for students who completed one course versus multiple courses. Few studies have more deeply examined the functional form of the relationship between the number of DE courses students complete and their postsecondary outcomes.

Although using continuous measures of DE course completion is a more accurate representation of dosage than the dichotomous indicator discussed previously, this approach still masks considerable heterogeneity in DE. Most notably, DE courses are offered in a wide variety of subjects, and the content of DE courses may moderate the relationship between DE and postsecondary outcomes. The coarsest categorization employed by researchers compares academic to technical, vocational, or career and technical education (CTE) DE courses. For example, Karp et al. (2007) estimated the benefits of DE separately for all students, for whom most DE was taken in academic subjects, versus students either enrolled in CTE programs (in Florida) or enrolled in CTE-focused high schools (in New York). Their estimates suggested that DE was equally beneficial for both academic and CTE students. However, it is unclear whether CTE students in their samples were necessarily taking DE courses in CTE subjects. More recent research which employed a similar categorization found demographic differences in the populations of students enrolled in either academic or CTE-DE, as well as disparate associations with secondary and postsecondary outcomes, where passing an academic DE course was negatively associated with enrollment at a public 2-year college after high school, and passing a CTE DE course was positively associated (Ryu et al., 2024). In a subject-specific analysis, Giani et al. (2014) used continuous measures of DE courses taken by subject and found that courses taken in core academic subjects tended to have stronger relationships with postsecondary outcomes, particularly persistence and completion; the estimated effect sizes of DE coursetaking on postsecondary outcomes were roughly twice as large for students who completed two DE courses compared to students who only completed one. However, there appeared to be limited additional benefit of taking more than two DE courses for many postsecondary outcomes.

Conceptual Framework of Dual-Enrollment Dosage: School Structures and Student Profiles

Generally speaking, dual-enrollment has been linked to "broad positive impacts on student outcomes," but students' "access is not equitable, and those positive outcomes are not shared equitably by all student populations" (Taylor et al., 2022, p. 2); this access is dictated by both structural, between-school mechanisms, like school reform model(s) and course availability, and student-level, within-school mechanisms like gender, race, socioeconomic status, eligibility requirements, and advising practices. Dual-credit programs tend to be less accessible via schools that serve larger proportions of students of color and low-income students, and research consistently shows that dual-credit participation varies across student characteristics, with "Students of Color, low-income students, male students, lower achieving students, English language learners, students with disabilities, foster youth, and students experiencing homelessness participat[ing] in dual enrollment at lower rates than their counterparts" (Taylor et al., 2022, p. 11). An analysis of patterns of enrollment across school districts in the United States found that the vast majority of districts have racial enrollment gaps in DE, and these gaps were larger in states with stronger accountability mandates on students' access to DE, and smaller in states with stronger financial support for DE participation (Xu et al., 2021).

A recent review specific to the causes of equity gaps in dual-credit programs identified several themes, including "access barriers due to racially biased eligibility parameters, implicit bias in recruitment and identification of participants … and lack of advising and support for underrepresented students" (Hooper & Harrington, 2022, p. 22). These within-school factors and others, like DE educators, can play a large role in determining whether students participate in dual-credit courses, where course-taking recommendations are sometimes made based on not only eligibility criteria, but also "personal considerations" and "non-cognitive factors," like educators' perceptions of a student's "maturity," "responsibility level," or "confidence" (Witkowsky & Clayton, 2020). These beliefs and biases may gatekeep access to and from particular students, even when DE courses are available at that school.

Methods

To build upon this understanding of the variety of school- and student-level factors that may influence DE participation and dosage rates, we employed a variety of analytic approaches to answer our research questions. Before describing our data and analytical approaches in detail, Table 1 provides a high-level overview of the sample and method used to address each question.

[Table 1]

Texas State Context

We conducted these analyses using longitudinal data from Texas, where the emphasis on DE in Texas state policy is large and growing, across several policy and accountability levers. Texas policy promotes a number of college and career ready school models (CCRSM), such as ECHS and P-TECH, which include substantial DE coursework as a key component of the reform model. Beyond school structure reforms, state policy mandates that all districts offer students at least 12 college-level credits, and districts may offer DE to fulfill this requirement. Additionally, students in Texas are considered college, career, and military ready (CCMR) in state accountability policy if they complete at least one DE or OnRamps course in high school. OnRamps courses are unique versions of DE courses developed by the University of Texas at Austin (UT Austin) where students may earn separate grades for the high school and college version of the same course and UT Austin faculty and staff grade the college-level assignments and assessments. In this study, we treat OnRamps courses as DE but do not distinguish OnRamps from other DE courses.

Data

The quantitative data we analyzed is from the Texas Education Research Center's (ERC) statewide longitudinal data system, which includes individual-level data on every K-12 public school student from the Texas Education Agency (TEA), public and private college enrollee data from the Texas Higher Education Coordinating Board (THECB), and employment data from the Texas Workforce Commission (TWC). The ERC contains TEA records of students' high school course-taking, test scores, demographic characteristics, school information (e.g. school ID number, school type), and district information (e.g. public vs. charter, region). Due to our focus on school models and structures, we added a supplemental data source collected by TEA that identifies the specific CCRSMs offered at each school. Because this data was only available from 2019-2023, we focus our analyses of school-level structures to these five years. Although TEA course records include indicators of DE courses, TEA's data on the characteristics of those courses are limited. For that reason, we used THECB's course-level data to examine the specific DE courses students completed, records which include variables for the subject and number (e.g. ENGL 1301) of the course, the number of semester credit hours the course conferred, the modality of the course, and so forth. The variables derived from these data sources used in our analyses are described further below.

Sample

Our full analytic sample included cohorts of students who graduated from Texas public schools between 2014-2023 (n = 3,434,626). We began with 2014 as our earliest cohort due to our reliance on THECB's course data to examine DE enrollment. These data began to be collected for the first time during the 2011-12 academic year. We therefore had DE data for the three years prior to high school graduation for the earliest cohort, and DE data for all years of high school for all other cohorts. Because few students enroll in DE courses during their freshman year of high school, the exclusion of freshman year DE courses for the 2014 cohort is unlikely to bias our results. Across the entire sample, 21.1% (n = 724,964) of students participated in at least one DE course. In our analyses examining student-level DE dosage profiles, we restrict the sample to the 21.1% of students who engaged in DE.

School-level data on the CCRSMs offered by each school was only collected beginning in 2019. The analyses of the school-level typology therefore restrict the sample to students who graduated between 2019-2023 (n = 1,809,033). High school graduates may not have received the full dosage of DE if their school adopted a CCRSM in the same year that the student graduated high school. For example, if a student graduated in 2019 and the school received an ECHS designation for the first time in 2019, one may be concerned that the student did not have access to an ECHS program for the majority of their high school experience. However, schools go through a two-year process of implementing a CCRSM, during which time they have provisional approval from TEA, before they receive an official CCRSM designation. Therefore, a student who graduated the same year that their school received the official CCRSM designation likely would have experienced at least three years of the school implementing the CCRSM. For that reason, we examine the relationship between students' DE dosage and the CCRSMs the school was designated with in the year students graduated from high school.

Our sample of courses is derived from THECB's college-level course records. All public colleges and universities in Texas report every course students enroll in, regardless of whether students pass and earn credit from the course. We delimited these records using a variable that identifies courses taken by high school students. This variable indicates whether the student enrolling in the course was: 1) not a HS student; 2) a HS student taking the course for both HS and college credit (a traditional DE course); 3) a HS student who is taking the course for college credit only (a dual-enrollment course); 4) a student who is not a HS graduate and is taking a developmental course. For our purposes, we retained students in the second and third categories. Our course sample therefore includes all college-level courses taken by students in high school.

Analytic Approach

Exploring DE Dosage

THECB's course-level data includes several other variables we used to describe students' DE coursetaking. Like all college courses in Texas, each course is assigned a course subject (e.g. MATH) and number (e.g. 2301). College courses in Texas are categorized as either academic or technical. Academic lower-division courses are described in THECB's Academic Course Guide Manual (ACGM). Technical courses are described in the Workforce Education Course Manual (WECM). Because technical/WECM courses are far less common than academic courses among DE participants, we combined all WECM courses into a single "DE-CTE" category. For academic courses, all public community colleges are required to use the Texas Common Course Numbering System (TCCNS), in which course subjects receive four-character prefixes and course numbers are four digits (e.g. MATH 2301). The majority of public universities use the same course numbering system, although some do not. For those universities, we recoded their course subjects and numbers to align with the TCCNS using the TCCNS matrix.[4] In addition to the course subject and number, the data includes variables for the type of instruction for the course (e.g. lecture, lab, other), its delivery mode (e.g. face-to-face, virtual, hybrid), and its location (e.g. college campus, high school, other). We used these variables to describe the characteristics of DE courses taken.

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[4] See https://tccns.org/

Each course record includes the number of semester credit hours (SCH) the course was attempted for and the grade students received in the course. This allowed us to create a number of different variables describing students' DE engagement. We summed the number of DE SCH attempted, both overall and by course subject, counting all courses regardless of the grade students received. We used the DE subject credits attempted variables as our LPA indicators. If the student received a passing grade in the course, we treated that course as conferring earned SCH. We similarly summed the number of DE SCH earned, both overall and by course subject. Finally, we calculated students' DE GPA by calculating the total grade points students earned in DE courses and dividing that figure by the number of DE SCH they attempted. We used the traditional grade points scale where A = 4, B = 3, C = 2, D = 1, and F = 0. Courses taken pass/fail or satisfactory/unsatisfactory were included in the SCH attempted and earned variables, but were excluded from the DE GPA variable since these courses do not confer grade points or get factored into students' GPA.

To address our first research question, we descriptively analyze DE participation rates and characteristics, both at the student and school levels, to inform our subsequent analyses. We calculate the percentage of high school graduates who completed any DE, the mean number of DE credits completed among them, and the percentage of graduates who were enrolled in a CCRSM school by cohort. We also calculate descriptive statistics of individual DE courses and course subjects to examine the types of DE courses students are most likely to complete.

School Structures and DE Dosage

In addition to the DE variables, we seek to examine how school structures shape students' engagement in DE coursework. In Texas, schools have been able to receive three different College and Career Readiness School Model (CCRSM) designations: 1) Early College High School (ECHS); 2) Pathways in Technology Early College High School (P-TECH); 3) and Texas Science, Technology, Engineering, and Mathematics Academy (T-STEM). The T-STEM designation has been phased out, but schools in our analysis were designated as T-STEM as well. The student-level data contained in the ERC includes identifiers for whether students are enrolled in one of these CCRSM programs. However, not all students in a school may be participating in the program, and we sought to categorize schools based on whether they offered the CCRSM rather than whether all students in the school were participating in the program. We therefore used an official list of CCRSM school-level designations maintained by the Texas Education Agency (TEA).[5] While CCRSMs have existed in Texas for decades, the TEA list of official school designations did not begin to be collected until the 2018-19 school year. We use the official CCRSM list to identify the DE models offered at schools and restrict our analyses to 2019-2023 student cohorts for all analyses using CCRSM school-level data.

To address our second research question, we created a typology of schools based on two variables: 1) the school's CCRSMs; 2) the percentage of high school graduates from the school who participated in DE. There were five possible categories for the first variable: 1) traditional high school (i.e. no CCRSM); 2) ECHS; 3) P-TECH; 4) T-STEM; 5) Multiple CCRSM. For the second variable, we calculated the median school-level DE participation rate of 23%. We dichotomized the participation rate into "high" and "low" values based on whether they were above or below the median, respectively. Combining the CCRSM variable with the dichotomous DE participation rate variable produces ten categories that schools are placed into. An eleventh category includes schools with a DE participation rate of 0%, referred to as "No DE Schools."

Latent Profile Analysis

Our third RQ was aimed at identifying latent profiles of students based on their observed DE coursetaking behaviors. To address this question, we used latent profile analysis (LPA). LPA assumes that a population of interest can be categorized into multiple unobserved or latent profiles

[5] See https://texasccrsm.org/.

based on observed variables, referred to as LPA indicators (Spurk et al., 2020). Theoretically, these unobserved latent categories are presumed to cause the observed indicators to manifest as they do. In our case, we assume that unobservable student characteristics such as their interests, aspirations, and abilities may relate to their latent profiles and subsequently predict students' DE coursetaking. The DE coursetaking measures we used were continuous variables counting the number of DE credits students earned in different broad subjects (e.g. English, History, Math). Because students in our sample completed DE courses in over 100 distinct subjects, we focused on the 12 most common DE subjects. Eleven of those subjects were academic courses, while the last variable counted the total number of DE-CTE credits students earned regardless of the specific CTE subject. Combined, these 12 subjects account for over 90% of all DE credits earned in the sample. Table 2 presents the descriptive characteristics of the twelve DE subjects included in our LPA analyses. Each DE subject excluded from the list comprised 1% or less of all DE credits earned by students in our sample.

[Table 2]

Our first step in LPA was to determine the number of profiles that best fit the data. To do so, we fit LPA models to the sub-sample of students who attempted at least 1 DE course in high school. Because this sub-sample was quite large (*n* = 724,941) and LPA is computationally intensive, we initially selected a random sample of 1% of DE students (*n* = 7,280) to determine the best-fitting model. The size of this random sample was still more than ten times as large as the minimum sample size of 500 for LPA models commonly recommended in the literature (Nylund et al., 2007; Spurk et al., 2020). Because LPA models tend to converge on a local solution that cannot be replicated, either in- or out-of-sample, we used different techniques to arrive at a global solution that could be replicated (Hipp & Bauer, 2006). Specifically, we set the random seed for each model so that the same solution would be achieved each time the model was fit. Each model was fit with ten replications, with the best-fitting model saved as the achieved model for that number of profiles. Additionally, we used the Laplacian approximation, which is faster but can be less accurate, to arrive at initial model convergence, but then used the saved results from that model as the starting values for a model fit with the mean-and-variance adaptive Gauss-Hermite quadrature to produce final model results.

Each model included the same 12 DE subject variables as LPA indicators, but with between 2-7 latent profiles. After fitting each model as described above, we compared the models' fit statistics to determine the best-fitting model. As recommended in the literature (Spurk et al., 2020), we examined Akaike's Information Criterion (AIC), Bayesian Information Criterion (BIC), and the log-likelihood (LL) values of the model. For all three fit statistics, smaller values indicate better fit. Although BIC is considered the most accurate fit statistic for determining the number of latent classes or profiles (Nylund et al., 2007), all three fit statistics decreased as the number of classes increased from 2-6 before the fit statistics increased for the model with seven profiles. These results suggested that a six-profile model best fit the data.

After determining that the six-profile solution was the best-fitting model for the 1% random sample, we applied this six-profile solution to the full sample of DE students. We then examined the predicted profile memberships and shape profiles (i.e. the predicted means of the DE subject indicators) for each latent profile. While the six-profile solution had the best model fit statistics, the model produced two pairs of latent profiles that were exceedingly similar. Specifically, the model included two profiles in which students attempted between 19-20 DE credits and took very similar DE courses on average. The key differences between these two profiles were that one profile was predicted to attempt two History courses and zero Economics courses, while the other profile was predicted to attempt one History course and one Economics course. Similarly, two other profiles had similar predicted total DE credits attempted (50 vs. 56) and the predicted DE credits attempted by subject were quite similar across most subjects, apart from the first profile predicted to attempt zero Economics courses and the second predicted to attempt one.

Due to our goal of identifying latent profiles that were both statistically sound and conceptually meaningful, we fit the five-profile solution to the full sample as well and examined the predicted class memberships and shape profiles. This model produced five latent profiles that were both conceptually meaningful and empirically distinct from each other. For example, the predicted number of total DE credits attempted for the five profiles were 11, 19, 25, 45, and 56, and the profiles varied on the specific types of DE courses they completed as well. For these reasons, we chose the five-profile solution as our final model and discuss the results of that model in more detail below. The results of the six-profile solution are available upon request to the corresponding author.

Multinomial Logistic Regression

To address our final RQ, we treated students' DE profile as an outcome variable and examined how student and school characteristics predict the DE profile in which we categorized students. In addition to the five DE profiles, we created a sixth category of the outcome variable for students who did not attempt any DE courses in high school, which is the majority of students in our sample (78.9%). We used multinomial logit models to examine the relationship between students' demographic and academic characteristics and their school characteristics, including CCRSM, and students' DE profile category. The category of students who attempted no DE courses served as the reference group. The model controls for a range of demographic, academic, and school-level variables housed in the ERC data warehouse. Demographics include race/ethnicity, free-or-reduced lunch/economic disadvantage, gender, English language learner (ELL)/emergent bilingual and limited English proficiency (LEP) status, special education status, and gifted status. Academic variables include students' STAAR test scores taken in middle and high school. The model specifying the comparison between each of the five latent profiles and the reference group is as follows:

$$ln\frac{\pi_j}{\pi_0} = \beta_j^T x + \delta_j^T z + \gamma_j^T d + \epsilon_j,\ 1 \leq j \leq 5$$

where π_j is the probability of being in the latent profile j; π_0 is the probability of being in the reference category ("No DE"); x, z, and γ are the vectors of student level controls (demographics, test scores, etc.), schools/campus level controls (CCRSM indicators, location type, campus size, etc.), and cohort dummies respectively; β_j is the vector of coefficients corresponding to the student level controls and the outcome j; δ_j is the vector of coefficients corresponding to the campus level controls and the outcome j; γ_j is the vector of cohort fixed-effects; and ϵ_j is the error term. The results are estimated in terms of odds ratios or relative risk ratios. To account for within campus correlation among students, standard errors were clustered at the campus level. In total, seven regression models were estimated, and the predictors were added sequentially to tease out the contribution of each group of student and campus level characteristics; the details on model building are available in the online appendix.

Limitations

Results

This section presents the results of our analyses. We begin by descriptively analyzing students' engagement in DE, including the percentage of students completing DE by year, the types of DE courses students complete, and the prevalence of DE school models (RQ #1). We then create a typology that categorizes all high schools in the state based on their CCRSM and the percentage of students engaging in DE and examine how student characteristics vary across school categories in this typology (RQ #2). Next, we present the results of our LPA analysis and examine the prevalence of the five latent DE profiles and how DE coursetaking varies across these profiles

(RQ #3). Finally, we examine how student and school characteristics predict students' DE profile category using multinomial logit models, including school-level CCRSM indicators in the models to examine the relationship between school structures and students' DE dosage profiles (RQ #4).

RQ #1: Characteristics and Trends in DE Dosage

Among the 3.4 million students in our sample, 21.1% (n=724,964) of students participated in DE; these students completed 6.4 courses on average. Table 3 provides an overview of overall DE participation rates and the average number of courses taken by graduation cohort. The DE participation rate rose steadily from 2015-2021 before declining slightly in 2022 and 2023. It is unclear whether this decline reflects a genuine reversal of the trend toward increasing DE participation or temporary, COVID-related declines in DE coursetaking. Notably, while the percentage of students who participate in DE has fluctuated between 18-24%, the average number of courses taken by participants has steadily increased from 5.24 to 7.42. The majority of these courses are in academic subjects. Although the mean number of DE-CTE courses has increased over time, high school graduates still averaged fewer than one DE-CTE course by 2023, the year with the highest mean number of DE-CTE courses attempted.

[Table 3]

To further examine the types of DE courses students complete, Table 4 reports the 20 most common DE courses in our sample. Two English courses, ENGL 1301 (Composition I) and ENGL 1302 (Composition II), are the two most common DE courses, comprising nearly 20% of all DE courses taken. Many of the most common DE courses are in the core academic areas of Government, History, Math, Psychology, and the like. Although over 1,000 unique college courses are taken by students in our sample, the 20 courses shown in Table 4 comprise roughly two-thirds of all DE courses attempted by our sample. Of note, none of the most common DE courses are DE-CTE.

[Table 4]

Given evidence that students participate in DE at different rates across demographic groups, we summarize patterns across students' demographics in Table 5. Compared to the sample average of 21.1%, female, non-Hispanic, Asian, White, and non-economically disadvantaged students participate in DE at higher rates. In contrast, male students, students of color, and economically disadvantaged students participate in DE at lower rates. In terms of courses completed, however, female, Hispanic, Black, Pacific Islander, and economically disadvantaged students complete more than the average of 6.40 courses.

[Table 5]

RQ #2: School Structures Shape, but do not Determine, DE Dosage

To examine the relationship between school structures and DE dosage, we linked student-level coursetaking with school-level CCRSM designations for the years in which TEA's CCRSM data was available (2019-2023). As shown in Table 6, the vast majority of schools in Texas can be described as traditional high schools in which no CCRSMs are present. However, the percentage of traditional high schools declined from 86.2%-80.2% from 2019-2023. In contrast, CCRSMs have become more prevalent. ECHS, which began in Texas decades ago, comprised 8.3% of all schools in 2019, a rate which increased to 10.2% by 2023. Although P-TECH schools are newer and only comprised 1.7% of schools in 2019, these schools experienced a far faster rate of growth during this five-year period and comprised 8.4% of schools by 2023. T-STEM academies, which have been phased out of new school CCRSM designations, were largely flat during this period. The percentage of schools with multiple CCRSM designations also tripled during this timeframe from 0.8% to 2.8%, although this is the least common model among Texas public schools.

[Table 6]

In Table 7 and Table 8, we further disaggregate schools into a more detailed typology based on the percentage of students at the school who complete any DE, using the median of the school-level DE participation rate of 22% to dichotomize schools into "High DE" or "Low DE" within each CCRSM category. Dual-credit courses were not available (i.e., No Dosage) at k=200 schools in the state, the vast majority of which were traditional high schools (k=196). Two findings are noteworthy from this analysis. First, as expected, some CCRSMs are much more likely to be High DE. For example, among ECHS, 137/161 (85%) are categorized as High DE schools. This rate is much higher than for traditional public high schools, among which only 45% are categorized as High DE. However, the results also show considerable variation in DE dosage among schools in the same CCRSM category. Although P-TECH schools are a form of early college high school, only about half (54%) are considered High DE schools. At the other 46% of P-TECH schools, less than 12% of students engage in any DE on average, and the number of DE courses they complete is modest. Similarly, while the majority of ECHS are High DE, among the roughly one in six ECHS that are Low DE, only 14% of students attempt any DE. Even students at these ECHS who complete DE courses only complete about six credits on average. School structures relate to, but do not determine, students' engagement in DE.

[Table 7]

[Table 8]

In Table 9, we examine trends in the distribution of schools across categories in our typology between 2019-2023. The results show distinctly different trends in the growth and decline of school categories. High DE categories of ECHS and P-TECH schools have grown considerably over time, as have the number of High DE schools that combine multiple CCRSM models. In contrast, the number of High DE traditional public schools and T-STEM schools has declined. However, trends within CCRSM categories differ between High DE and Low DE schools. For example, the number of Low DE ECHS has declined despite the increase in High DE ECHS, and the number of Low DE traditional public schools and T-STEM academies has remained relatively constant, even as the High DE types of these schools declined. Finally, both High DE and Low DE version of P-TECH schools have grown.

[Table 9]

Latent Profiles Shape Distinct Patterns of DE Dosage

To examine whether students can be categorized into distinct groups based on their DE coursetaking, we used LPA. As discussed in the methods, we first fit LPA models with between 2-7 latent profiles to the same set of DE subject indicators to determine the best-fitting model. These model fit statistics, shown in Table 10, indicate that model fit improved as the number of profiles increased between 2-6, before model fit worsened once a seventh profile was added to the model. However, due to two pairs of profiles being highly similar in the six-profile solution, we chose the five-profile solution as our preferred LPA model and discuss the results of that model below.

[Table 10]

Table 11 presents the five profiles estimated through the LPA model and the means of DE variables disaggregated for each profile, and Table 12 presents the means of students' demographic, academic, and school characteristics by profiles categorization. Table 11 excludes students who did not participate in DE, given that they could not be included in the DE LPA models, whereas Table 12 includes the additional category of students who did not participate in any DE in order to compare the characteristics of students in the DE profiles to non-DE students. We describe the five profiles of DE students, in order of the average number of total DE credits they attempt, in the following manner: 1) DE Dabblers; 2) DE Explorers; 3) DE-CTE; 4) ECHS Non-Completers; and 5) ECHS Completers. In the sections below, we describe each of these profiles in terms of their DE engagement as well as their demographic, academic, and school characteristics.

DE Dabblers

DE Dabblers attempt 3-4 DE courses, on average, earning roughly nine credits. The DE courses they attempt can be roughly described as "random acts of dual enrollment." They are most likely to complete an English course, and do not average more than one course (three credits) in any other DE subject. The next most common subjects they attempt are History, Math, and Government. They also have the highest rate of failing DE courses (11.9%), a rate more than three times higher than students in the DE Explorers group (3.4%). White students are the one demographic group over-represented in DE Dabblers compared to non-DE students. All other racial/ethnic groups and economically disadvantaged students are underrepresented among DE Dabblers compared to non-DE students. These students are also overwhelmingly enrolled in traditional high schools, with only 22% enrolled in a school with a CCRSM.

DE Explorers

In some respects, DE Explorers resemble DE Dabblers in terms of the types of DE courses they enroll in, simply attempting roughly twice as many DE courses compared to DE Dabblers (19 vs. 11). The typical DE explorer completes two English courses, one Economics course, one Government course, and one History course, with an average of 1.5 Math credits (half of a course). However, the demographic characteristics of DE Explorers are starkly different than the characteristics of students in other DE profiles. DE Explorers have the highest rates of Asian and White students, the lowest rates of Hispanic/Latino and Black students, and the lowest rates of economically disadvantaged students. These students also have the highest average of advanced courses (e.g. Advanced Placement and International Baccalaureate) completed at 4.45, although the means of students in the two ECHS profiles are similar. This group is also the most likely to be enrolled in a traditional high school, with only 15% of DE Explorers enrolled in a school with a CCRSM.

DE-CTE

DE-CTE students are the most unique in terms of the DE courses they engage in. Although they attempt even more credits than DE Explorers on average (25 vs. 19), they attempt very few academic DE courses. Indeed, they do not average more than one credit in any of the DE academic subjects included as LPA indicators. In contrast, they average roughly 19 DE-CTE credits, the equivalent of roughly six DE courses completed in CTE subjects. ECHS Completers are the only other profile that averages more than one DE-CTE credit, but their DE-CTE engagement pales in comparison to students in the DE-CTE profile. Whereas less than 2% of the DE credits earned by ECHS Completers are in CTE subjects, 78% of the DE credits earned by DE-CTE students are in CTE subjects. DE-CTE students are also the most likely to earn industry certifications at a rate more than twice as high as No-DE students (27% vs. 11%) and higher than all other DE categories (15-17%). Additionally, DE-CTE students have the highest proportions of students from populations historically underrepresented in higher education. Three-quarters of DE-CTE students are students of color and 86% are economically disadvantaged, higher rates than even students in the No-DE category. Despite their concentration in CTE subjects, nearly two-thirds (64%) of these students are enrolled in traditional public high schools, and they are more likely to be enrolled in ECHS (20%) than P-TECH (13%) or T-STEM (9%) schools.

ECHS Non-Completers

The fourth category of DE students is referred to as ECHS Non-Completers. These students attempt a large number of credits (45) in a broad array of academic subjects, averaging 3-7 credits in Biology (3.95), English (7.20), Government (4.70), History (5.47), and Math (4.17). Although less common, ECHS Non-Completers also attempt 1-3 credits in Arts (1.44), Psychology (2.37), Sociology (1.50), Spanish (1.50), and Speech (2.38). In short, these students tend to pursue a broad curriculum generally aligned with a transfer-oriented associate's degree. However, at an average of 45 credits, these students do not quite complete the number of credits typically associated with an associate's degree. ECHS Non-Completers also closely resemble the demographic characteristics of No-DE students, with roughly equivalent percentages of students of color (68% vs. 65%) and economically disadvantaged students (75% vs. 75%). Roughly half of ECHS Non-Completers are enrolled in an ECHS school and 57% are enrolled in a school with at least one CCRSM, rates roughly equivalent with ECHS Completers.

ECHS Completers

The final DE profile is ECHS Completers. These students average 56 DE credits attempted, close to the minimum number of credits attempted needed for an associate's degree (60). In general, ECHS Completers attempt the same types of DE credits as ECHS Non-Completers at equivalent or slightly higher amounts. They attempt 0.5-1.5 more credits than ECHS Non-Completers in Arts, Biology, English, Government, History, and Math, with 0.0-0.5 more credits in all remaining subjects. As mentioned above, they attempt one DE-CTE credit on average, the highest rate of any DE profile apart from the DE-CTE group, but still a small fraction of their overall DE portfolio. Demographically, ECHS Completers also closely resemble the population of No-DE students, with similar rates of Asian (6% vs. 5%), Black (10% vs. 14%), Hispanic/Latino (53% vs. 51%), White (29% vs. 28%), and economically disadvantaged (71% vs. 75%) students. While the majority of ECHS Completers are enrolled in ECHS campuses (51%) and schools with any CCRSM (57%), it should be noted that nearly half of ECHS completers are enrolled in schools that do not have an official ECHS designation from TEA.

[Table 11]

[Table 12]

How Student and School Characteristics Predict Students' DE Profile

In our final analysis, we examine how students' demographic and academic characteristics and the characteristics of their schools predict the likelihood that they are in a particular DE category. As described in our methods, we use multinomial logit models with No-DE students as the reference group. The relative risk ratio (RRR) estimates can be interpreted as the change in risk of being in an outcome category compared to the reference group (No-DE) for every one unit change in the predictor (for continuous variables) or between the group indicated by a variable and its reference group (for dichotomous and categorical variables). RRRs greater than one indicate the covariate relates to an increased probability of students being in the outcome DE category compared to the No-DE group, whereas RRRs less than one imply a decreased probability. In the sections below, we organize our discussion of results by the category of covariates included in the model.

Student Demographic Characteristics

Students' demographic characteristics are related to their likelihood of being in different DE profiles, but the patterns are highly varied. White students are the most likely to be DE Dabblers; all other racial/ethnic groups have lower likelihood of being DE Dabblers vs. No-DE compared to White students. Asian students are also less likely than White students to be in the DE-CTE and ECHS Non-Completer profiles, but they are as likely as White students to be DE Explorers and ECHS Completers. Black and Hispanic/Latino students are less likely than White students to be in all DE categories apart from the DE-CTE profile, for which there are no significant differences between either group and White students. Female students are significantly more likely than male students to be in all DE groups vs. the No-DE category, with the exception of males being more likely to be in the DE-CTE group. Gifted students are significantly more likely than non-gifted students to be in all DE categories compared to the No-DE group, although the estimate for the DE-CTE outcome is nonsignificant. For both economically disadvantaged and LEP students, their risk of being in all DE groups is lower than their non-disadvantaged and non-LEP peers, respectively, apart from non-significant differences between them for the DE-CTE outcome.

Students' Academic Characteristics

Students' academic achievement tends to be positively and significantly related to their likelihood of being in every DE profile compared to the No-DE reference group, with some exceptions. Reading test scores are positively and significantly related to all DE profiles, whereas math test scores are inversely associated with all DE categories apart from the DE-CTE outcome, for which there is a positive relationship. Advanced coursework completion is also positively and significantly associated with membership in all DE groups apart from the DE-CTE, as the estimate for advanced coursework is non-significant in the DE-CTE model. The receipt of industry certifications in high school is positively associated with being in the DE Dabblers, DE Explorers, and DE-CTE group, but is unrelated to membership in the two ECHS profiles. However, the number of certifications students earned in high school is positively and significantly related to being an ECHS Completer.

Campuses and Cohorts

The estimates for cohort fixed effects imply that the likelihood of membership in all of the DE profiles compared to the No-DE group has declined over time. For example, the 2023 cohort is significantly less likely to be in all five DE profiles compared to the 2019 reference group. However, we note that the model also controls for school models, and a growing number of schools have adopted CCRSM over time, which may offset the descriptive trend toward greater DE engagement over time. In terms of school CCRSMs, we find that school models are strongly associated with students' DE profiles. Students enrolled in ECHS are positively and significantly more likely to be in all DE categories vs. the No-DE group compared to students in traditional public high school. Unsurprisingly, students are up to 11 times more likely to be ECHS Completers if they attend an

ECHS. Conversely, enrollment in a P-TECH campus is associated with a decreased risk of being a DE Explorer – the only significant, negative relationship between CCRSM and DE profiles across models – and an increased risk of being a DE-CTE student. P-TECH campus enrollment is unrelated to students' risk of being in the other DE groups. T-STEM Academy enrollment is positively associated with the DE Dabbler, DE-CTE, and ECHS profiles but unrelated to the other DE categories. Finally, students enrolled in schools with multiple CCRSM are more likely to be DE Dabblers, ECHS Non-Completers, and ECHS Completers.

Discussion

DE is one of the most prominent strategies for promoting students' access to and preparedness for higher education, and a growing literature base has touted the postsecondary benefits of DE (An & Taylor, 2019; Schaller et al., 2023; Taylor et al., 2022; What Works Clearinghouse, 2017). However, DE models and pathways are highly diverse, from singleton DE courses and "random acts of dual enrollment" (Fink & Jenkins, 2023) to highly structured ECHS where students complete associate's degrees in high school. Despite the known variation in DE coursetaking patterns, research suggesting that DE courses can have cumulative effects (Giani et al., 2014), and calls from the research community to more deeply conceptualize, measure, and examine students' DE dosage (Taylor et al., 2022), the field still lacks evidence of students' DE profiles, how they relate to school structures, and the factors associated with students' DE dosage. This is particularly critical for efforts to promote equity in higher education access and success, given the racial/ethnic and socioeconomic inequalities in students' DE engagement (Hooper & Harrington, 2022; Taylor et al., 2022; Xu et al., 2021).

Our study addresses these gaps in a number of ways. First, congruent with prior literature (Ryu et al., 2024), our results suggest that the vast majority of DE coursetaking is concentrated in core academic subjects typically associated with a foundational liberal arts pathway and "core curriculum" in higher education. The twenty most popular DE courses are in subjects such as English, Government, History, and Math. Indeed, while high school students in Texas complete DE courses in over 100 subjects, the twelve most common DE subjects included in our LPA analysis comprise more than 90% of all DE credits earned by our sample. DE-CTE credits, of any subject, comprise less than 10% of DE courses attempted. Although literature on DE-CTE is growing (Edmunds et al., 2024a; Edmunds et al., 2024b; Giani, 2022; Ryu et al., 2024), it still remains relatively uncommon compared to DE in core academic subjects.

Perhaps the most rigorous evidence of the effects of DE comes from research on ECHS, particularly studies in which students were randomized to ECHS or not (Edmunds, et al. 2024a). This body of literature suggests that ECHS can substantially increase students' likelihood of degree attainment and significantly decrease time-to-degree (Edmunds, et al. 2024a; Song et al., 2024). However, this research only examines a sliver of ECHS models, and research on the relationship between students' DE dosage and their school models has been understudied. Our analyses show that school models do relate to students' likelihood of engaging in DE and the dosage of DE they receive. However, our results also show considerable variation in DE dosage across school models. While the vast majority of ECHS are High-DE schools, both P-TECH and traditional high schools are roughly evenly split between High-DE and Low-DE models. This suggests that examining variation within school models, and examining within-school variation in students' propensity to participate in DE and the DE pathways they pursue, is particularly critical.

To that end, our LPA analyses identified latent profiles of students based on their actual DE coursetaking, rather than designated school models or pre-defined pathways that school leaders or reformers may create. These models produced five profiles of students distinguished by the DE credits they attempted in different subjects, which correlated strongly with students' demographic and academic characteristics and the types of schools they enrolled in. Aligned with prior literature suggesting that "random acts of dual enrollment" are common (Fink & Jenkins, 2023), nearly two-thirds of all DE students were categorized in the DE Dabblers profile, attempting 3-4 credits in a handful of core academic subjects. At the other end of the DE dosage continuum, two of the profiles seemed to indicate students enrolled in ECHS, some of which appeared to complete the roughly 60 credits needed for an associate's degree (ECHS Completers) and another profile that attempted a large number of credits but short of the associate's degree threshold (ECHS Non-Completers).

However, our LPA models also identified two profiles of DE students that have received less attention in the literature, and which happen to be the two most distinct profiles in terms of students' demographic characteristics. DE Explorers attempt a modest number of credits (19) in core academic subjects, which does not appear particularly noteworthy. However, this profile had disproportionately high percentages of Asian and White students, considerably lower rates of students of color, and lower rates of economically disadvantaged students. In contrast, DE-CTE students attempted even more credits on average than DE Explorers, but their coursework was highly concentrated in CTE areas, and both students of color and economically disadvantaged students were overrepresented in this profile. In our multinomial logit models, students of color and low-income students were less likely to be in any of the DE categories compared to White students, with the exception of the DE-CTE profiles, for which there were no significant differences between these racial/ethnic groups. The literature is replete with studies demonstrating that students of color and low-SES students are underrepresented in DE (Taylor et al., 2022). While true on average, our results extend and complicate this finding by highlighting heterogeneous patterns in the relationship between students' demographic backgrounds and their DE profiles and identifying DE profiles with relatively high numbers of DE credits attempted where students from historically marginalized backgrounds are overrepresented.

By examining the relationship between students' DE profiles and school structures, our results also underscore the importance of examining within-school heterogeneity in students' DE pathways. The majority of students in the No-DE, DE Dabblers, DE Explorers, and DE-CTE categories are enrolled in traditional high schools. Indeed, more than 85% of DE Explorers, which are disproportionately Asian, White, and not economically disadvantaged, are enrolled in traditional high schools. Understanding the mechanisms through which traditional public schools without any clearly defined school structures or reform models provide opportunities for students to engage in considerable amounts of DE is critical. Similarly, although the majority of students in the two ECHS profiles are enrolled in schools with CCRSMs, more than 40% of students in both categories are not enrolled in CCRSM schools. Simply relying upon designated school structures or reform models to understand students' intended and realized DE pathways overlooks important within-school mechanisms that shape student opportunity.

Our results also illuminate how DE dosage relates to students' academic achievement and engagement in other college and career preparatory activities in high school. We find that higher achieving students are more likely to be in all five of the DE profiles compared to their likelihood of being No-DE students, congruent with prior literature. Additionally, while researchers have questioned the tradeoffs between DE and other college and career opportunities such as CTE coursework, industry certifications, and even advanced coursework (e.g. AP and IB), our results suggest that engagement in many of these opportunities may be mutually reinforcing. For example, rather than evidence of substitution between advanced coursework and DE, our results suggest that students in all DE profiles completed multiple advanced courses on average, and advanced coursework is positively associated with students' likelihood of being in all of the DE profiles apart from the DE-CTE group. Similarly, CTE coursework is positively associated with the likelihood of being a DE Dabbler, DE Explorer, or DE-CTE student. Researchers have recently sought to identify potentially promising combinations of DE, advanced, and CTE coursework that students may integrate into coherent and multifaceted pathways (Velasco et al., 2025). Our findings suggest students are already combining these diverse college and career opportunities, and more research is needed to understand the interactions between students' DE pathways and the other curricular opportunities they pursue. Our analyses also lay the foundation for future research examining how the intersection of school structures and DE profiles relates to students' postsecondary outcomes.

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Tables & Figures

Table 1: Analytical Overview

#	Question	Sample	Characteristics	Method	Table(s)
1	How much dosage of DE do students engage in during high school?	2014-2023 Cohorts (*n* = 3,434,626)	Student and Course	Descriptive Statistics	2-4
2	How can schools be categorized based on structure and dosage?	2019-2023 Cohorts and Schools (*n* = 1,809,033; *k=2,031*)	Course and School	Descriptive Statistics	5-9
3	How can students' DE dosage profiles be categorized?	2014-2023 Cohorts, restricted to DE Participants in (*n* = 724,946)	Student and Course	Latent Profile Analysis	10-12
4	How do student and school characteristics relate to dosage profiles?	2019-2023 Cohorts and Schools (*n* = 1,809,033; *k* = 2,031)	Student, Course, and School	Multinomial Logistic Regression	13

Table 2: Descriptive Characteristics of Twelve Most Common Dual Enrollment Subjects

DE Subject	*N*	Mean	SD	Min	Max	DC %	Cum. %
English	724,941	3.96	4.20	0	27	0.24	0.24
History	724,941	2.30	2.90	0	21	0.14	0.38
Math	724,941	1.67	3.04	0	28	0.10	0.48
Government	724,941	1.63	2.11	0	18	0.10	0.58
CTE	724,941	1.63	4.81	0	88	0.10	0.68
Biology	724,941	0.91	2.57	0	28	0.05	0.73
Economics	724,941	0.79	1.35	0	15	0.05	0.78
Speech	724,941	0.54	1.20	0	18	0.03	0.81
Psychology	724,941	0.52	1.34	0	30	0.03	0.85
Spanish	724,941	0.39	1.66	0	25	0.02	0.87
Arts	724,941	0.28	0.97	0	27	0.02	0.89
Sociology	724,941	0.25	0.86	0	12	0.02	0.90

Notes: The table presents descriptive characteristics of DE credits attempted by subject for 2014-2023 high school graduates in Texas. The sample is the subset of students who earned attempted any DE credits in high school. DE courses, like other college courses in Texas, typically confer three credits per course. The mean is the number of credits attempted by subject. The "DC %" column indicates the percentage of all DC credits attempted by our sample that were taken in that subject. The "Cum. %" column indicates the cumulative percentage of credits earned in all subjects including and above that row.

Table 3: Dual Credit Participation Rates and Average Number of Courses Completed per Student, by Cohort

Cohort	N	DC Participants	Percentage	Mean Courses Completed	Academic DC Participants	Academic Courses Completed	CTE DC Participants	CTE Courses Completed
2014	302,557	61,241	20.2%	5.24	55,505	4.65	11,476	0.59
2015	313,192	55,013	17.6%	5.61	48,650	4.92	11,683	0.70
2016	323,269	59,944	18.5%	5.77	52,840	4.93	13,751	0.84
2017	333,320	63,620	19.1%	5.85	56,252	5.13	13,211	0.72
2018	346,602	72,185	20.8%	5.81	63,992	5.10	14,327	0.71
2019	354,515	77,399	21.8%	6.31	68,904	5.54	15,311	0.78
2020	358,953	81,359	22.7%	6.61	73,059	5.84	15,710	0.82
2021	358,201	85,526	23.9%	7.05	77,627	6.22	15,713	0.83
2022	367,716	83,723	22.8%	7.25	75,940	6.41	15,406	0.84
2023	372,301	84,954	22.6%	7.42	76,984	6.54	15,915	0.88
Totals:	*3,434,626*	*724,964*	*21.1%*	*6.40*	*649,753*	*5.53*	*142,503*	*0.77*

Table 4: 20 Most Frequently Taken Courses, Enrollment Amounts, and Percentage of Total DE Enrollments

Rank	Course Code	Participants	Percentage of DC Enrollments
1	English 1301	425,258	9.8%
2	English 1302	374,042	8.6%
3	Government 2305	314,789	7.1%
4	History 1301	286,975	6.5%
5	History 1302	286,248	6.5%
6	Economics 2301	188,307	4.3%
7	Math 1314	171,676	3.9%
8	Government 2306	106,286	2.3%
9	Psychology 2301	104,999	2.3%
10	English 2322	90,348	2.0%
11	Speech 1315	77,252	1.7%
12	English 2323	65,204	1.5%
13	Sociology 1301	65,204	1.5%
14	Arts 1301	63,333	1.3%
15	Math 2412	59,621	1.3%
16	Biology 1406	58,493	1.3%
17	Speech 1311	54,507	1.2%
18	Math 1414	48,947	1.1%
19	Education 1300	48,825	1.0%
20	Biology 1407	44,748	1.0%
Total	Top 20 Courses	2,935,062	66.2%

Table 5: Dual Credit Participation Rates and Average Number of Courses Completed per Student, by Demographic Indicators

Demographic	*N*	Percentage of Sample	DC Participants	Participation Rate	Mean Courses Completed
Gender					
Male	1,715,112	50.0%	307,669	18.1%	6.13
Female	1,715,253	50.0%	416,758	24.3%	6.60
Ethnicity					
Hispanic	1,712,454	50.0%	330,059	19.3%	6.82
Non-Hispanic	1,712,911	50.0%	394,368	23.0%	6.04
Race					
Asian	157,596	4.6%	35,182	22.3%	5.75
Black	426,419	12.4%	53,690	12.6%	6.60
Native American	12,464	0.4%	2,435	19.5%	6.25
Pacific Islander	5,125	0.2%	753	14.7%	6.95
Multiracial	69,121	2.0%	14,234	20.6%	5.95
White	1,043,381	30.4%	288,048	27.6%	5.98
Economic Status					
Disadvantaged	2,461,270	71.2%	444,971	18.1%	6.73
Non-Disadv.	966,095	28.2%	279,456	28.9%	5.86

Table 6: Campus-Level CCRMS Descriptives, by Cohort

	2019	2020	2021	2022	2023
K (number of schools)	1966	1948	1952	1993	2031
High School Models					
Traditional	86.2%	84.7%	83.7%	82.2%	80.2%
ECHS	8.3%	9.1%	9.4%	9.8%	10.2%
PTECH	1.7%	3.0%	4.0%	6.0%	8.4%
T-STEM	4.6%	4.7%	4.7%	4.5%	4.3%
Multiple CCRSMs	0.8%	1.5%	1.7%	2.4%	2.8%

Table 7: High Dual-Credit Schools: Campus Characteristics

	Traditional	ECHS	PTECH	TSTEM	Multiple
K=	647	137	67	26	38
Campus Size	60	104	78	70	361
DC Participants	45.4%	58.8%	46.9%	46.1%	34.6%
DC Courses Taken per Student	2.75	6.10	3.59	3.21	2.88
Academic DC Courses Taken	2.43	5.55	2.60	2.44	2.60
CTE DC Courses Taken	0.07	0.11	0.45	0.04	0.11
Amongst DC Participants					
DC Courses Taken per Student	7.33	13.40	9.00	7.06	9.26
Academic DC Courses Taken	6.57	12.80	6.63	5.99	8.88
CTE DC Courses Taken	0.20	0.30	1.38	0.13	0.45

Table 8: Low Dual-Credit Schools: Campus Characteristics

	Traditional	ECHS	PTECH	TSTEM	Multiple
K=	785	24	58	31	18
Campus Size	107	323	306	95	418
DC Participants	15.0%	13.7%	11.8%	17.0%	16.4%
DC Courses Taken per Student	0.50	0.93	0.51	0.52	1.01
Academic DC Courses Taken	0.40	0.77	0.39	0.44	0.83
CTE DC Courses Taken	0.01	0.04	0.05	0.00	0.07
Amongst DC Participants					
DC Courses Taken per Student	4.00	5.36	4.10	3.22	5.40
Academic DC Courses Taken	3.25	4.74	3.23	2.76	4.49
CTE DC Courses Taken	0.11	0.28	0.35	0.00	0.52

Table 9: Distribution of High Schools Across Typology Categories

	2019	2020	2021	2022	2023
High-Traditional	706	684	666	673	647
High-ECHS	118	126	130	121	137
High-PTECH	4	21	38	48	67
High-TSTEM	41	35	36	29	26
High-Multiple	9	17	22	33	38
Low-Traditional	783	787	806	787	785
Low-ECHS	30	28	26	36	24
Low-PTECH	23	19	18	38	58
Low-TSTEM	35	37	31	30	31
Low-Multiple	7	12	11	14	18
No-All Models	210	182	168	184	200
Totals	1,966	1,948	1,952	1,993	2,031

Table 10: Model Fit Statistics for Latent Profile Analysis Models

Classes	N	LL (model)	DF	AIC	BIC
2	7,280	-202389	46	404870	405187
3	7,280	-196454	62	393032	393460
4	7,280	-192649	78	385454	385992
5	7,280	-190483	94	381154	381802
6	7,280	-188892	110	378004	378763
7	7,280	-188967	126	378187	379055

Table 11: Means of Dual-Enrollment Variables by LPA Profiles

	DE Dabblers	DE Explorers	DE-CTE	ECHS Non-Compl eters	ECHS Completers
Overall DE Engagement					
DE Credits Attempted	10.98	19.47	24.69	45.02	56.14
DE Credits Earned	9.67	18.81	23.18	42.34	53.89
DE Credits Failed	1.30	0.66	1.51	2.67	2.25
DE Credit Failure Rate	11.9%	3.4%	6.1%	5.9%	4.0%
DE Subject LPA Indicators					
DE Arts Credits	0.11	0.11	0.10	1.44	1.92
DE Biology Credits	0.46	0.54	0.16	3.95	4.80
DE Economics Credits	0.00	3.01	0.00	0.00	3.21
DE English Credits	3.06	5.17	0.94	7.20	8.71
DE Government Credits	0.73	2.83	0.20	4.70	5.34
DE History Credits	1.63	2.88	0.41	5.47	5.82
DE Math Credits	1.23	1.53	0.61	4.17	5.54
DE Psychology Credits	0.24	0.37	0.16	2.37	2.54
DE Sociology Credits	0.09	0.14	0.05	1.50	1.35
DE Spanish Credits	0.24	0.19	0.17	1.50	1.87
DE Speech Credits	0.25	0.42	0.21	2.38	2.65
DE CTE Credits	0.90	0.64	19.37	0.66	1.06
n	459,164	150,998	31,150	47,324	36,304
Class Proportion	63.34	20.83	4.30	6.53	5.01

Table 12: Demographic and Academic Characteristics of DE Profile Categories

	No DE	Random DE	DE Explorers	DE-CTE	ECHS Non-Comp leters	ECHS Completers
Race/Ethnicity						
Asian	.05	.04	.08	.01	.02	.06
Black	.14	.08	.06	.08	.07	.10
Hispanic/Latino	.51	.46	.33	.68	.61	.53
Multiracial	.02	.02	.02	.01	.01	.02
White	.28	.39	.51	.22	.28	.29
Student of Color	.65	.54	.39	.76	.68	.63
Female	.48	.57	.60	.39	.65	.65
Econ. Dis. Ever	.75	.63	.46	.86	.75	.71
Advanced Course Credits	2.64	4.09	4.45	2.16	4.32	4.44
CTE Course Credits	4.88	5.59	5.60	7.63	5.65	5.31
Industry Cert (Any)	.11	.15	.15	.27	.18	.17
Industry Cert (Count)	.14	.21	.21	.39	.24	.24
CCRSM (2019-2023)						
ECHS	.11	.14	.08	.20	.49	.51
T-STEM	.05	.06	.04	.09	.09	.04
P-TECH	.07	.07	.05	.13	.09	.07
Any CCRSM	.20	.22	.15	.36	.57	.57

Table 13: Relative Risk Ratios from Multinomial Logit Models of DE Profile Categories

	DE Dabblers	DE Explorers	DE_CTE	ECHS Non-Com pleters	ECHS Completers
Race/Ethnicity (White)					
Asian	0.698***	0.943	0.587***	0.537***	0.994
	(0.039)	(0.093)	(0.085)	(0.075)	(0.139)
Black/African American	0.721***	0.559***	0.851	0.709*	0.685***
	(0.021)	(0.028)	(0.098)	(0.101)	(0.073)
Hispanic	0.817***	0.704***	1.070	0.853*	0.806***
	(0.016)	(0.024)	(0.059)	(0.056)	(0.051)
Multiracial/Other	0.826***	0.761***	0.710***	0.738***	0.796**
	(0.017)	(0.026)	(0.058)	(0.052)	(0.057)
Native American	0.828***	0.787***	1.045	0.786	1.022
	(0.035)	(0.055)	(0.154)	(0.111)	(0.130)
Native Hawaiian/Pacific Islander	0.712***	0.655**	1.136	0.903	1.247
	(0.052)	(0.086)	(0.304)	(0.205)	(0.237)
Female	1.441***	1.754***	0.683***	2.083***	2.061***
	(0.014)	(0.023)	(0.034)	(0.047)	(0.053)
Gifted	1.194***	1.269***	1.113	1.635***	1.681***
	(0.035)	(0.051)	(0.076)	(0.091)	(0.119)
Limited English Proficient	0.683***	0.580***	0.978	0.527***	0.385***
	(0.016)	(0.030)	(0.049)	(0.034)	(0.031)
Economically Disadvantaged	0.691***	0.433***	1.034	0.665***	0.587***
	(0.017)	(0.015)	(0.054)	(0.038)	(0.033)
8th Grade Math Ach. Test (SDs)	0.976*	0.917***	1.064*	0.910**	0.887***
	(0.011)	(0.018)	(0.026)	(0.031)	(0.028)
8th Grade Reading Ach. Test (SDs)	1.449***	1.740***	1.129***	1.717***	1.558***
	(0.027)	(0.046)	(0.021)	(0.086)	(0.129)
Course Credit	1.080***	1.142***	1.015	1.239***	1.242***
	(0.004)	(0.008)	(0.010)	(0.016)	(0.018)
Failed Course Credit	1.064***	1.191***	1.137***	1.224***	1.282***
	(0.005)	(0.009)	(0.011)	(0.013)	(0.017)
Advanced Course Credit	1.061***	1.042***	1.018	1.061***	1.071***
	(0.006)	(0.010)	(0.013)	(0.017)	(0.021)
CTE Course Credit	1.039***	1.040***	1.356***	0.968*	0.954*
	(0.005)	(0.009)	(0.018)	(0.015)	(0.020)
Industry Certification (any)	1.131***	1.191***	1.411***	0.964	0.994
	(0.025)	(0.048)	(0.099)	(0.057)	(0.084)
Industry Certification (Count)	1.082***	1.144***	1.197***	1.073	1.271***
	(0.013)	(0.019)	(0.038)	(0.039)	(0.060)
Urbanicity (City)					
Rural	1.340***	1.871***	0.919	1.930***	2.166***
	(0.085)	(0.210)	(0.143)	(0.333)	(0.385)

Town	1.112	1.466***	0.563***	1.546*	1.690*
	(0.063)	(0.146)	(0.088)	(0.282)	(0.357)
Suburb	1.280**	2.405***	0.835	1.704*	2.884***
	(0.110)	(0.348)	(0.168)	(0.435)	(0.615)
Cohort (2019)					
2020	1.033*	0.902***	1.001	0.982	1.007
	(0.016)	(0.027)	(0.053)	(0.051)	(0.071)
2021	1.076***	0.819***	0.922	1.013	0.858
	(0.022)	(0.031)	(0.057)	(0.072)	(0.089)
2022	0.990	0.686***	0.780***	0.825*	0.737*
	(0.025)	(0.029)	(0.055)	(0.070)	(0.090)
2023	0.917**	0.638***	0.701***	0.767**	0.630***
	(0.025)	(0.033)	(0.058)	(0.072)	(0.083)
School Size	0.933***	0.996	0.961	0.685***	0.742***
	(0.018)	(0.031)	(0.076)	(0.038)	(0.050)
School Size^2	1.002	1.002	0.998	1.021***	1.012*
	(0.001)	(0.002)	(0.008)	(0.005)	(0.006)
School Model (Traditional)					
ECHS	1.465***	1.352**	2.149***	7.318***	11.485***
	(0.084)	(0.157)	(0.375)	(1.261)	(2.191)
P-TECH	1.018	0.616*	1.831***	1.291	0.606
	(0.093)	(0.117)	(0.305)	(0.346)	(0.291)
T-STEM	1.255*	1.079	2.145***	1.753	1.697*
	(0.139)	(0.212)	(0.494)	(0.508)	(0.437)
Multiple CCRSM	1.321***	0.760	1.511	5.501***	3.263***
	(0.110)	(0.157)	(0.341)	(1.376)	(0.893)
Pseudo R-squared			0.174		
Num of observations			1809033		
Log-Likelihood			-1191077		
Akaike Information Criterion			2382664		
Bayesian Information Criterion			2385828		

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