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UNIVERSITY OF CALIFORNIA,
IRVINE

An Evaluation of Three Community College Practices

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Education

by

Joshua Dorman

Dissertation Committee:
Associate Professor Di Xu, Chair
Associate Professor Jade Jenkins
Associate Professor Rachel B. Baker

2024

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ABSTRACT OF THE DISSERTATION

An Evaluation of Three Community College Practices

by

Joshua Dorman

Doctor of Philosophy in Education

University of California, Irvine, 2024

Associate Professor Di Xu, Chair

This dissertation examines the effectiveness of three distinct practices within the community college education system, focusing on their impact on student outcomes. The first study evaluates the Extended Opportunities Program & Services (EOPS), a long-standing initiative designed to support academically and financially disadvantaged students through specialized counseling, additional financial supports, and enhanced access to other campus resources. Utilizing a quasi-experimental methodology (e.g., propensity score weighting or matching), the study assesses both short-term and long-term impacts on student success metrics such as persistence, transfer-level course completion, and degree attainment. The findings reveal that the effect of the program varies across these outcomes. Potential reasons why that may be the case and opportunities for future studies to explore these differences further are discussed.

The second study investigates the impact of embedded tutoring in English and Math courses at a southern California community college. The study examines how the presence of embedded tutors influences course success and retention rates. Using a variety of fixed effects models, the outcomes of students enrolled in embedded tutor sections are compared to students enrolled in similar courses without embedded tutors. The findings reveal that the program did not produce significant effects, with consistently negligible or non-significant differences for overall

and even between course comparisons. Potential limitations, member check feedback, and recommendations to potentially improve the efficacy of tutoring are discussed.

The third study explores the effects of simultaneous enrollment at multiple community colleges using a national longitudinal dataset. An instrumental variable approach is employed to identify the causal impact of this enrollment pattern on academic outcomes, including transfer and degree completion. Although the results may be constrained by sample size, sensitivity analyses suggest a positive relationship between simultaneous enrollment and academic success.

The findings from these studies help better inform policymakers and practitioners seeking to enhance the effectiveness of support services and interventions within community colleges, ultimately aiming to improve educational outcomes for diverse student populations.

INTRODUCTION

Community College Students in the U.S.

Public two-year community colleges (CC) are the largest provider of postsecondary education, serving roughly 28% of postsecondary students nationwide (NCES, 2018). A substantial portion of the population served is composed of members of historically underserved groups such as students from low socioeconomic backgrounds, first-generation college students, and/or students of color (Krogstad, 2016; NCPPHE, 2011). The vast majority (80%) of CC students intend to transfer to a 4-year baccalaureate granting institution, but only about 25% transfer within four years and even fewer (17%) earn a bachelor's degree within six years (Bailey et al., 2015; Hossler et al., 2012).

Community Colleges in California

California Community Colleges (CCCs) play a critical role in providing higher education to the largest number of post-secondary students in the country. In the five most recent years, the 115 CCCs throughout the state have served an average of 2.4 million students (CCCO, 2022). The system serves the most students in the state, with an estimated 30% of every Californian age 18-24 being currently enrolled (FCCC, 2022). The system is a key gateway for many historically underserved groups, with an estimated 69% students from diverse ethnic backgrounds, and 53% being female. Roughly 51% of graduates of the California State University and 29% of the University of California systems are students who, at some point, transferred from a CCC. Apart from these accomplishments, however, many CCC students are still struggling to achieve their goal(s) (e.g., earn an Associate's, transfer, etc.). For example, less than 18% of students per cohort (2011-2012 to 2014-2015) of first-time starting students successfully earned an

Associate's degree and less than 30% transferred to a four-year within a six-year time frame statewide (CALPASS, 2023).

Purpose of the Study

The aforementioned opportunities for growth have been the topic of discussion for researchers and practitioners alike for years (Bailey et. al, 2015). As more and more national attention is drawn to the perceived shortcomings of the system and the fact that a college education is related to economic indicators, more pressure is being put on the institutions to address these shortcomings without costing the taxpayer additional money. What I hope to accomplish with the following studies is to explore how two existing services and a potential enrollment policy relate to student outcomes. In other words, are these existing services which institutions, state- or nation-wide, are investing in having any measurable impact on academic outcomes and is there an opportunity for administrators to implement new policies to engage students in other potentially effective behaviors?

Study 1

The Extended Opportunities Program & Services (EOPS) is a statewide initiative provided in CCCs for nearly 50 years, but the literature examining the impact of the program has yet to provide robust causal estimates. This study seeks to contribute to the literature by utilizing a quasi-experimental methodology to measure the impact of the program within a local community college district. More specifically, I use data on seven cohorts from the two colleges within the district to evaluate the short and long-term impacts of participation in EOPS. While there have been a number of studies that have done descriptive analyses or correlated participation with outcomes, this study extends the existing body of work by using various

propensity score balancing techniques to find a suitable counterfactual and, most importantly, measure the relationship with the ultimate goal of many students, bachelor's attainment.

Study 2

Community colleges have sought to improve the course success rates of students using some form of tutoring for decades, but the embedded tutor variation is still a relatively new approach. This distinct form of tutoring entails having a tutor present in the course to collaborate with the professor in helping students while also being available in a tutoring center for the students to utilize at their own discretion. Using eight terms of data on select math and English courses from a local community college, I assess the impact of enrollment in an embedded tutor section on course outcomes. Results shared with local staff and administrators will be used in conversations to modify, scale up, or reduce the program.

Study 3

Researchers and practitioners have attempted to describe and categorize the distinct enrollment patterns that community college students exhibit but there is limited work understanding the potential academic impacts of the distinct forms. The current study utilizes the nationally representative National Center for Education Statistics' Beginning Postsecondary Students [12:17] and companion Post-Secondary Education Transcript Study [12:17] datasets to explore these patterns. More specifically, I explore the prevalence and causal impact of lateral (two community colleges) simultaneous enrollment. Prior work has begun studying these patterns, but I intend to extend the existing work by exploiting the exogeneity of access to institutions to explain the uptake of the pattern. Using this instrumental variable approach, I attempt to answer the question of whether this enrollment pattern has a relationship with academic outcomes such as transfer or degree attainment.

CHAPTER 1: Extended Opportunities Program & Services Evaluation

Starting in 1969, the Extended Opportunity Program and Services (EOPS) has been implemented throughout the California CCs in an effort to provide equal opportunity to students who have been historically underserved. The program was designed to provide access to a wide array of services (e.g., academic counseling, access to textbooks, emergency funding, etc.) that were thought to be of the greatest benefit to students who are both academically and financially disadvantaged.

While most studies investigating the effectiveness of EOPS have offered generally positive findings, they are typically historical and/or use non-experimental approaches. This study builds upon the current literature by attempting a quasi-experimental approach, accounting for selection biases that may influence one's decision to participate in the program. The current study also includes more longitudinal outcomes (e.g., degree completion) than were included in prior studies.

This study intends to answer the following research questions:

1. Does EOPS participation increase one's probability of achieving a number of short-term key performance indicators (e.g., persistence, transfer-level English course completion, etc.)?
2. Does EOPS participation increase one's probability of achieving a number of long-term outcomes (e.g., Associate's degree, transfer to a 4-year college or university, Bachelor's degree)?

These analyses extend the existing literature on EOPS and provide practitioners with an understanding of the value-added of EOPS implementation at their respective institutions.

Conceptual Framework

To better contextualize the potential relationship between EOPS involvement and academic outcomes, I will use Coleman's (1988) concept of social capital. Coleman's model, a variation of Bourdieu's (1984) cultural capital framework, explains how one's social relationships or networking determines one's access to information and opportunities. Moreover, if one establishes strong relationship channels, that is strong relationships with certain stakeholders or agents within an institution or group, one will yield greater access to information through trust with stakeholders.

In the context of the current study, students who partake in EOPS are required to meet with an assigned counselor frequently. Most of these meetings are focused on academics, where a counselor reviews their academic plan and progress towards their goals. Apart from helping the students stay on track and encouraging them to apply for degrees or certificates, the counselors refer the students to other resources on campus who can further a student's academic network, or social capital. Some examples of services or programs that students are referred to include student health and wellness center, the transfer center, student clubs, food pantry, and more. They are also made aware of opportunities for scholarships or job opportunities that are currently available. The culmination of all these various forms of contextual social capital help explain why EOPS students may have differential outcomes from other similar students who do not participate in the program.

About the Program

The EOPS program is a California statewide initiative offered in all public community colleges designed to provide select services to students who are considered financially and

academically disadvantaged. Such services may vary from school to school, but may include any of the following:

a. Tutoring
b. Specialized Academic Counseling
c. Book/calculator loans or assistance
d. Childcare
e. Emergency Loans
f. Gas/Grocery cards
g. Priority enrollment[1]
h. University of California and California State University application fee waivers
i. Parking passes

These provided services are believed to enhance academic persistence and academic achievement for students (Crawford, 1999). The latest five academic years (2018-2019 to 2022-2023) of data from the California Community College Chancellor's office shows that EOPS students are on average about 3.9% of the entire community college population. The participants have greater representation of certain historically underrepresented groups, such as Hispanic (56.7%), African-American (8.2%), and female (66.4%) students.

The statewide budget for EOPS in the 2021-2022 academic year was $135,151,100, a 16.4% increase over prior year (CCCO, 2022).

[1] Priority enrollment is a privilege extended to select students, allowing them to have an earlier opportunity to register for classes. This is known to be a considerable privilege, because it affords one a greater opportunity to register for the classes they need, at times that work for them or with professors they're interested in working with before the class is full.

Relevant Literature

Effectiveness of EOPS

Despite the longevity and ubiquity of EOPS in California, there are few peer-reviewed studies available. One of the more recent studies by Soltani et al. (2017) used a mixed-methods approach to find positive correlations between EOPS, student learning (e.g., GPA), and non-cognitive measures at a single college. And while the paper attempts to triangulate said findings with a series of qualitative measures, the authors stress that their analyses are limited in that they are not adequately accounting for selection biases that may be explaining differences in outcomes. The next most notable recent study by Rams (2010) explored the experience of African American males participating in EOPS at three California CCs. The study conducted an ANOVA and regression analysis using data collected from 230 students' pre- and post-surveys measuring self-efficacy and racial identity of the participants. Rams concludes that EOPS programs provide an effective service to students by providing them with a greater ability to recognize and utilize available campus resources which will in turn increase their probability of persistence. A more historical but substantial study was conducted by Rudmann et al. (2008) at eight California CCs. The authors sought to explore the relationship between GPA and participation in EOPS and Disabled Student Programs and Services, along with a variety of other variables. They found positive results that indicated that EOPS participation is strongly correlated with academic outcomes. Again though, a potential limitation of these findings is an inadequate specification of the selection mechanisms that might be explaining the observed differences between the groups.

Apart from the peer-reviewed literature, the only other recent literature investigating the effectiveness of EOPS is a handful of dissertations and reports compiled by select agencies (Gandara, 2012; Meehan, 2010; Reyes et al., 2022; Willet & Hayward, 2012). Meehan (2010),

for example, explored the success of EOPS students at Santa Barbara City College and found that the program provided students with the necessary tools (e.g., academic counseling, tutoring, and financial support) to ensure they reach their academic goal. In an effort to capture the administrative perspective of EOPS, Gandara et al. (2012) used qualitative methods to find that counselors and staff viewed EOPS as a critical service for underrepresented students and would often personally recommend it to students. The Research and Planning Group, a third-party partner of the California Community College Chancellor's office, has put forth two technical reports on their assessment of the program using statewide data and quasi-experimental methods (e.g., propensity score weighting) to assess whether participants had higher odds of successfully completing a number of outcomes (Reyes et. al, 2022; Willet & Hayward, 2012). Their results in both reports suggest that EOPS students have a greater likelihood of succeeding across a wide array of outcomes (e.g., units completed, GPA at certain time points, or degree completion) but have lower odds for a select few outcomes (e.g., transfer within three years to California State and University of California universities).

Eligibility for EOPS

EOPS is a program that was created to specifically serve students who are California state residents (or AB-540), 18 years or older, and deemed financially and academically disadvantaged. The two latter criteria are the critical focus of EOPS, helping those who have both financial and academic needs. Both criteria have to be true for one to be eligible, but the challenge with that requirement is that it is open to interpretation between (and sometimes even within) institutions. In doing a surface level scan of a random sample of 10 community college EOPS websites, the determination of one being financially disadvantaged is arguably the simpler of the two, because it is typically based solely on one's Free Application for Federal Student Aid

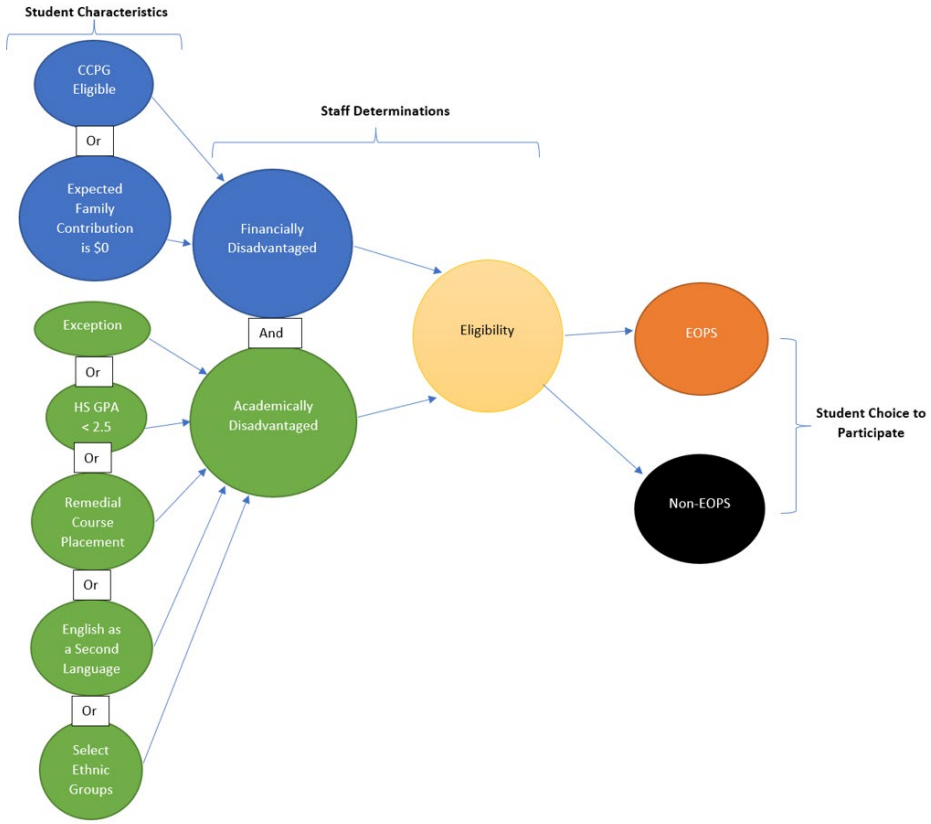
(FAFSA). One is deemed to be financially disadvantaged if they qualify for the California College Promise Grant (CCPG), previously known as the Board of Governor's Fee Waiver (BOGW). There are three different types of CCPG, typically referred to as *A*, *B*, or *C*. Type *A* is granted when a student or their parent(s) are on some form of public assistance (e.g., TANF/CalWORKS, or general assistance). Type *B* is granted to students who are deemed to be low-income based on their household income and family size. Type *C* is for students who do not qualify under either of the previous types, but can prove that they or their family will have some form of financial need. The determination of academic disadvantage, on the other hand, is far more complex in that it can be based on a variety of factors. Based on the same scan of sites, possible criteria for eligibility include:

A. Not having graduated high school or obtained a G.E.D.
B. High school GPA less than 2.5
C. Previous enrollment in non-transfer level coursework (e.g., English/math)
D. First-generation college-student
E. Being a member of a certain under-represented ethnic group
F. Parent's native language is not English
G. Completion of less than a certain number of cumulative units

These criteria for eligibility are crucial in designing an adequate quasi-experimental model to measure the effectiveness of EOPS. The first step in the process of recruitment entails EOPS counselors identifying students who are potentially eligible based on their FAFSA application and then reaching out to them via email to offer them the opportunity to join by completing an

online form.[2] Upon completion of the form, staff at each school utilize a distinct eligibility form checklist to ensure that the individual meets both criteria of academic and financial disadvantage and then are offered official admission if they agree to maintain a certain number of enrolled units per term and minimum GPA (See Figure 1.1).

Figure 1.1 EOPS Eligibility Criteria



A critical aspect of the eligibility determination process is the fact that program directors have the authority to certify the student as eligible based on an exception. There are no explicit reasons for an exception written in state guidelines, but in speaking with local staff, I have learned that exceptions may be made for a number of reasons. They emphasized that these are made largely based on the context of the school and the population which they serve. The recent

[2] Within the context of the current sample, students are deemed eligible by EOPS counselors using similar guidelines but even between the schools there may be selection biases that come into play. I will explain how I attempt to address these potential biases later on.

emphasis on addressing equity gaps among disproportionately impacted groups plays a significant role in influencing local exceptions. In essence, local exceptions often align with the goal of addressing disparities among specific student groups identified as disproportionately impacted.

To illustrate the subjective nature of eligibility criteria, consider a hypothetical scenario involving two colleges within the same district, College A and College B. College A has identified an equity gap among non-traditional aged students (those aged 25 or older). In contrast, College B recognizes an equity gap among female first-generation students. Consequently, each college has developed policies tailored to these findings. At College A, a young female first-generation student under the age of 25 would not automatically meet the criteria for academic disadvantage. An eligibility officer at College A would need to assess if she qualifies under any other set criteria. However, at College B, this same student would be classified as academically disadvantaged based solely on her status as a first-generation student, regardless of her age. This example highlights how colleges may implement differing criteria. Moreover, enforcement of these criteria can be flexible. For instance, College B might adjust its policies to attract the student from College A by recognizing her as academically disadvantaged, thus securing her enrollment. This flexibility illustrates the variability and subjectivity in how academic disadvantage criteria are applied across institutions.

Methodology

Data

The Lavender Community College District, based in Southern California, collects and hosts a wealth of data for all students who attend their two colleges, Poppy and Mums colleges (all names are pseudonyms). In an effort to conduct a robust analysis with current cohorts and at

the same time allow for enough time to have elapsed since initial enrollment for students to accomplish longitudinal outcomes, the cohorts of 2010-2016 are used in the current analyses.

The inclusion criteria for these analyses are stringent, with only first-time college students enrolled in credit units during the summer or fall of a given year considered part of a cohort. Specifically, individuals must have met eligibility for EOPS at some point by satisfying one of the academic and financial criteria described above. These additional criteria, while rigorous, are implemented to ensure that the comparison group is as well-matched to EOPS participants as possible.

Variables examined include the cohort in which students commenced their college journey, demographics encompassing ethnicity, gender, age at the onset of enrollment, disability status, first-generation status, English as a Second Language (ESL) status, utilization of financial aid, high school GPA, and the current college of attendance.

Moreover, key outcomes of interest include the completion of transfer-level math and English courses within the first year, GPA at the conclusion of the 2nd and 4th years, attainment of an Associate's degree by the conclusion of the 2nd and 4th years, transfer to a 4-year institution by the conclusion of the 2nd and 4th years, and the eventual attainment of a Bachelor's degree (For an operationalization of each outcome, see appendix A). These metrics provide valuable insights for practitioners and researchers alike, facilitating a comprehensive understanding of student trajectories and program effectiveness. The local data warehouse also provided student level indicators as to which student was officially a member of EOPS in any given term. Upon review of the data for the cohorts in question, however, I learned several key facts about when students typically first start in the program and their subsequent enrollment in the program over time. For each given cohort who are ever EOPS, the vast majority, on average,

start within their first year. Furthermore, the enrollment in the program in subsequent terms was not necessarily consistent for all participating students, largely due to the student not enrolling in a given term(s) but also potentially because of academic performance issues. In other words, students who had sporadic enrollment patterns or low academic performance would likewise have sporadic terms flagged as being an EOPS student. These patterns vary dramatically and there is currently no panel data available for me to track and account for these patterns. Regardless, in talking with program staff, I learned that the program's unofficial mantra is "we don't abandon you once you're out of the program." They explained that while former EOPS students may not have access to particular financial resources, the student would still be able to visit with their EOPS counselor, attend workshops, or receive other forms of non-monetary support. Because of these complexities in enrollment and likelihood that students are still likely receiving some forms of services after their initial enrollment in the program, I decided to identify participants as those who ever were in EOPS, and conversely, the comparison group are other first-time students who never were in the EOPS program but were at some point eligible. In other words, I determined their eligibility based on their data as of each term of their enrollment.

The descriptives of our sample reveal notable differences between EOPS students and their non-EOPS counterparts, as detailed in table 1.1. Specifically, a higher proportion of EOPS students are female, first-generation, and come from a variety of ethnic backgrounds, particularly Hispanic/Latino, which is significantly more represented among EOPS students (55.9%) compared to non-EOPS (41.2%). This supports the EOPS program's focus on supporting underserved populations. Additionally, there are significant differences in the proportion of

Table 1.1 EOPS Sample Descriptives

Demographic (%)	Non-EOPS	EOPS	P Value
Cohort			
2010	8.2	7.2	0.001
2011	13.9	12.6	
2012	14.6	12.6	
2013	15.6	15.4	
2014	17.2	17.2	
2015	15.2	17.6	
2016	15.3	17.4	
Female	50.5	59.1	<0.001
Foster Youth	1.2	4.2	<0.001
First Generation	22.3	32.3	<0.001
Ethnicity			<0.001
American Indian or Alaska Native	0.2	0.2	
Asian	14.1	10.9	
Black or African American	2.5	4.8	
Hispanic / Latino	41.2	55.9	
Native Hawaiian or Pacific Islander	0.2	0.1	
Two or More Races	5.3	3	
Unreported or Unknown	1.3	1.3	
White	35.1	23.8	
Disabled Student Programs and Services (DSPS)	6.6	11.8	<0.001
English as a Second Language	1.8	7.7	<0.001
Latest Educational Goal, Group			0.991
Career	5.7	5.6	
Degree or Certificate	8.6	8.2	
GED/Basic Skills	1.3	1.3	
Personal Development	2.9	3.3	
Transfer	76.7	77	
Undecided	4.6	4.4	
Vocational Certificate/Transfer	0.2	0.2	
Financial Aid Recipient	99	99.4	0.183
Poppy College	41.3	54.9	<0.001
Age at first Credit Term (mean(SD))	18.1(1.51)	18.4(2.48)	<0.001
High School Grade Point Average (mean(SD))	2.66 (0.63)	2.61 (0.65)	0.005
n	8,153	1,207	

Note.

students receiving services for disabilities and those who identify English as a second language, both higher among EOPS students. Interestingly, the variation in age and high school GPA between the groups is notable, with EOPS students tending to be older and having slightly lower high school GPAs on average.

These demographic and educational characteristics highlight the targeted outreach and support strategies employed by EOPS to engage students who may face greater barriers to academic success. Given these substantial differences, it is crucial to account for potential selection biases when analyzing academic outcomes. This will ensure that the effects attributed to EOPS participation are not confounded by the pre-existing disparities between the groups. The alignment of these differences with EOPS eligibility criteria suggests that the program effectively identifies and enrolls students who could most benefit from additional support, reinforcing the need for rigorous analytical approaches to isolate the true impact of the program on student success.

EOPS students had better achievement than the comparison group on some outcomes, but inferior outcomes on others. The raw difference in outcomes is inconsistent in both the short and long term (See table 1.2). EOPS students have significantly higher success rates of certificate achievement within four years, Associate's in four years, and ever achieving an Associate's. In some cases (e.g., completion of transfer English in the first year and transfer within two years), EOPS students have a significantly lower success rate.

Table 1.2 Outcomes by EOPS

		Non-EOPS	EOPS	Difference
Outcomes, Success Rates				
	Transfer English in 1st Year (%)	34.8	28.2	-6.6**
	Transfer Math in 1st Year (%)	21.6	20.2	-1.4
	End of Year 2 GPA	2.4	2.4	0
	End of Year 4 GPA	2.5	2.5	0
	Certificate in 2 Years (%)	6.7	6.3	-0.4
	Certificate in 4 Years (%)	23.4	31.1	7.7**
	Associate in 2 Years (%)	5.2	4.8	-0.4
	Associate in 4 Years (%)	22.8	30.3	7.5**
	Associate, Ever (%)	29.6	37.7	8.1**
	Transferred in 2 Years (%)	12.3	7.0	-5.3**
	Transferred in 4 Years (%)	37.5	35.1	-2.4
	Transfer, Ever (%)	47.1	45.1	-2
	Bachelor's, Ever (%)	37.3	34.8	-2.5
	n	8,153	1,207	

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

Basic Empirical Model

As a first step in accounting for selection biases, I run linear regression models with a vector of controls. Doing so is a useful first step in understanding how demographic and academic characteristics (See table 1) potentially differentiates students' opportunities.

$$Y_{ic} = \alpha_0 + \beta_1 EOPS_{ic} + \delta X_{ic} + \varepsilon_{ic} \quad (1)$$

Where β_1 is the coefficient of interest, providing the estimated effect of student *i* of cohort *c* ever being EOPS on our outcomes of interest (*Y*), controlling for various demographic characteristics, *X*. While this basic model offers valuable insights into the association between EOPS participation and outcomes, it has limitations. Notably, the model assumes that observed covariates adequately capture all relevant factors influencing both the treatment assignment and the outcomes. In real-world scenarios, unobservable factors, unmeasured heterogeneity, or omitted variables may persist, leading to potential selection biases.

Propensity Score Weighting

To mitigate the influence of potential confounding factors related to program uptake and academic outcomes, I intend to employ propensity score weighted models following the approach proposed by Rosenbaum and Rubin (1983). These models facilitate balance by minimizing confounding factors between pre-treatment group differences and treatment effects. In the absence of proper confound adjustment, analyses are prone to under/overestimating the effects of exposure to a given condition.

Recognizing the diversity in propensity score modeling techniques, I aim to enhance the robustness of my analysis by incorporating three distinct types: logistic regression probability weights, coarsened exact matching, and weights generated from a generalized boosted model. This comprehensive strategy is designed to minimize the risk of under/overestimation and better ensure a more accurate assessment of the program's impact. All of the propensity score models will provide an ATT, or the average treatment effect on the treated estimand. The model is effectively the same computation as in model 1, but now incorporating the likelihood of student *i* receiving the treatment, *EOPS.*

The logistic regression probability weights are derived by fitting a logistic regression model to estimate the propensity scores, in this case the propensity for one to participate in EOPS. These scores are calculated as the predicted probabilities from the logistic regression model. Subsequently, the computed inverse probability weights are employed as weights in the analysis, specifically when predicting a student's outcome of interest (Model 2).

The second form of weighting used, Coarsened Exact Matching (CEM), provides distinct advantages over other propensity score methods, particularly in handling categorical variables (Iacus et al., 2008). CEM is especially effective with binary or categorical variables such as gender, first-generation status, and language proficiency. Unlike traditional matching that may struggle with high-dimensional data, CEM coarsens each covariate into broader categories, effectively reducing the dimensionality of the data. This coarsening process facilitates exact matching on these broader categories, thereby ensuring that the treated and control groups are not only comparable across key characteristics but are also structured to reflect a similar distribution within these categories.

After matching, CEM prunes all unmatched units, which enhances the quality of the resulting dataset by retaining only those comparisons that are truly comparable, leading to more accurate and reliable estimates. Moreover, CEM tends to be less sensitive to outliers in the covariate distribution compared to other methods, as the coarsening process limits the influence of extreme values. Additionally, CEM can improve the efficiency of the estimation process by focusing the analysis on a subset of well-matched observations, thus increasing the power of the statistical tests used in subsequent analyses.

Overall, CEM's ability to ensure a high degree of balance on observed covariates and to create well-defined comparison groups makes it an invaluable tool in the study of causal

relationships, particularly when dealing with categorical data that could otherwise introduce significant biases into the analysis. Moreover, CEM is distinguished by its avoidance of certain assumptions. In contrast to Propensity Score Matching (PSM), which assumes that, conditional on covariates (including continuous variables), treatment assignment is ignorable, CEM relies on exact matching within coarsened categories, thereby sidestepping some of these assumptions. This characteristic offers an alternative perspective on reducing selection bias. However, a noteworthy limitation of CEM is the possibility of the sample being reduced dramatically as a result of non-matched cases being dropped.

In summary, CEM stands out for its effectiveness with binary categorical variables, emphasis on exact matching, computational efficiency, and reduced reliance on assumptions compared to other propensity score matching approaches.

The final iteration includes weights generated using the Toolkit for Weighting and Analysis of Nonequivalent Groups (TWANG) R software package (Ridgeway et al., 2017). The package, a product of the RAND Corporation, utilizes Generalized Boosted Models (GBM) to estimate propensity score weights rather than logistic regression models. The GBM uses an automated, nonparametric machine learning technique using user specified pre-treatment covariates to balance the treatment and control groups. The advantage of using this approach is that it does not rely on a strong ignorability assumption, like most propensity score matching approaches. In other words, I do not need to assume that I have controlled for all potential confounders but instead will run a series of diagnostic tests to assess the convergence of the gradient boosting algorithm. In theory, if an ample number of trees are run through the GBM, the tool should sufficiently explore complicated models to achieve the greatest balance between the groups. The available convergence diagnostic checks will allow me to assess which stopping

criteria minimized the average absolute standardized effect size between the groups' covariates and the average absolute standardized effect size or the maximum Kolmogorov-Smirnov (KS) statistic. Once I ensure that there is indeed balance between the treatment and control groups, the propensity score weights will be applied to the same model described above, and help compute a plausibly causal estimate of the effect of being in EOPS as compared to otherwise similar students.

The resulting models may be inevitably susceptible to omitted variable bias or unobserved heterogeneity between the groups. However, since I am using post hoc secondary data where there is no implementation of random assignment, this approach is likely the most robust and valid approach possible. There were hopes that I could conduct a regression discontinuity as well, but the categories (e.g., high school grade point average of 2.5) that were thought to have meaningful cutoff points determining treatment were inevitably found to be problematic. None of these running variables demonstrated a consistent cutoff point related to treatment assignment, due to the fact that there are so many criteria which satisfy the requirements.

Results

Naïve Estimates

The initial linear regression model using my vector of controls finds that EOPS has a positive relationship with select outcomes of interest (See table 1.3).

Starting with the more short-term outcomes, EOPS has a statistically significant negative coefficient of -0.03 ($p < .05$) for Transfer English completion in the first year. However, when examining Transfer Math completion in the first year, the coefficient is insignificantly different

Table 1.3 Regression Models Predicting Outcomes Using EOPS Status

Outcome	Models			
	1	2	3	4
Transfer English in 1st Year (%)	-0.03*	-0.02*	0.00	-0.02
	(0.03)	(0.01)	(0.02)	(0.01)
Transfer Math in 1st Year (%)	0.00	0.01	0.03	0.01
	(0.02)	(0.01)	(0.02)	(0.01)
End of Year 2 GPA	0.07*	0.11***	0.15***	0.11***
	(0.06)	(0.02)	(0.04)	(0.03)
End of Year 4 GPA	0.06	0.10**	0.11**	0.10**
	(0.06)	(0.02)	(0.04)	(0.03)
Certificate in 2 Years (%)	0.00	0.00	0.02	0.00
	(0.02)	(0.00)	(0.01)	(0.01)
Certificate in 4 Years (%)	0.09***	0.09***	0.15***	0.10***
	(0.03)	(0.01)	(0.02)	(0.01)
Associate in 2 Years (%)	0.00	0.00	0.01	0.00
	(0.01)	(0.00)	(0.01)	(0.01)
Associate in 4 Years (%)	0.09***	0.09***	0.15***	0.10***
	(0.03)	(0.01)	(0.02)	(0.01)
Transferred in 2 Years (%)	-0.04***	-0.03**	-0.04**	-0.03**
	(0.02)	(0.00)	(0.01)	(0.01)
Transferred in 4 Years (%)	0.00	0.01	0.03	0.01
	(0.03)	(0.01)	(0.02)	(0.01)
Bachelor's, Ever (%)	0.01	0.02	0.02	0.02
	(0.03)	(0.01)	(0.02)	(0.01)
Model Features				
Vector of Controls	Yes	Yes	Yes	Yes
Logit Weights		Yes		
Coarsened Exact Matching Weights			Yes	
Gradient Boosting Machine Weights				Yes
n	9,360	9,360	2,589	9,360

Note. Standard errors are reported in the parentheses. All coefficients reported are unstandardized for ease of interpretation.

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

from zero, indicating that EOPS does not appear to have a significant effect on transfer rates for Math courses in the first year.

Moving to academic performance, the end of year two GPA exhibits a positive and statistically significant coefficient of 0.07 ($p < .05$), implying that students in the EOPS program tend to achieve a higher GPA at the end of their second year. In contrast, the end of year four GPA, while positively inclined (coefficient of 0.06), is not statistically significant, suggesting that the effect of EOPS on GPA at the end of the fourth year is not reliably different from zero.

Turning to certificate attainment, the model indicates that EOPS does not significantly influence the likelihood of obtaining a certificate within two or four years, as evidenced by non-significant coefficients ($p > .05$) for either outcome.

On the other hand, for Associate Degree attainment, both iterations (in two or four years) show non-significant coefficients ($p > .05$), suggesting that EOPS does not significantly impact the likelihood of obtaining an associate degree within specified time frames.

Exploring transfer outcomes, a significant negative association ($\beta_1 = -0.04$, $p < .001$) is observed for transfer within two years, indicating that EOPS participants are less likely to transfer within the first two years. However, for the four-year time frame the coefficient is insignificantly different from zero, suggesting that EOPS does not significantly influence the likelihood of transferring within four years.

Finally, with regard to the attainment of a Bachelor's degree, the coefficient is non-significant, indicating that EOPS participation does not have a statistically significant impact on the likelihood of obtaining a bachelor's degree.

Logit Weight Models

In the logit weight models, the application of generated logit weights successfully achieved a balance between the treatment and comparison groups, as evidenced by the balanced distribution across all covariates (See Appendix B). The standardized effect size, representing the estimated difference between the treatment and control distributions, is no longer statistically significant and near zero, indicating a successful mitigation of covariate imbalances within the model.

Upon the integration of logit weights into the model, notable adjustments in the coefficients are observed compared to Model 1. Completion of transfer level English in the first-year remains negative and significant (-0.02, $p < .05$). The positive coefficient for end of year two GPA increases to 0.11 ($p < .001$), suggesting a larger positive effect of EOPS on GPAs at the end of year two. The coefficient for end of year four GPA (0.10, $p < .01$) becomes significant, suggesting a positive impact on GPA at the end of the fourth year. Other outcomes, such as certificate and associate degree attainment, maintain their patterns from Model 1.

Coarsened Exact Matching

The CEM used for the final analysis achieved a strong balance between the groups, demonstrated by the standard mean difference between the groups being near zero across all the covariates (See Appendix Table C). The final variation used was one that yielded the largest sample (n = 2,589) and achieved the greatest balance on the covariates.

The results of model 3 are not consistent with the prior models. First off, the model indicates that completion of transfer-level English within the first year is not significantly influenced by EOPS participation. End of year two (0.15, $p < .001$) and end of year four (0.11, $p < .01$) GPA both show positive and significant coefficients, suggesting a substantial positive relationship with academic performance. Certificate and associate degree attainment outcomes

remain consistent with the previous models. Transfer achievement in two years shows a significant negative coefficient (-0.04, $p < .01$), indicating a lower likelihood of transfer within two years among EOPS participants.

Generalized Boosted Model Weights

A key initial step in using generalized boosted model (GBM) weights involves checking if the model successfully completed its calculations with the set number of decision trees we planned to use (See appendix D). Essentially, we need to ensure that the model finished its process effectively and identified the specific step—at which point during its calculations—it best balanced the differences between the groups being compared. This balance is measured using two methods: the average size of effects across all comparisons and the maximum difference in distribution characteristics between the groups. The *ess.treat* and *ess.ctrl* columns demonstrate that almost half of the current control group are significantly unlike the treatment cases and thus were not used in generating the treatment effect. Lastly, comparing the unweighted and weighted average absolute standardized effective size (*mean.es)*, the mean for both stop method variations are very similar and significantly smaller than the unweighted value.

Applying the resulting GBM weights (model 4) generated similar results to Model 2. The EOPS coefficient for completion of transfer English within the first-year remains negative and significant (-0.02, $p < .05$), and the positive effect of EOPS on GPAs (End of year two GPA: 0.11, $p < .001$; end of year four GPA: 0.10, $p < .01$) persists. Certificate and associate degree attainment outcomes also maintain their patterns from previous models. The effect on transfer within two years (%) is significant and negative (-0.03, $p < .01$), indicating a reduced likelihood of transfer within two years for EOPS participants.

It's important to note that the sample sizes differ across models, with Model 3 focusing on a subset of the data. Additionally, the choice of weighting methods influences the observed patterns in the coefficients. The results collectively contribute to a more confident understanding of the relationship between EOPS participation and educational outcomes under different modeling approaches.

Discussion

In examining the relationship between EOPS participation and educational outcomes, my analysis finds that the impacts of the program are not uniform, in the short or long-term. While certain outcomes, such as academic performance as measured by GPAs, showed consistently positive associations with EOPS participation across multiple models, other aspects such as transfer rates and degree attainment presented more varied results.

All models found a negative relationship between EOPS and completion of transfer-level English in the first year. However, the relationship with successful completion of transfer-level Math within the first year is less discernible, with non-significant coefficients in certain models. This finding contrasts somewhat with statewide technical reports, which found positive differences for both subjects (Reyes et al., 2022; Willet & Hayward, 2012). It is unclear why this discrepancy exists, but it may be attributed to differences in institutional practices within the current study's district compared to others in the state. Perhaps, the placement procedures were more stringent, resulting in a higher proportion of students being placed in lower-level Math/English courses initially, potentially setting them behind in terms of progress.

Another key distinction between the current study and the latest state report is that all cohorts included precede the implementation of AB 705 policies. None of the current cohorts were exposed to current policies aimed at maximizing the probability of completing college-level

Math/English within the first year, whereas the later years included in the state report (2018-2019) may have been exposed to these policies in select schools. This absence of exposure to such policies may have influenced the outcomes observed in the current study.

Academic performance emerges as a notable positive aspect, particularly in terms of GPAs. The consistently positive and significant coefficients for the end of year two and year four GPAs suggest that EOPS participants tend to achieve higher grades in their coursework. These GPA findings are consistent with prior work (Reyes et al., 2022; Soltani et al., 2016; Willet & Hayward, 2012). These observed differences are likely the result of several factors. Firstly, counselors purposefully direct students to campus and community resources, such as tutoring, student clubs, and childcare, to support them throughout the term. Secondly, counselors may assist students in better managing their academic plans, such as recommending manageable unit loads per term or advising them to avoid certain instructors, which could contribute to their improved academic performance.

On the fronts of certificate and associate degree attainment, the findings reveal a more complex relationship. While the data indicates that EOPS students may not necessarily attain a certificate or an AA earlier, they demonstrate a higher likelihood of achieving one or the other after four or more years. It's crucial to consider that although most students in both groups expressed an intention to transfer, there might be a notable discrepancy in the number who also aimed to obtain a degree or certificate before transferring. With the current dataset, it's challenging to ascertain whether students originally aimed for both goals. Future research should aim to collect more detailed data on students' academic goals throughout their enrollment.

Another potential explanation for the higher Associate’s degree/certificate attainment rate among EOPS students could be attributed to their more frequent interactions with EOPS

counselors. These appointments offer counselors additional opportunities to monitor students' academic progress and to encourage them to apply for degrees/certificates for which they meet the minimum requirements. In fact, in sharing the results with the EOPS staff, they shared that this is not surprising because as part of their regular check ins, the counselors review their transcripts

The models examining the relationship with transfer outcomes indicate that EOPS participants do not exhibit higher transfer rates. In fact, each model reveals that EOPS students are less inclined to transfer within two years, despite the comparison group being ostensibly similar. However, the four-year outcome suggests that this difference is not statistically significant. There could be confounding factors contributing to this contrast within the two-year timeframe. For instance, while I attempt to control for financial status, it's plausible that EOPS students face additional unobserved financial constraints, potentially prolonging their time at the community college and delaying transfer. Alternatively, EOPS students might, on average, possess lower social capital, posing greater challenges in navigating both the college and university transfer requirements. Another plausible explanation is that certain aspects of the program might extend their time to transfer; for example, program counselors might recommend additional preparatory coursework to ensure their success upon transfer. All of these explanations are theoretical, and thus sets the stage for future research to investigate what specific mechanisms or unobserved factors explain the observed differences in transfer rates.

In congruence with the transfer relationship estimates, the models found no significant difference in bachelor attainment rates. There are several potential factors that could contribute to this outcome. For instance, it's conceivable that the same financial constraints and lower social capital affecting transfer rates also impact bachelor attainment. Moreover, other unobserved

factors, such as personal circumstances or academic preparedness, could play a role in both transfer and bachelor attainment rates. It is also arguably the fact that students no longer continue to receive support from EOPS upon departure from the college; they no longer are regular checking in with counselors or receiving any programmatic/financial supports (social capital). Future work could potentially attempt to follow a cohort of EOPS transfer students at various institutions and explore their experience navigating said institutions. Regardless, this provides a reasonable groundwork for the first attempt at exploring this long-term outcome for the first time. These theoretical explanations lay the groundwork for future research endeavors to delve deeper into the specific mechanisms or hidden variables that may elucidate the observed differences in transfer and bachelor attainment rates among EOPS participants.

As with any analysis, these findings should be considered within the context of their limitations. While positive associations with academic performance are evident, the nuanced impact on transfer rates and degree attainment prompts a consideration of additional factors not captured in the current analysis. Future work should explore using alternative modeling techniques, depending on data availability and the local context of implementation, to further enhance the understanding of the intricate relationship between EOPS participation and student success.

Future Research

Future research has the potential to enhance the current findings in several significant ways. Firstly, by incorporating more recent data from a broader array of locations, researchers can offer a more comprehensive understanding of the effectiveness and impact of EOPS throughout the state. Secondly, triangulating quantitative results with qualitative insights through interviews with EOPS participants at crucial junctures, such as the commencement and

conclusion of their EOPS membership, could provide richer context and deeper insights into their experiences as EOPS students. Additionally, surveying and interviewing program staff could offer valuable perspectives on program implementation and efficacy. Moreover, if feasible, future studies could address potential unobserved selection biases by employing randomized control trial assignment methods within the framework of EOPS, thus strengthening the validity of findings and allowing for more robust causal inferences regarding the program's impact. By incorporating these methodological advancements, future research endeavors can contribute significantly to the ongoing understanding and improvement of EOPS in California community colleges.

CHAPTER 2: Embedded Tutors Evaluation

Community colleges serve as critical access points for higher education, catering to a diverse array of students, including many who are first-generation, working adults, or those returning to education after a significant amount of time. This diversity poses many challenges to institutions, particularly in regards to academic preparedness. Many students enrolled in community colleges struggle with college-level coursework, particularly in essential subjects like mathematics and English. This academic unpreparedness can lead to low success rates in these courses, and lead to increased time to degree or even increase the chances of the student simply leaving without finishing (Bailey et al., 2015).

This study explores an intervention that many colleges are employing to address this challenge, variations of embedded tutoring. While this intervention takes on many forms and different names, the general concept is to provide a tutor during, and sometimes outside, class time. The qualifications and roles that these individuals have vary from institution to institution, making it difficult to generalize any conclusions about their effectiveness. Furthermore, existing studies often do not adequately account for selection biases that may be explaining the uptake of treatment and thus eventual outcomes. Even still, the existing evidence does strongly suggest a positive relationship between tutoring and course success. The current study intends to investigate a distinct form of embedded tutoring offered at a southern California Community College, “Mums” college. The program entails assigning and making a specific tutor available during a specific course section (e.g., an introductory psychology class taught on Mondays at 1 P.M. by instructor X). These tutors are also, in some cases, made available to students in the campus tutoring center, a physical location that hosts tutors for any subject on campus that is free

for any current student to use. Given the financial costs of implementing this intervention, assessing its efficacy is critical for the institution.[3]

While the upfront costs are significant, the investment in embedded tutoring could lead to considerable long-term educational gains, making it a worthwhile expenditure for the institution. If the program effectively helps students master course content and complete a course, especially certain milestone courses that are known to be barriers, this could translate to higher degree completion or transfer rates. Within California, specifically, public community colleges operate under the Student-Centered Funding Formula, which awards the schools funding based on the counts of rates of certain performance metrics (e.g., completion of transfer-level English/math within first year counts, degrees awarded, etc.). These awards increase if the students achieving said milestones are also members of certain disproportionately impacted groups. Focusing on the two subjects that are typically of the highest priority to community college administrators and researchers, English & mathematics, I assess the effectiveness of embedded tutoring sections and tutoring center usage using a quasi-experimental approach. The results yielded provide critical insights regarding the impacts of embedded tutor usage for community college students in English and Math courses.

Conceptual Framework

To help understand the phenomenon in question, I employ Vygotsky's zone of proximal development (ZPD) framework. This theory posits that there is a space between what a learner can accomplish independently and what they can achieve with guidance from a more knowledgeable or experienced person (Vygotsky, 1978). More specifically, the ZPD represents

[3] Embedded tutors are compensated at an hourly rate of $16.00, and they typically work between 5 to 19 hours per week. With an average of 15 embedded tutors operating each semester over a 16-week term, using a back of the napkin calculation, the total cost per term for ETs ranges significantly from $19,200 to $72,960.

the range of tasks that a learner can perform with the help of a tutor, teacher, or peer, which they cannot perform independently. This concept underscores the importance of social interactions and instructional scaffolding in the learning process.

In the context of this study, the ZPD framework suggests that students who receive additional support from embedded tutors will achieve higher levels of learning development than they would without such support. Embedded tutors serve as the "more knowledgeable other" who provide the necessary scaffolding to help students complete concepts or tasks that are potentially just beyond their current understanding or abilities. The assumption is that if the tutors are capable of bridging such gaps, students will be more capable to accomplish certain tasks alone that they were unable to do before without some sort of additional help.

Specifically, if students are assisted by embedded tutors, their development will be greater compared to their counterfactual development without tutoring. This aligns with Vygotsky's assertion that optimal learning occurs within the ZPD, where the learner is challenged but not overwhelmed, and the guidance provided is crucial for mastering new skills and knowledge. Furthermore, the theory implies that the increased duration or varied forms of support should correlate with even greater degrees of learning. The more sustained and diverse the support provided by the embedded tutors, the more opportunities students have to engage in meaningful learning experiences within their ZPD.

This study tests these hypotheses by comparing the performance of students who receive embedded tutoring against those who do not, and by examining the impact of utilizing additional tutoring on student learning outcomes. With this in mind, I intend to answer the following questions:

RQ1: Does enrollment in an Embedded Tutor section have an effect on the likelihood of passing and/or the retention rate of a given English/math course?

RQ2: Does the effect of Embedded Tutoring vary between subjects and/or courses within a given subject?

Relevant Literature

Tutoring Interventions in Community Colleges

Various tutoring interventions have been implemented in community colleges for years, under a wide variety of names and using an equally wide variety of approaches (Henry et al., 2011; Yancy McGuire, 2006). Tutoring services generally consist of an additional staff member being made available to students during and sometimes even outside of class time. Some colleges establish a tutoring center which hosts a number of specialized tutors offering support to students on a drop-in or scheduled basis. One of the original and most well-known tutoring programs is the supplemental instruction (SI) intervention, first created in 1973 by Deanna Martin of the University of Missouri: Kansas City. The SI design entails the offering of an out of course time tutoring session typically led by the instructor. Another form of tutoring offered is that of embedded tutoring, where a tutor is present during the course to help the professor facilitate and support students during class activities (Henry et al., 2011; Yancy McGuire, 2006). There is evidence that this form of tutoring is offered internationally in 29 countries to hundreds of thousands of students each year (Arendale, 2002; Martin, 2009). The qualifications and assigned role of tutors varies. Some tutoring models require that tutors be former students who earned exceptional grades in a particular course, while other models require the tutors be a paraprofessional with at least a completed bachelor's degree in a relevant field. The responsibilities of an ET can include any number of the following:

A. Acting as a teacher's aide or support during class, offering individual or group support to students
B. Hosting an out-of-class section where students can, or in some cases are required to, attend to receive additional support with coursework
C. Holding office hours outside of course time to provide individualized attention to students
D. Help instructor in facilitating course activities

In summary, even though there is potential variation in the programs, the models can generally be described as having a qualified individual assist students and professors in and/or outside course hours. The goal of making these individuals available to students in and/or outside the classroom is, within the ZPD framework, to bridge the gap between what students can do independently and that which is otherwise out of reach.

Scholars have sought to measure the effectiveness of the various forms of tutoring but have found it challenging to offer conclusive findings given the wide variety of forms of tutoring, analytical methods, and data samples used.

The most recent comprehensive review of supplemental instruction programs was done by Dawson et al. (2014). The authors initially tried to conduct a meta-analysis but found that it was extremely difficult due to "methodological heterogeneity, poor method quality, and insufficient description of method; additionally, the data set contained many qualitative results." As a result, they instead used a systematic review methodology. They compiled relevant literature (29 articles) and systematically assessed the rigor and resulting findings of each. The summary of the selected articles reported that the majority found evidence of a positive relationship between participation in supplemental instruction or tutoring and several academic

outcomes (e.g., higher-grade point averages, higher course grade, lower failure and withdrawal rates, higher retention and graduation rates) (Bowles & Jones, 2003; Bronstein, 2008; Congos & Mack, 2005; Dancer et al., 2007; Fayowski & MacMillan, 2008; Gattis, 2002; Hodges & White, 2001; Hodges et al., 2001; Mahdi, 2006; Miller et al., 2004; Moore & LeDee, 2006; Ning & Downing, 2010; Ogden et al., 2003; Parkinson, 2009; Peterfreund et al., 2008; Phelps & Evans, 2006; Rath et al., 2007; Stansbury, 2001; Wright et al., 2002).

Even still, Dawson et al. (2014) stress that a portion of these studies lack statistical power due to small sample sizes, use of largely anecdotal data, and/or do not offer credibly causal estimates due to selection biases that are unaccounted for. Of the 29 articles reviewed, only seven allowed for a comparison of effect sizes, and the authors found that the effect was consistently positive (ranging from $d = 0.29$ to 0.60). In summary, they find that their conclusions are consistent with prior work done by the U.S. Department of Education, but they stress that there is still great opportunity for researchers to determine what specific mechanisms (e.g., improved study habits, increased awareness of assessment demands, motivation) explain the observed relationships.

There are several small-scale studies that provide a starting point in understanding the effect of embedded tutoring. Studies that specifically evaluated the effectiveness of embedded tutors in writing courses have found that those students who utilized their embedded tutor with regularity scored higher on writing assessments or achieve higher grades in the course (Dvorak et al., 2012; Hendriksen et al., 2005). Students who interact with an embedded tutor during class time also received more psychological or emotional support (Henry et al., 2014). Dvorak et al. (2012) administered a survey at the end of a first-year writing course with ETs, and 83% reported that they hope to have an embedded tutor in the future.

Apart from the literature specifically related to embedded tutoring's efficacy, it is essential to understand the temporal context and impact of embedded tutoring at the subject college. More specifically, it is crucial to examine three pertinent areas: the landscape of community college transfer-level courses, the effects of the COVID-19 pandemic on educational practices, and the role of online courses. These sections provide essential background on the challenges and developments that shape the implementation and efficacy of embedded tutoring.

Community College Transfer-Level Courses

Community colleges across the nation typically have a requirement for all students pursuing a degree or transfer to complete a minimum transfer-level math and English course. A transfer-level course can be applied towards an associate's degree and/or it can be transferred, or articulated, to a four-year university for a bachelor's degree. Transfer-level courses are regarded as pre-requisite knowledge for many upper division college courses. Historical trends show that many students, especially underserved students, were placed in remedial courses and were considered unprepared for college level work (Guillory, 2009; Hodges, 2001). But now colleges are offering less remedial courses but at the same time they are providing students with more resources to successfully complete transfer-level courses.

In California specifically, students who begin college in remedial coursework are 28% points less likely to eventually transfer and/or earn a degree than those who started in transfer-level (CCCCO, 2019). In response to these trends, the California Community College Chancellor's office helped pass Assembly Bill 705 (AB 705) which went into effect in January 2018. The bill requires all community colleges or districts to "maximize the probability that a student will enter and complete transfer-level coursework in English and math within a one-year timeframe..." (AB-705, 2012). The bill outlines several specific practices to achieve this goal,

including placement into varying degrees of support based on what practitioners describe as multiple measures placement. A survey administered about two-years after the law went into effect found that colleges across the state have taken different approaches when trying to satisfy this new requirement, including: curriculum changes, varying levels of corequisite/support courses, creation of additional services/supports (Kretz & Newell, 2020). Assembly Bill 705 has increased the number of college students who successfully complete transfer-level English and math (Hayward, Kanno, Rios-Aguilar, and Vo, 2022); however, it has not closed equity gaps. Hispanic, African American, low-income, first-generation college students, and students with low high school GPA continue to have lower success rates than their peers (Browhan, K., Newell, M., Fagioli, L., 2021). Providing access to students provided many students the opportunity to complete transfer-level courses, but now institutions need to focus on how to support students who may need this additional support.

COVID-19

The COVID-19 pandemic has significantly influenced community college operations and student support services, including embedded tutoring. This period was critical in assessing the adaptability of embedded tutoring programs, with many institutions enhancing technological support for both tutors and students. The shift to remote learning required embedded tutors to adjust to virtual interactions, posing challenges in maintaining consistent and effective support. According to Means, Neisler, and Hartshorne (2020), the rapid transition to online modalities during the pandemic highlighted significant issues related to accessibility and quality of education, underscoring the need for robust support systems. In California specifically, a survey of a distance education leaders (n = 45) in the community college system found that respondents had to make drastic changes and that some were more able to do so due to existing resources

(Hart et al., 2021). While about 62% overall claimed to have virtual tutoring and counseling pre-COVID, none of the lower resource campuses had any available. After the onset of the pandemic, nearly all schools reported that they had adopted some form of virtual tutoring or counseling. This adaptation likely required not only the deployment of digital tools but also training for tutors to effectively use these tools in remote learning settings. Such changes were likely crucial in sustaining student engagement and support during an unprecedented shift in educational delivery.

Dramatic shifts in how services were provided was challenging not only for the staff but also for the students intending to receive them. Many community college students are members of groups (e.g., people of color, low-income, first-generation) that are already disproportionately impacted by systemic challenges, so this chaotic shift that required so many forms of adaptation was likely more difficult and potentially detrimental to said groups. Members of these groups were more likely to be at risk of COVID-19 exposure and furthermore were more likely to be essential workers without the ability to work remotely (Center for Disease Control and Prevention [CDC], 2020). With all that in mind, it is critical that we keep in mind these potentially vulnerable populations while assessing the impact of a service offered during such a tumultuous period.

Online Courses

In the Fall of 2019, a significant shift occurred in higher education as colleges were mandated to place all students into transfer-level courses. Subsequently, in the following term, Spring 2020, the landscape was further transformed by the onset of the Covid-19 pandemic. Facing unprecedented challenges, most educational institutions, including community colleges, were compelled to adopt predominantly online instructional formats. These formats

encompassed both synchronous methods, involving live teleconferencing through platforms like Zoom, and asynchronous approaches, characterized by pre-recorded content and communication via email.

When examining the effectiveness of online courses in community colleges, previous investigations have primarily relied on non-causal methods to address selection biases. However, these studies have yielded mixed results (Caldwell, 2006; Cavus & Ibrahim, 2007; Coates, Humphreys, Kane, & Vachris, 2004; Figlio, Rush, & Lin, 2010; LaRose, Gregg, & Eastin, 1998; Mentzer, Cryan, & Teclehaimanot, 2007; Odell, Abbitt, Amos, & Davis, 1999; Peterson & Bond, 2004; Schoenfeld-Tacher, McConnell, & Graham, 2001).

Notably, Xu and Jaggars (2011, 2013, 2014) have undertaken more robust analyses, leveraging statewide data and employing methods such as propensity score matching and instrumental variable approaches in their recent work. In their 2011 study, Xu and Jaggars analyzed data from 23 community colleges in Virginia, finding that students enrolled in online courses were significantly less likely to complete them and achieved lower grades compared to face-to-face courses. Building on this, their 2013 study used an instrumental variable approach with data from 34 community and technical colleges in Washington State, showing even more pronounced negative impacts of online learning on both course persistence and final grades. Their 2014 study further examined performance gaps, revealing that while online learning posed challenges for all students, males, younger students, and those with lower prior academic achievement were particularly disadvantaged.

In 2020, Xu and Xu explored the broader context of distance learning, highlighting how online formats can exacerbate educational inequities, particularly for academically less-prepared students, while benefiting those with work and family commitments.

The consistent findings from these robust analyses suggest that policymakers and college administrators need to improve the quality of online learning before further expanding online course offerings. Enhancing instructor presence, providing better support systems for online learners, and ensuring that online courses are as interactive and engaging as face-to-face courses could help mitigate these negative outcomes. Additionally, the findings stress the importance of considering the specific needs and challenges of community college students when designing and implementing online education policies. The integration of embedded tutoring within online courses could be a critical component of these support systems, helping to bridge the gap in student support and interaction, which are essential for successful learning outcomes.

Data and Setting

Data and Institutional Context

In the 2015-2016 academic year, Mums college was awarded funding through the Basic Skills Student Outcomes and Transformations Grant from the state of California Community College Chancellor's Office. The initiative allocated $60 million Proposition 98 funds to accelerate the progression of basic skills students (non-transfer level math/English) to college level instruction. Across the state, 64 qualifying colleges received grants of $1.5 million over a period of three years. Each school pursued the same goal, but had flexibility in how they would use the funds. The local college decided to utilize a portion of the funds to implement a locally designed form of embedded tutoring in multiple courses. At inception, the embedded tutor program was focused on training and assigning tutors within the Math, English, and STEM related (e.g., Chemistry, Biology) departments on campus. The administration prioritized courses that students need to satisfy most degree or transfer requirements (e.g., transfer-level math and English) and had a Support section attached. These courses are known to be critical milestones for many students.

The typical protocol for embedded tutor assignment starts with the embedded tutor director notifying faculty in one of said courses that an embedded tutor shall be assigned to them. The faculty then either selects an individual that they would like to be the embedded tutor or simply have the director assign them whoever is available at that time. A critical point to note is that faculty have the final say as to whether they eventually officially accept one and furthermore to what extent they are utilized in the course.

The embedded tutors are recent students of the target course who earned at least an A grade. At the onset, the embedded tutor is trained in the Socratic method, an inquiry-based method of teaching guided by the rule that the student or learner should be doing 90% of the talking (Overholser, 1993). The embedded tutor role is a paid part-time position which recommends that the tutor provides services during the course section each week and is available in an on-campus tutoring center several hours (four on average) per week, free of charge to the student. The tutoring center is freely accessible to all students, including those not enrolled in embedded tutor sections. This center offers a range of support services across various subjects, aiming to enhance overall student success and retention. While the embedded tutor does not have any influence on the course content, primary pedagogical approach, or course grading, they facilitate activities to assist students individually or in groups as they work on assignments.

A survey was designed and administered to try to capture the perceptions and practices of faculty involved. Only 15 responses were collected from two terms during the time period of interest of the 42 professors who hosted an embedded tutor over the eight terms included. Nearly all those who responded indicated they were very satisfied and would host an embedded tutor again (See appendix E). There was also a question that asked how they used the tutor, providing them with a check list of specific activities. Of the activities listed, the only activity that was

reportedly less common than the others was allowing tutors to lead or contribute in small group discussions (67%). Apart from that, the majority claimed that they had the tutor administer a presentation on the tutoring center, encouraged tutors to walk around the classroom, ensured the tutor had access to the Canvas learning management system, and met with the tutors regularly to clarify assignments/lessons. This provides a general sense of what their perception was and their self-reported utilization of tutors, but it must be stressed that these limited results may not truly capture the population's collective perceptions or practices throughout the duration.

All current data was made available through a partnership with Mums college and the local research department. The dataset includes 39,824 course enrollments for 20,829 students in Math and English courses, spanning eight primary terms (e.g., Fall/Spring) across three academic years: 2018-2019, 2019-2020, 2022-2023. Several terms (Spring 2020, Fall 2021, and Spring 2022) included in the dataset are during the COVID-19 pandemic. The campus suspended embedded tutor assignment for the 2020-2021 academic year because local leads did not feel confident that they could implement the program with the same fidelity as in-person courses since instructors were already being challenged with transitioning to online instruction already. The transition to online, starting in Fall 2021, was reportedly not easy and required staff to be intentional as to how to ensure continuity of tutoring services. The analysis only includes data for select Math and English courses at the college specified by the institution. There were embedded tutors assigned to other courses within either subject, but their implementation was extremely limited and would not offer much within group variance for the purposes of this study. It was decided to include only those courses where at least one section had an embedded tutor in a given term and either are still being offered or had at least two terms with embedded tutor sections (See table 2.1).

Table 2.1 Descriptives of Courses Included

Subject	Course Title	Section, Count	% with ET	Total Enrollments
English				
	Composition I	567	16%	13,417
	Composition I H	23	22%	574
	Composition II	351	3%	8,131
	Composition II H	34	9%	817
	Subtotal	975	8%	22,939
Mathematics				
	Algebra for Calc.	37	14%	1,270
	Geo. & Calc. I	65	8%	2,452
	Geo. & Calc. II	44	30%	1,517
	Pre-Calc	51	10%	1,845
	Statistics	204	12%	7,532
	Trig	57	32%	2,269
	Subtotal	458	15%	16,885
	Total	1,433	13%	39,824

Generally speaking, the courses included are transfer-level courses but a select few are considered the greatest priority because so many students take them and rely on them to satisfy transfer or degree requirements. For English, the Composition I course is the highest priority for the administrators and students. In math, the course of concern is Statistics.

This analysis was conducted using larger subsets of data. The larger subsets include the pooled variation (n = 39,824) where I include all courses, and then by division: English (n = 22,939) and Math (n = 16,885). Given the differences in course content and instructional methods between the Math and English divisions, it might be cleaner to compare within subjects. Comparing within subjects helps to control for these inter-divisional variations, providing a more accurate assessment of the impact of embedded tutor enrollment on student outcomes.

Key Variables

Outcomes

The outcomes of interest are whether the student passed the course (e.g., grade of A/B/C/Passing) and whether they retained in the course (e.g., did not withdraw after census date[4]). The institution considers these outcomes critical, with pass rates of transfer-level math and English being required milestones for a substantial portion of students. It is generally preferable to use a dichotomous indicator of course success or failure because there may be a great deal of biases influencing specific grading practices and furthermore the specific percentile grade is not available for use.

Controls

To control for other factors that might be influencing the outcomes of interest, I acquired data related to the students, the course section itself, and the instructor.

The student characteristics were selected to account for baseline propensities or biases that may be related to student outcomes (See appendix G). Such baseline characteristics include a flag of whether it is their first attempt of a given course, enrollment status (e.g., first-time or continuing student), their high school GPA quartile, cumulative college grade point average (GPA)/units earned as of the beginning of the term, latest educational goal (e.g., transfer, degree/certificate, professional development, etc.), age as of the start of the term, gender, ethnicity, recipient of financial aid, first-generation, and whether they are a full-time student (e.g., taking 12 or more units in the same term). Tutoring center usage is also captured per course and term for each student.[5] The tutoring center records the specific course and section for which

[4] Each term there is a designated census date, the established deadline as to when a student can drop a course from their enrollment and no longer have it reflected on their transcript.

[5] Data capturing which tutor was seen and whether it was online/in-person was not available for the current analysis.

the student is receiving, as well as the duration of the visit. This service is available to any Mum's college student free of charge, so non-embedded tutor students have hours that I captured as well.

I also selected a variety of course section characteristics that are often thought to be related to student outcomes. The fields include whether the course was delivered in an online format or not, the number of students enrolled in the course as of section census, and whether it had an associated support section.

Select instructor characteristics were also made available. One key variable indicates whether an instructor is full-time or part-time during a given term. Another variable captures the instructor's historical failure rate, reflecting the proportion of students who have failed the instructor's courses in prior terms. This measure provides insight into the instructor's past performance and potential influence on student outcomes. Furthermore, I include an imputed variable that indicates whether an instructor has been predominantly full-time or part-time over the majority of terms they have taught historically. These instructor fields help to account for variations in instructional quality and commitment, which may affect student performance and the overall effectiveness of embedded tutoring.

Descriptives

Student Characteristics

Exploring the characteristics of the students enrolled by section type, several notable differences emerge between embedded tutor sections and non-embedded tutor sections (See table 2.2). Non-embedded tutor sections exhibit slightly higher cumulative GPAs at the beginning of the term (BOT) compared to embedded tutor sections, with a mean GPA of 2.53 versus 2.40 in the pooled data. This trend holds true across both English and Math, suggesting that embedded

tutor sections might be strategically targeting or attracting students who initially may require additional academic support. Similarly, embedded tutor sections also show a slightly lower mean (20.76) cumulative units earned as of BOT compared to non-embedded tutor sections (21.29). This pattern is more pronounced in English, where embedded tutor section enrollees average significantly fewer units (11.65) than non-embedded tutor sections (17.24), aligning with the observation that embedded tutor sections could be serving less advanced or potentially at-risk students.

Enrollment status reveals a higher proportion of first-time college students in embedded tutor sections, especially notable in English where 37.5% are first-time students compared to 24.8% in non-embedded tutor sections. This indicates a strategic placement or choice of embedded tutor sections for newcomers who might benefit the most from additional tutoring support. Conversely, continuing students are more prevalent in non-embedded tutor sections across all data subsets, suggesting different academic needs or support structures between these student groups. Full-time student status is more frequent among embedded tutor sections in the pooled and English subsets, though slightly less so in Math.

Financial aid recipients and first-generation students are also more common in embedded tutor sections across all subsets, reinforcing the notion that embedded tutor initiatives may be effectively targeting or being selected by students who might face financial and generational challenges in higher education.

In terms of high school GPA, students in embedded tutor sections tend to come from the lower quartiles, suggesting that these sections are indeed reaching students who may start their college careers at an academic disadvantage. The use of tutoring center resources is significantly

higher in embedded tutor sections, which likely reflects the embedded support structures designed to improve their academic success.

Given these findings, it becomes apparent that embedded tutoring programs are not only reaching but are actively utilized by students who might derive the most benefit from additional academic support. This alignment suggests the effectiveness of the embedded tutor model in targeting and impacting the academic trajectory of students likely to face greater challenges. The higher use of tutoring services by students in embedded tutor sections further points to a successful integration of these resources into their academic routines, potentially leading to improved outcomes.

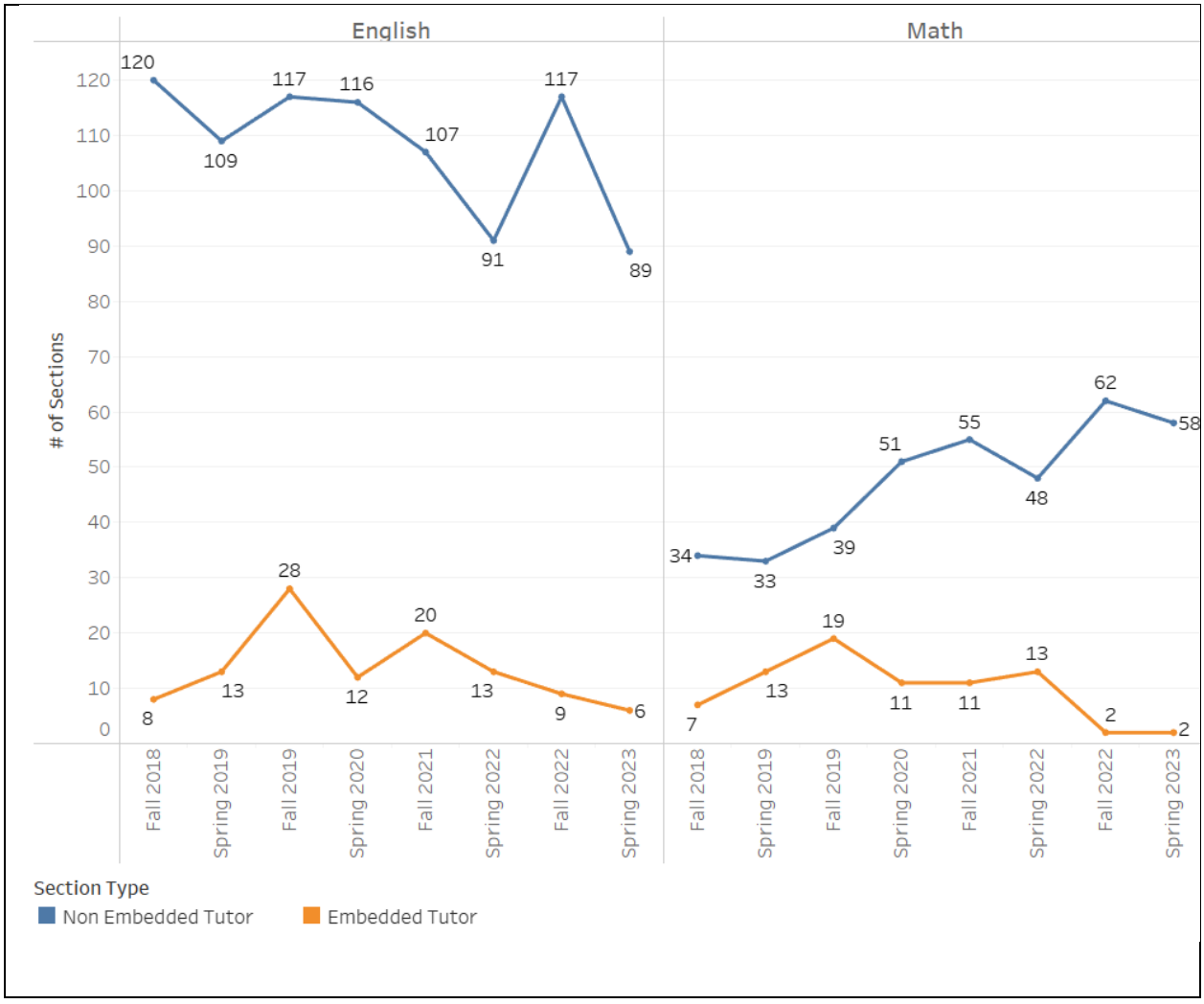
Table 2.2 Student Descriptives

	Pooled			English			Math		
	ET Sections	Non-Et Sections	P Value	ET Sections	Non-Et Sections	P Value	ET Sections	Non-Et Sections	P Value
Age (mean (SD))	20.80 (5.68)	20.75 (5.57)	0.562	20.37 (5.71)	20.58 (5.55)	0.069	21.18 (5.63)	21.00 (5.59)	0.115
Cumulative GPA BOT* (mean (SD))	2.40 (1.48)	2.53 (1.41)	<0.001	2.03 (1.59)	2.44 (1.45)	<0.001	2.74 (1.28)	2.67 (1.34)	0.016
Cumulative Units Earned BOT* (mean (SD))	20.76 (24.07)	21.29 (22.43)	0.111	11.65 (16.82)	17.24 (18.59)	<0.001	28.84 (26.52)	27.19 (25.97)	0.002
Educational Goal (%)			0.266			0.156			0.003
Career	111 (2.0)	614 (1.8)		54 (2.1)	387 (1.9)		57 (2.0)	227 (1.6)	
Degree or Certificate	313 (5.7)	2024 (5.9)		200 (7.7)	1344 (6.6)		113 (3.9)	680 (4.9)	
GED/Basic Skills	45 (0.8)	372 (1.1)		26 (1.0)	204 (1.0)		19 (0.7)	168 (1.2)	
Personal Development	31 (0.6)	235 (0.7)		16 (0.6)	109 (0.5)		15 (0.5)	126 (0.9)	
Transfer	4719 (85.9)	29446 (85.8)		2134 (82.7)	17249 (84.7)		2585 (88.7)	12197 (87.3)	
Undecided	275 (5.0)	1639 (4.8)		151 (5.9)	1065 (5.2)		124 (4.3)	574 (4.1)	
Enrollment Status (%)			<0.001			<0.001			<0.001
Concurrent High School Student	49 (0.9)	387 (1.1)		24 (0.9)	177 (0.9)		25 (0.9)	210 (1.5)	
Continuing Student	3722 (67.7)	24241 (70.6)		1451 (56.2)	13882 (68.2)		2271 (78.0)	10359 (74.1)	
First Time College Student	1434 (26.1)	7641 (22.3)		968 (37.5)	5053 (24.8)		466 (16.0)	2588 (18.5)	
Other	1 (0.0)	19 (0.1)		1 (0.0)	11 (0.1)		0 (0.0)	8 (0.1)	
Returning Student	288 (5.2)	2042 (5.9)		137 (5.3)	1235 (6.1)		151 (5.2)	807 (5.8)	
Ethnicity (%)			0.085			<0.001			0.632
American Indian or Alaska Native	12 (0.2)	62 (0.2)		6 (0.2)	41 (0.2)		6 (0.2)	21 (0.2)	
Asian	567 (10.3)	3614 (10.5)		246 (9.5)	2042 (10.0)		321 (11.0)	1572 (11.3)	
Black or African American	92 (1.7)	564 (1.6)		44 (1.7)	345 (1.7)		48 (1.6)	219 (1.6)	
Hispanic / Latino	1758 (32.0)	10248 (29.9)		921 (35.7)	6208 (30.5)		837 (28.7)	4040 (28.9)	
Native Hawaiian or Pacific Islander	18 (0.3)	102 (0.3)		8 (0.3)	64 (0.3)		10 (0.3)	38 (0.3)	
Two or More Races	366 (6.7)	2457 (7.2)		166 (6.4)	1413 (6.9)		200 (6.9)	1044 (7.5)	
Unreported or Unknown	93 (1.7)	548 (1.6)		36 (1.4)	335 (1.6)		57 (2.0)	213 (1.5)	
White	2588 (47.1)	16735 (48.7)		1154 (44.7)	9910 (48.7)		1434 (49.2)	6825 (48.8)	
Financial Aid = 1 (%)	2297 (41.8)	13380 (39.0)	<0.001	1107 (42.9)	7961 (39.1)	<0.001	1190 (40.9)	5419 (38.8)	0.040
First Attempt = 1 (%)	5086 (92.6)	31725 (92.4)	0.694	2433 (94.3)	19131 (94.0)	0.585	2653 (91.1)	12594 (90.1)	0.129
First Generation = 1 (%)	1001 (18.2)	5181 (15.1)	<0.001	540 (20.9)	3205 (15.7)	<0.001	461 (15.8)	1976 (14.1)	0.020
Gender (%)			0.004			0.247			0.074
Decline	91 (1.7)	574 (1.7)		36 (1.4)	334 (1.6)		55 (1.9)	240 (1.7)	
Female	2386 (43.4)	15795 (46.0)		1195 (46.3)	9731 (47.8)		1191 (40.9)	6064 (43.4)	
Male	3011 (54.8)	17920 (52.2)		1348 (52.2)	10264 (50.4)		1663 (57.1)	7656 (54.8)	
Non-binary	6 (0.1)	41 (0.1)		2 (0.1)	29 (0.1)		4 (0.1)	12 (0.1)	
Full-Time Student = 1 (%)	3949 (71.9)	23644 (68.9)	<0.001	1880 (72.8)	14000 (68.8)	<0.001	2069 (71.0)	9644 (69.0)	0.035
High School GPA, Quartiles			<0.001			<0.001			<0.001
1 (0.00-2.8)	1365 (24.8)	7002 (20.4)		779 (30.2)	4525 (22.2)		586 (20.1)	2477 (17.7)	
2 (2.81- 3.19)	965 (17.6)	6684 (19.5)		473 (18.3)	4064 (20.0)		492 (16.9)	2620 (18.8)	
3 (3.2-3.50)	996 (18.1)	7388 (21.5)		438 (17.0)	4316 (21.2)		558 (19.2)	3072 (22.0)	
4 (3.51-4.00)	726 (13.2)	5864 (17.1)		295 (11.4)	3298 (16.2)		431 (14.8)	2566 (18.4)	
Missing/Unknown	1442 (26.2)	7392 (21.5)		596 (23.1)	4155 (20.4)		846 (29.0)	3237 (23.2)	
Tutoring Center Hours (mean (SD))	0.45 (0.99)	0.21 (0.68)	<0.001	0.38 (0.79)	0.16 (0.57)	<0.001	0.52 (1.13)	0.28 (0.81)	<0.001
Used the Tutoring Center = 1 (%)	1261 (23.0)	3706 (10.8)	<0.001	625 (24.2)	1807 (8.9)	<0.001	636 (21.8)	1899 (13.6)	<0.001
n	5,494	34,330		2,581	20,358		2,913	13,972	

Course and Section Characteristics

At a more macro level, I captured data at the course (e.g., Statistics, Composition I, etc.) and section level. In examining the distribution of embedded tutor sections across various courses, I observed that on average, 15.70% (*SD* = 9.4) of course sections per course included an embedded tutor. English courses had a lower assignment rate of 12.36% (*SD* = 8.26) compared to math with 17.97% (*SD* = 10.16). Overall enrollment in the courses varies, with some being critical courses for students pursuing degree attainment or transferring to a four-year university (See figure 2.1).

Figure 2.1 Count of Sections, by Subject, Term & Section Type



There is also potential variation within the more granular section characteristics (See table 2.3). There are significant differences in the characteristics of the embedded tutor sections and the others. First off, only a small portion of embedded tutor sections were taught online (18.7%), far less than non-embedded tutor sections (42.1%).

Table 2.3 Characteristics of Course Sections

	Pooled			English			Math		
	ET Sections	Non-ET Sections	P Value	ET Sections	Non-ET Sections	P Value	ET Sections	Non-ET Sections	P Value
Online = 1 (%)	35 (18.7)	524 (42.1)	<0.001	20 (18.3)	409 (47.2)	<0.001	15 (19.2)	115 (30.3)	0.067
Associated Support Section = 1 (%)	80 (42.8)	33 (2.6)	<0.001	58 (53.2)	2 (0.2)	<0.001	22 (28.2)	31 (8.2)	<0.001
Full-time Faculty = 1 (%)	129 (69.0)	673 (54.0)	<0.001	62 (56.9)	393 (45.4)	0.030	67 (85.9)	280 (73.7)	0.032
Students Enrolled (mean (SD))	29.38 (8.93)	27.55 (7.95)	0.004	23.68 (3.04)	23.51 (3.44)	0.621	37.35 (8.32)	36.77 (7.63)	0.549
n	146	1287		109	866		78	380	

Next, another key difference is the substantial difference in support sections assigned to English, with only 2% not having one. As discussed earlier, these are students that likely would have been placed into remedial coursework using prior placement protocols, but are now being guided to a college-level course with greater support to maximize the probability of them passing.[6] These support sections involve increased weekly instruction time (typically between one to two hours). The program director prioritized these sections when assigning tutors, leading to a greater portion of them having an embedded tutor over time. Next, exploring the proportion that are adjunct or full-time in a given term is critical, with current research suggesting that contractual form is related to student academic outcomes (Ran & Xu, 2018). A higher proportion of embedded tutor sections, across all large subsets of data, had a higher proportion of full-time faculty leading them. Next, the number of students enrolled in each course section is included, given that class size has been shown to potentially influence outcomes (Kokkelenberg et al.,

[6] It is necessary to stress the fact that under AB 705 guidelines, that even if the college recommends that students enroll in sections with added support, students make the final decision as to whether they follow that guidance. Unfortunately, I was not able to acquire access to the guided self-placement data as of writing this manuscript.

2005). On the whole, embedded tutor sections appear to have about one more student enrolled, but all smaller subsets suggest that the difference is negligible.

Instructor Information

Another critical aspect of the intervention is the potential impact of the instructor, not only on the student's success in the course but also on whether they have an embedded tutor and how they end up utilizing them (See table 2.4). The usage rate of embedded tutors varied widely within those who used them; the average proportion of sections taught with an embedded tutor by professor was 33%. Amongst those who used tutors, 29% of all sections they taught in total (n = 843), had an embedded tutor. They on average taught only about four sections (*SD* = 3.89), with some only teaching one over the entire duration. The next key point is that, similar to the per-term data, a greater portion of embedded tutor faculty have historically fulfilled a full-time teaching load in most terms they have taught, further highlighting the potential experiential difference between the groups. Lastly, across all large subsets, a higher portion of embedded tutor faculty are female (significantly more except for math).

Table 2.4 Professor Characteristics by Embedded Tutor Usage

	Pooled			English Professors			Math Professors		
	ET Professors	Non-ET	P Value	ET Professors	Non-ET	P Value	ET Professors	Non-ET	P Value
Historical Failure Rate (mean (SD))	0.16 (0.09)	0.16 (0.08)	0.98	0.12 (0.05)	0.13 (0.07)	0.489	0.25 (0.09)	0.24 (0.06)	0.862
ET Section Count (mean (SD))	4.07 (3.89)	--	--	3.76 (2.90)	--	--	4.59 (5.23)	--	--
Full-Time, Overall (mean (SD))	0.50 (0.51)	0.20 (0.40)	<0.001	0.43 (0.50)	0.13 (0.34)	0.002	0.64 (0.50)	0.33 (0.48)	0.055
Female (mean (SD))	0.64 (0.48)	0.42 (0.50)	0.016	0.71 (0.46)	0.41 (0.50)	0.008	0.50 (0.52)	0.43 (0.50)	0.688
n	46	80		28	54		14	30	

Notes. The ET Professor column is only inclusive of professors who had at least one section with an ET assigned. Non-ET are those who never had an ET section within the current sample. All values are computed as of the first term each instructor taught within the given time frame. The Full-Time, Overall flag is a flag [0,1] of whether they've held a full-time faculty position in most of their prior terms.

As an initial step in addressing RQ1, I examined the unadjusted differences in academic outcomes between embedded tutor and non-embedded tutor sections across different groups (See table 2.5). The analysis revealed that overall, sections with embedded tutors tend to exhibit slightly lower pass and retention rates. However, this difference is statistically significant only in the pooled data. The results indicate that the impact may be particularly influenced by the English courses, as suggested by the slight differences of 1 to 2 percent in pass and retention rates and a substantially larger sample size of approximately 6,000 cases in this subset.

Disaggregating the data by specific course, however, I found that the success rates are not consistent over time (See appendices H & I). When examining specific courses within English, Composition I shows a negligible difference in pass rates between embedded tutor and non-embedded tutor sections, but lower retention rates for embedded tutor sections. Interestingly, for honors sections of Composition I and II, the presence of embedded tutors seems more beneficial. Composition I H (honors) shows a higher pass rate and retention rate in embedded tutor sections, with differences of four or three percentage points, suggesting that embedded tutoring is potentially effective for honors students in this course. Similarly, while Composition II has slightly better outcomes in pass rates for embedded tutor sections, Composition II H shows a significant decrease in retention rates for embedded tutor sections (-0.06), indicating that the benefits of embedded tutoring may not be consistent within different honors courses. However, the sample size of the honors courses is relatively small; it was only implemented at a small scale and so the differences seen here may be severely biased.

Within the math courses, the presence of embedded tutors does not appear to significantly affect pass rates in most courses, as evidenced by the minimal differences between the section types. However, retention rates show more variability with some notable findings. In particular,

Table 2.5 Outcomes by Section Type, Subject, and Course

Subject	Course	Metric	ET	Non-ET	Difference	n (ET)	n (Non-ET)
Pooled		Passed	0.7	0.68	-0.03***	5,494	34,330
		Retained	0.8	0.84	-0.03***		
English							
	Overall	Passed	0.7	0.75	-0.02	2,581	20,358
		Retained	0.9	0.88	-0.01		
	Composition I	Passed	0.7	0.7	0.01	2,145	11,272
		Retained	0.9	0.87	-0.01		
	Composition I H	Passed	0.9	0.85	0.04	132	442
		Retained	1	0.93	0.03		
	Composition II	Passed	0.8	0.8	0.04	232	7,899
		Retained	0.9	0.89	0.01		
	Composition II H	Passed	0.9	0.91	-0.06	72	745
		Retained	0.9	0.94	-0.06*		
Math							
	Overall	Passed	0.6	0.57	0	2,913	13,972
		Retained	0.8	0.78	0		
	Algebra for Calc.	Passed	0.6	0.55	0.04	203	1,067
		Retained	0.8	0.73	0.08*		
	Geo. & Calc. I	Passed	0.6	0.57	0.01	209	2,243
		Retained	0.9	0.78	0.07*		
	Geo. & Calc. II	Passed	0.7	0.66	0.01	532	985
		Retained	0.8	0.82	-0.01		
	Pre-Calc	Passed	0.6	0.54	0.03	189	1,656
		Retained	0.7	0.78	-0.06		
	Statistics	Passed	0.5	0.58	-0.08***	1,087	6,445
		Retained	0.7	0.78	-0.07***		
	Trig	Passed	0.6	0.54	0.07***	693	1,576
		Retained	0.9	0.76	0.09***		

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

for Algebra for Calculus and Geometry & Calculus I, the retention rates are significantly higher in embedded tutor sections, with differences of eight and seven percentage points. Conversely, embedded tutor sections of Statistics exhibit lower pass and retention rates compared to non-embedded tutor sections. Trigonometry shows a positive impact of embedded tutoring, with both pass and retention rates being higher in embedded tutor sections. This suggests that the effectiveness of embedded tutoring may vary significantly across different types of math courses.

Looking at the metrics over time also reveals that the differences between the section types is not consistent from term to term. Furthermore, it amplifies the point noted earlier that the utilization of embedded tutoring was not consistent for all courses over the duration. While the preliminary examination reveals subtle differences likely influenced by English courses, further investigation is warranted to understand the underlying dynamics. Variations in student, section, and professor characteristics underscore the complexity of the academic outcomes, necessitating a more robust analytical approach.

Empirical Framework

To comprehensively evaluate the impact of the embedded tutor program on student learning outcomes, I am utilizing a series of increasingly detailed fixed effects and instrumental variable models. These models are specifically designed to assess how enrollment in embedded tutor sections affects students' probability of passing or completing a course, while effectively accounting for a range of potentially confounding factors.

The approach for each model is predicated on several key considerations and assumptions. The use of fixed effects is aimed at capturing within-group variance. I am using this within-group variation to estimate the effect of embedded tutoring. This method helps to

control for unobserved variables that could differ between groups but are consistent within groups, such as instructor effects or course-specific characteristics. As I introduce more dimensions of fixed effects (e.g., term, instructor) the subset of my sample that includes cases with necessary within-group variance diminishes. This reduction is due to the stringent requirement for each category (e.g., specific courses taught by specific instructors in specific terms) to have enough variability in embedded tutor sections available.

Despite the potential reduction in within-group variance with extensive fixed effects, I have decided to include all cases in the current sample. This decision is aimed at maximizing statistical power and providing a more comprehensive examination of the program's effectiveness across various educational contexts. By including all available data, the analysis encompasses a broader range of situations and conditions, significantly enhancing the generalizability of the findings. This all-inclusive approach ensures that the results reflect a wide array of educational settings and student experiences.

This analytical strategy acknowledges that not all courses will have both embedded tutor and non-embedded tutor sections. Like any study, it is crucial to interpret the findings within the context, understanding that some of the variability in student outcomes might be attributed to factors other than the intervention itself.

Model 1 is my first attempt at isolating the effect of embedded tutor assignment using a selection of fixed effects that provide the greatest within-group variance.[7] The two fixed effects include the course (e.g., Composition I, Trigonometry, etc.) and what term it was taught. These were chosen because courses themselves may have unique attributes or challenges associated with them that contribute to variance in outcomes. Also, differences may arise from offering

[7] To see a table of the count of cases where the relevant within-group variance is present per data subset and model, see appendix F.

these courses in different academic terms, such as variations in curriculum pacing, assessment methods, or any events transpiring beyond the campus (e.g., COVID, economic turmoil, etc.). So, to predict the outcome (*Y*) for student *i* in section *j,* during term *t,* I leveraged the variance in these courses per term with the following logistic regression model:

$$log\left(\frac{Y_{ijt}}{1-Y_{ijt}}\right) = \beta_0 + \beta_1 EmbeddedTutor_j + X_i + \gamma_{it} + \delta_j + \theta_j + \theta_t + \varepsilon_{ijt} \quad (1)$$

Where Y_{ijt} is the course outcome (passing/retained), $EmbeddedTutor_j$ is a dichotomous variable indicating if the section had an embedded tutor, and β_1 is the estimated effect of being in an embedded tutor section. β_0 represents the intercept term, which is the expected value of the course outcome (passing/retained) when all predictor variables are set to zero. X_i is a vector of student covariates that do not change over time (e.g., ethnicity, gender, first-generation) and γ_{it} includes other student covariates that do potentially change from term to term (e.g., cumulative GPA/units earned as of the beginning of the term, age, etc.).[8] The term δ_j includes specific characteristics of the course section and instructor (e.g., enrollment count, online/in-person, failure rate of the professor, etc.). The model includes fixed effects at the course (θ_j) and term level (θ_t) and ε_{ijst} represents the error term.[9]

A potential threat or limitation to the fixed effects approach described above is endogeneity. It may be the case that my endogenous predictor of interest, embedded tutoring, is correlated with unobserved confounders that are otherwise related to the outcomes of interest (Wooldridge, 2013). To address this, I will employ an instrumental variable (IV) approach aimed

[8] Student fixed effects were not included in any models because most students appear less than twice within each subset, providing little to no variance, especially when considering other fixed effects dimensions.

[9] Ideally, I would like to have run the same models with an added fixed effect for the instructor, but unfortunately there were very few cases that provided variance within term, course, instructor, and embedded tutor usage. In fact, only about 7% of the current sample would provide within group variance for such a model.

at leveraging the exogenous variation in embedded tutor section availability. Specifically, I use term-by-term variation in the proportion of sections within a given course with an embedded tutor as an instrument for the student's likelihood of taking a course with embedded tutoring.

Varying levels of access to embedded tutor sections in a given term influence the probability that a student is part of the treatment or control group. Students have no way of knowing which sections have an assigned embedded tutor, so their chances of enrolling in the section vary depending on the degree of availability. It is important to note that certain sections or instructors may have been more likely to host an embedded tutor, or specific characteristics of those sections may have made them more appealing. To account for this potential bias, I will include controls for these factors in my models. The proportion of embedded tutor sections in a given term fluctuates depending on the availability of tutors, scheduling challenges, or potentially other contextual factors unbeknownst to the researcher. This observed variation in embedded tutor availability thus serves as a plausible instrument, once controlling for term and instructor fixed effects.

The key assumption underlying the IV approach is that the variations in the availability of embedded tutors over time are exogenous. This means that changes in the proportion of sections with embedded tutors should follow a random pattern, fluctuating over time without being systematically related to other factors that could influence student outcomes. There should also be no concomitant factors that change over time (e.g., implementation of other interventions or changes in staffing) that are related to both the instrument and the student outcomes. In this context, this means that the instrument—proportion of sections with embedded tutors—should affect the outcome (e.g., student pass/retention rates) only by influencing the endogenous

variable (enrollment in an embedded tutoring section) and not through any other direct or indirect means.

Before proceeding with the IV approach, I test the exclusion restriction by examining whether the error term from Model 1 is correlated with my instrument. Additionally, I assess whether the proportion of sections with embedded tutors is correlated with embedded tutor section enrollment. To evaluate the strength of the instrument, I use the F-test in the first stage. Generally, an F-test value greater than 20 is considered sufficient to establish instrument strength (Staiger & Stock, 1997; Stock, Wright, & Yogo, 2002). I use a two-stage residual inclusion (2SRI) approach as a means of parsing out the exogenous effect of embedded tutor offerings on the potentially endogenous predictor (embedded tutor enrollment) to estimate an average treatment effect (Model 2). The first stage predicts enrollment in an embedded tutor section using the proportion of sections with an embedded tutor as an instrument.

$$\text{1st Stage: } \widehat{EmbeddedTutor}_{ijt} = \alpha_0 + \alpha_1 I_{jt} + \alpha_2 X_i + \theta_j + \theta_t + \delta_{jt} + \epsilon_{ijt}$$

Where $\widehat{EmbeddedTutor}_{ijt}$ is the predicted value of enrollment in an embedded tutor section of a given course in a given term, I_{jt} is the instrument, X_{it} is a vector of student level-covariates, δ_{jt} is a vector of instructor and section characteristics, θ_j and θ_t are fixed effects for course, and term and ϵ_{ijt} is the error term. I follow common practice by assessing the strength of my instrument.

The second stage predicts the outcomes of interest (passing or retention) using the enrollment in an embedded tutor section, the vector of student-level characteristics, the vector of instructor and section characteristics, the residuals from the first stage regression ($\hat{\epsilon}_{ijt}$) along with course and term fixed effects.

$$\text{2nd Stage: } log\left(\frac{Y_{ijt}}{1-Y_{ijt}}\right) = \beta_0 + \beta_1 EmbeddedTutor_{ijt} + \beta_2 X_i + \gamma\hat{\epsilon}_{ijt} + \theta_j + \theta_t + \varepsilon_{ijt}$$

The residual from the first stage regression acts as an endogeneity correction; if the coefficient of the residuals is significant, it suggests that there were unobserved factors affecting both embedded tutor enrollment and the outcome that are not being captured by the other predictors in the current model. The significance of residuals validates the need for using an IV approach; it confirms that simply including embedded tutor enrollment without addressing endogeneity would lead to potentially biased estimates.

To address RQ2 regarding the impact of embedded tutoring, I will use linear probability models (LPMs) with interaction terms, ensuring a clear and interpretable analysis of the effects. Given the challenges in interpreting interaction terms within logistic regression models, the linear probability model provides a more straightforward interpretation of coefficients, particularly when assessing the impact of embedded tutoring across different courses. Model 1 will be modified as follows:

$$Y_{ijt} = \beta_0 + \beta_1 EmbeddedTutor_j + \beta_2(EmbeddedTutor_j * Course_c) + X_i + \gamma_{it} + \delta_j + \theta_j + \theta_t + \varepsilon_{ijt}$$

Similarly, I will use a two-stage least squares (2SLS) approach to estimate the impact of embedded tutoring while accounting for potential endogeneity. The model is effectively the same in both stages, except the error term of the first stage is not used in the second stage. Instead, the predicted linear probability value of enrolling in an embedded tutor ($\widehat{EmbeddedTutor}$) is used. The 2SLS model is specified as follows:

$$\text{1st Stage: } \widehat{EmbeddedTutor}_{ijt} = \alpha_0 + \alpha_1 I_{jt} + \alpha_2 X_{it} + \theta_j + \theta_t + \delta_{jt} + \epsilon_{ijt}$$

$$\text{2nd Stage: } Y_{ijt} = \beta_0 + \beta_1 \widehat{EmbeddedTutor}_{ijt} + \beta_2 (\widehat{EmbeddedTutor}_{ijt} * Course_c) + \beta_3 X_{it} + \theta_j + \theta_t + \varepsilon_{ijt}$$

The results will focus on the interaction terms to understand if embedded tutoring has differential impacts across courses. The reference group for each subject is set to the course with the largest sample size (Composition I for English and Statistics for Math) to provide a meaningful

comparison. The primary goal of this analysis is to identify courses where embedded tutoring may be more or less effective, providing a foundation for future research to explore these differences further.

Results

Regression Models

Model 1 analysis across pooled data, English, and Math subjects shows no significant differences in academic outcomes between sections with and without embedded tutoring (See table 2.6). This suggests that without addressing potential endogeneity, there is no clear evidence that embedded tutoring impacts these outcomes.

For the pooled data, the odds ratio (OR) for passing was 0.96 with a 95% confidence interval (CI) of [0.79, 1.17], indicating a 4% decrease in passing likelihood for students in sections with embedded tutoring. However, this result was not statistically significant, with the value of 1, or parity between groups, falling within the confidence interval. Similarly, retention showed an OR of 0.92 [95% CI, 0.69, 1.23], also non-significant. Similar patterns were observed in English and Math subjects, with no statistically significant results for passing or retention.

The error term from the regression of passed/retention on embedded tutor enrollment was correlated with the instrument (proportion of course sections with embedded tutors in a given term), indicating potential endogeneity. With reason to believe there is endogeneity in the model, I systematically investigated whether the instrument is relevant. First, using the pooled data, the instrument was found to be strongly correlated with embedded tutor enrollment [$r(39{,}822 = .39$, $p < .001)$]. Looking at the relationship per subject, the instrument demonstrated a stronger correlation for math courses [$r(16{,}883 = .44$, $p < .001$) than English courses [$r(22{,}937) = .31$, $p < .001)$]. Next, the first stage of the 2SRI model further substantiated the strength of the

instrument, with all of the F-tests on the excluded instrument being significant ($p < .001$) and large, ranging from 172 to 623 (See appendix J).

Given the endogeneity evidence, the IV approach was used for unbiased estimates, reported in Model 2 (See table 2.6). Interestingly, the residual term of the first stage model was only significant in the pooled iteration of passing. This significant residual in the pooled data might reflect underlying differences in how embedded tutoring impacts student outcomes across different subjects or even specific courses within subject. The reason for this inconsistency is difficult to identify definitively but I would argue there are possible explanations to consider. First off, this could suggest heterogeneity in impact. The pooled data, representing a broad spectrum of courses, may reveal more overarching or general trends that are not as apparent or identifiable within the smaller and homogenous groups of English and math courses alone. Next, it could be that the pooled iteration simply has greater statistical power to detect effects that are otherwise too small in the subject-specific samples.

The pooled data IV estimates showed a significant negative effect of embedded tutoring on passing, with an OR of 0.61 [95% CI, 0.47, 0.78], indicating a 39% decrease in passing likelihood. However, subject-specific models for English and Math did not show significant effects of embedded tutoring on passing or retention.

These findings suggest that the significant negative impact of embedded tutoring observed in the pooled data should be interpreted with caution, as this effect was not consistently observed within the individual subjects of English and Math. The pooled result might be due to the overall trend across all subjects, which could be influenced by factors that become less pronounced in subject-specific analyses. Pooled data increases sample size and statistical power, potentially detecting effects that are not apparent in narrower, subject-specific analyses.

Table 2.6 Models Predicting Academic Outcomes, Using Course & Term Fixed Effects

		Pooled		English		Math	
Outcome		1	2	1	2	1	2
Passing							
	OR	0.96	0.61***	1.03	0.71	1.03	0.85
	95% CI	[0.79, 1.17]	[0.47, 0.78]	[0.87, 1.22]	[0.37, 1.36]	[0.78, 1.36]	[0.62, 1.17]
Retention							
	OR	0.92	0.90	0.95	1.42	1.06	1.14
	95% CI	[0.69, 1.23]	[0.67, 1.20]	[0.75, 1.20]	[0.58, 3.51]	[0.66, 1.69]	[0.80, 1.62]
	n	39,824	39,824	22,939	22,939	16,885	16,885
Model Features	Course ID & Term FE	Yes	Yes	Yes	Yes	Yes	Yes
	IV		Yes		Yes		Yes

Note. * $p < .05$, ** $p < .01$, *** $p < .001$
All models include the variables: First Attempt, Support Section, Cumulative Units Earned as of Beginning of Term (BOT), Cumulative GPA as of BOT, First-Generation, Enrollment Status, High School GPA, Online, Ethnicity, Full time status, Financial aid, and Number of Students Enrolled.
Faculty characteristics include gender, failure rate, overall employment status, and term load (full-time/part-time).

Subject-specific variations and dynamics could also dilute these overarching trends when analyzed separately.

However, it's important to note that the confidence intervals for some estimates are quite large. This is a known issue with the 2SRI method, which can result in increased standard errors (Wooldridge, 2010; Angrist & Pischke, 2008). Despite this, the significant findings in the pooled data provide strong evidence of an overall negative effect of embedded tutoring on passing rates. This result remains defensible because the use of instrumental variables appropriately addresses endogeneity, thereby providing more reliable estimates than those obtained from the initial, non-IV models.

Falsification Test

In order to validate the IV approach used, a falsification test was conducted. This test aimed to confirm that the observed effects attributed to the presence of embedded tutors were not due to unobserved/omitted variables or systemic biases in the model. To this end, a distinct dataset was created, consisting solely of English and Math courses within the same terms of interest that have never utilized embedded tutoring. The rationale was that these courses should remain unaffected by embedded tutoring availability in other courses during the same terms, thus serving as a control group to test the exogeneity of the instrumental variable used in the main analysis.

For this control group, a specific measure was calculated, representing the proportion of sections with embedded across all the originally investigated English and Math courses each term. This measure served as a proxy to test whether external factors related to embedded tutor provision might inadvertently influence courses without embedded tutors.

The analysis then proceeded with regression models predicting student retention and passing, utilizing the same vector of covariates as in the main analysis but applied to the test non-embedded tutor dataset. The results of the falsification test revealed that the proportion of embedded tutor sections per term variable was not significant in predicting either student retention or passing outcomes in the courses without embedded tutoring. This non-significant finding supports the validity of the instrumental variable used in the main study, suggesting that it adequately isolates the effect of embedded tutoring availability without being confounded by external factors affecting courses that do not participate in the program.

Robustness Check

In order to further verify the accuracy of the estimates described above, I revised models 1 and 2 to address suspected endogeneity issues, particularly the omission of instructor fixed effects. To include these effects without losing a significant portion of the sample—which was necessary to maintain sufficient within-group variance—I re-implemented the models incorporating only course and instructor fixed effects. This approach was justified on the grounds that many of the included controls provided adequate information about the students and instructors at the start of each term. This revised modeling approach yielded consistent results across most analyses, suggesting that the effects of the program were negligible or not significant (See table 2.7). However, an exception was noted within the pooled dataset: there was no significant difference in pass rates between sections with embedded tutors and those without, indicating that the impact of embedded tutoring on pass rates might be less pronounced when controlling for instructor-specific effects.

Table 2.7 Models Predicting Academic Outcomes, Using Course & Instructor Fixed Effects

		Pooled		English		Math	
Outcome		1	2	1	2	1	2
Passing							
	OR	1.09	0.91	1.01	1.38	1.06	0.86
	95% CI	[0.89, 1.33]	[0.70, 1.18]	[0.83, 1.23]	[0.71, 2.66]	[0.79, 1.41]	[0.64, 1.14]
Retention							
	OR	0.98	1.04	0.89	1.24	0.99	1.05
	95% CI	[0.82, 1.17]	[0.76, 1.42]	[0.78, 1.00]	[0.52, 2.97]	[0.74, 1.33]	[0.76, 1.45]
	n	39,824	39,824	22,939	22,939	16,885	16,885
Model Features	Course ID & Instructor FE	Yes	Yes	Yes	Yes	Yes	Yes
	IV		Yes		Yes		Yes

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

All models include the variables: First Attempt, Support Section, Cumulative Units Earned as of Beginning of Term (BOT), Cumulative GPA as of BOT, First-Generation, Enrollment Status, High School GPA, Online, Ethnicity, Full time status, Financial aid, and Number of Students Enrolled. Faculty characteristics failure rate and term load (full-time/part-time).

Other Model Trends

In examining the estimates from the large grouping models, several consistent trends emerge, lending credibility to our analytical framework (refer to appendix C for detailed outputs). Foremost among these is the influence of baseline academic performance, as indicated by the flag for their first attempt and cumulative and high school GPAs. As expected, students who were not repeating a given course, entering terms with higher GPAs, both from previous college terms and high school, are more likely to succeed in their math or English courses. Along those same lines, being a full-time student is consistently positive and significant in all the current models.

Another consistently significant predictor is the first-generation student status, which unfortunately shows a negative effect. This suggests that first-generation students are less likely to complete their courses successfully, highlighting a potential area for targeted academic support.

In terms of section and instructor characteristics, there were several factors that were consistent across the models. The mode of course delivery also plays a critical role, with online courses consistently showing a negative relationship with student outcomes. This finding is in line with existing research, which often points to the challenges posed by online learning environments. Likewise, faculty failure rate is consistently negative and significant, meaning the higher the historical failure rate of the faculty, the less likely the student is to succeed holding all else equal.

Interestingly, the presence of a support section within courses did not uniformly impact outcomes across all models. This variability suggests that the effectiveness of support sections

may depend heavily on their specific implementation or could be overshadowed by more influential factors, such as GPA measures.

Exploration of Heterogeneity of Embedded Tutoring within Courses

Table 8 summarizes the differential effects of embedded tutoring by course. For ease of interpretation, the linear probability coefficients are reported instead of ORs as in previous models. The findings strongly indicate that the effectiveness of embedded tutoring does vary significantly across different courses within the same subject area, especially within math courses. For example, the interaction terms for Pre-Calculus are negative and significant for both passing and retention. To answer our specific research question as to whether embedded tutors had a differing effect in each course, we would need compare the effect of embedded tutoring in statistics (0.07) to embedded tutoring in Pre-calculus (-0.25). In more plain terms, the impact of embedded tutoring on pass rates in Pre-Calculus is 32 percentage points lower than in Statistics courses with an embedded tutor, more or less. In English, there were only select cases that suggested a possible interaction, Composition II and Composition II H. Interpreting the differential impact in retention particularly due to the greater confidence in the embedded tutor main effect, a positive interaction with Composition II H is observed. However, when aggregating the effects, that difference is merely one percentage point and arguably a minimal difference in impact. It is important to note that across all other cases of potential interaction, the aggregate difference is uncertain due to one or more of the included estimates not being statistical significance. In totality, it would appear that there is greater evidence of heterogeneity within the math courses across both outcomes and models used.

Table 2.8 Differential Effects of Embedded Tutoring by Course

		Passed		Retention	
		1	2	1	2
English Courses					
[Reference: Composition I]	Composition I H	0.01	0.01	-0.01	0.17
		(0.02)	(0.12)	(0.01)	(0.10)
	Composition I H * ET	0.00	0.00	0.01	-0.16
		(0.02)	(0.11)	(0.01)	(0.09)
	Composition II	0.03*	0.09	0.01	0.08
		(0.01)	(0.11)	(0.01)	(0.09)
	Composition II * ET	-0.04	-0.06	-0.03	-0.06
		(0.03)	(0.11)	(0.02)	(0.09)
	Composition II H	0.02	0.17	-0.01	0.27*
		(0.01)	(0.17)	(0.01)	(0.13)
	Composition II H * ET	-0.10	-0.14	-0.07	-0.26*
		(0.06)	(0.16)	(0.05)	(0.12)
	Embedded Tutor (ET) Main Effect	0.02	0.04	0.01	0.19**
		(0.02)	(0.08)	(0.04)	(0.06)
Mathematics Courses					
[Reference: Statistics]	Algebra for Calc.	-0.10	0.31**	-0.04	0.18*
		(0.02)	(0.10)	(0.03)	(0.09)
	Algebra for Calc. * ET	0.07	-0.26**	0.08	-0.17*
		(0.06)	(0.08)	(0.06)	(0.07)
	Geo. & Calc. I	-0.09***	-0.14	-0.05**	-0.20*
		(0.01)	(0.10)	(0.01)	(0.09)
	Geo. & Calc. I * ET	0.04	0.06	0.09	0.17*
		(0.06)	(0.09)	(0.05)	(0.08)
	Geo. & Calc. II	-0.04	0.09	-0.02	0.10
		(0.03)	(0.09)	(0.02)	(0.08)
	Geo. & Calc. II * ET	0.00	-0.11	0.00	-0.11
		(0.04)	(0.07)	(0.05)	(0.06)
	Pre-Calc	-0.07	0.29***	-0.01	0.33***
		(0.04)	(0.08)	(0.03)	(0.07)
	Pre-Calc * ET	0.03	-0.32***	-0.02	-0.31***
		(0.07)	(0.07)	(0.04)	(0.06)
	Trig	-0.02	0.17*	-0.02	0.10
		(0.04)	(0.07)	(0.03)	(0.06)
	Trig * ET	0.06	-0.14**	0.10	-0.09
		(0.06)	(0.13)	(0.05)	(0.05)
	Embedded Tutor (ET) Main Effect	-0.02	0.07	-0.02	0.09
		(0.03)	(0.04)	(0.03)	(0.03)
Model Features	Course & Term FE	Yes	Yes	Yes	Yes
	Proportion ET IV		Yes		Yes

Note. Linear probabilities shown for ease of interpretation. Standard errors are in parentheses.
* $p < .05$, ** $p < .01$, *** $p < .001$

Discussion

The findings indicate that, based on the data available, the impact of embedded tutor enrollment on student outcomes is generally minimal, with most models resulting in negligible differences or non-significant findings. Even in the select cases where minor differences are significant, the inconsistencies across the models and subsets used suggests that embedded tutor enrollment alone does not significantly influence student success.

In English courses, initial analyses suggested a potential benefit from embedded tutoring in improving passing rates. However, this positive effect was not consistently observed in later models that accounted for more nuanced variables such as course-specific and term variability. This indicates that while there may be initial improvements in passing rates due to embedded tutoring, these effects do not consistently hold when additional complexities are introduced into the model. Additionally, analysis of potential variability among courses within the English department revealed that none of the interaction terms were significant. This indicates that the effects of the embedded tutoring program did not differ substantially across courses, nor from the reference group, emphasizing a lack of measurable impact across the department.

In Mathematics, the initial positive outcomes linked to embedded tutoring varied and were not consistent in more detailed analyses accounting for the exogeneity of per term availability of embedded tutor sections. This variability highlights the complex interaction between embedded tutoring and course-specific factors, which may dilute or mask the effects of tutoring in broader analyses. Despite this, there were indications that some courses might have experienced better performance than others, suggesting that under certain conditions or in specific courses, embedded tutoring could potentially enhance academic outcomes. Similar to

English, the retention rates in Mathematics courses did not show consistent improvements across models.

In summary, the embedded tutor program did not consistently demonstrate an effect on improving passing and retention rates across the evaluated courses. The programs' effectiveness may depend heavily on how they are implemented alongside other supportive measures.

Member Checking

During various stages of my research, I engaged with local stakeholders to validate and deepen the interpretation of my findings. This process not only confirmed the emergent trends but also provided crucial insights into the evolving perceptions of the embedded tutor program.

English Department Experiences

Initially, the English faculty were enthusiastic adopters of the embedded tutor program. Many expressed a keen interest in integrating tutors into their sections and participated in formal training sessions. These sessions were spearheaded by the then-department chair, who was instrumental in promoting effective use of tutors, particularly in support sections designed to facilitate extensive group work. The physical setup of these classrooms was specifically adapted to enhance this collaborative learning environment.

However, over time, this initial enthusiasm potentially waned amongst some. Faculty members reported diminishing confidence in the tutors' preparedness and effectiveness, leading to a preference for dedicating more direct attention to students rather than on tutor training. Additionally, internal discussions among staff, fueled by local data, began to question the efficacy of the tutoring program, contributing to a gradual disengagement.

Math Department Experiences

The reception in the Math department contrasted sharply with that of the English department. Anecdotal evidence suggested significant initial resistance. Faculty perceived the tutors as an additional burden rather than an asset, citing difficulties in integrating tutors with their teaching styles and challenges in recruiting suitable candidates. Particularly in disciplines like statistics, finding appropriately skilled tutors proved both challenging and time-consuming. Furthermore, some faculty members preferred to maintain a lecture-based pedagogy, limiting opportunities for tutors to engage actively with students during class sessions. This led to a reluctance to incorporate embedded tutors, with some opting to utilize tutor support solely within the tutoring center.

Impact on Program Utilization

These departmental perspectives are reflected in the significant decline in the utilization of embedded tutors over time, which can be seen as indicative of the eroding confidence in the program's value. The number of courses incorporating embedded tutors plummeted from a peak of 47 sections in Fall 2019 to just 8 in Spring 2023. This stark reduction not only underscores a declining belief in the program's benefits but also suggests that diminished support could have compromised its effectiveness in later terms.

The study has several limitations that could influence the robustness and generalizability of the findings. Despite meticulous efforts to control for various covariates, there remain unobserved confounders that could affect the relationship between embedded tutor enrollment, tutoring center usage, and student outcomes. Additionally, the specific datasets and subsets utilized in this study may not accurately reflect other contexts or educational settings, potentially limiting the broader applicability of the results.

A significant limitation of the current study is the lack of detailed data regarding the tutors themselves. Specific information about which tutors were assigned to each section, the frequency of their deployment, and their effectiveness in different contexts was not available. While it would also be ideal to include some sort of measure on dosage or duration of exposure to tutors within a given course, whether it be one-on-one or in group settings, capturing that detail is arguably difficult and impractical for the tutors and professors. Even still, this absence of data prevents a more nuanced analysis of how tutor characteristics and exposure to tutors might influence educational outcomes.

Another critical gap in the data is the lack of detail on how faculty members utilized the embedded tutors. There is considerable variability in how tutors can be integrated into course structures—ranging from active participation in classroom activities, assistance during online sessions, or a more passive role of just sitting alongside the other students during class. Understanding the specific roles tutors played within different sections would provide deeper insights into the effectiveness of the embedded tutor program. The current data does not capture this variability, thus limiting the ability to ascertain the impact of different tutoring strategies on student learning.

The study also suffers from a lack of comprehensive historical data on the implementation of the embedded tutor program. Complete data from the initial phases of the program's implementation would have offered greater statistical power and allowed for a more robust analysis of its long-term effects on student outcomes. The absence of detailed records from earlier terms, including which sections had embedded tutors and the extent of their integration, restricts our understanding of the program’s evolution and its impact over time.

To address these limitations, future research should aim to collect more detailed data on the deployment and activities of embedded tutors, including specific information about their assignments to sections, the frequency of their interactions with students, and the nature of these interactions. Additionally, it would be beneficial to track the utilization patterns of tutors within the tutoring center to directly link specific tutor-student interactions to academic outcomes. Understanding the diverse ways in which faculty members employ embedded tutors will also be crucial for evaluating the program's effectiveness across different pedagogical contexts. Lastly, establishing a comprehensive database that tracks the historical implementation and outcomes of the embedded tutor program will significantly enhance the ability to conduct longitudinal studies and evaluate the sustained impacts of tutoring on student success.

Future Work

The results have several important implications. The findings highlight the complexity of the relationship between embedded tutor enrollment and student outcomes, indicating that embedded tutor enrollment alone, in its most current form, might not be sufficient to improve passing and retention rates. The positive indirect effects of tutoring center usage underscore the importance of such resources in enhancing student success. The current results strongly suggest that local policymakers and practitioners should consider somehow further incentivizing, or even somehow requiring greater usage of the free local resource.

Future research could build on these findings by exploring potential mediators, such as usage of the on-campus tutoring center, other forms of student engagement, or self-efficacy to provide a more comprehensive understanding of how embedded tutor enrollment affects student outcomes. Also, the inclusion of more terms of data and more granular data on dosage (e.g., time working with tutor individually in class, number of hours tutors worked, etc.) and specifics on

tutor assignment (e.g., background of the tutor specifically, which tutor is assigned to each section, etc.) could provide greater statistical power and generalizability. Another critical component that is lacking in the current analysis is qualitative data, capturing the perceptions of all groups involved (e.g., students, professors, tutors, etc.). Replicating the study in different educational settings with similar programs could test the generalizability of the findings and potentially help to refine intervention strategies accordingly.

Lastly, exploring the specific utilization of embedded tutors in certain math classes where interaction terms suggested higher effectiveness could be particularly enlightening. Discussions with professors who have successfully integrated tutors in their teaching could reveal effective practices and strategies that might be replicated in other settings. This could involve detailed interviews or focus groups with these faculty members to understand the pedagogical approaches and tutor management techniques that contributed to successful outcomes.

In conclusion, while the overall impact of embedded tutor enrollment on passing and retention is generally non-significant, certain classes or instructors may offer us some insights as to how implement the intervention with greater efficacy. Addressing the identified limitations and pursuing future research directions can further inform practitioners and researchers about what aspects or mechanisms of such interventions improve student outcomes.

CHAPTER 3: An Investigation of the Impacts of Lateral Simultaneous Enrollment Amongst Community College Students

Public two-year community colleges (CC) in the United States represent society's commitment to providing accessible educational opportunities. As open-access institutions, these post-secondary schools provide access to a college-level education to anyone with a high school degree, or equivalent, who is interested in attending. Public community colleges are the largest provider of postsecondary education, serving roughly 28% of postsecondary students nationwide (NCES, 2018). A substantial portion of the population served by these schools are members of historically underserved groups such as students from low socioeconomic backgrounds, first-generation college students, and students of color (Krogstad, 2016; NCPPHE, 2011). The vast majority (80%) of community college students report an intention to transfer to a 4-year baccalaureate granting institution, but only about 25% transfer within four years and even fewer (17%) earn a bachelor's degree within six years (Bailey et al., 2015; Hossler et al., 2012). While community colleges are pivotal in providing access, the pathways students take through these institutions are not always straightforward or linear.

Many studies have described non-linear postsecondary enrollment paths that community college students take through their college career, such as successively enrolling at multiple institutions (swirling), with or without formal transfer, or taking classes at more than one institution (either simultaneously or successively) (DesJardins et al. 2002; Ishitani, 2006; Pascarella & Terenzini, 2005; Wang & Wickersham, 2014). In this study, we focus on a specific form of *simultaneous enrollment,* the practice of enrolling in multiple post-secondary institutions at the same time, and its effect on student academic outcomes. The number of students ever simultaneously enrolling in any two institutions for at least a month has increased substantially, from 11% in the cohort entering college in 2003 to 34% in the cohort of students entering in

2011 cohort (estimates based on authors' calculations using Beginning Postsecondary Education Student Study [BPS: 04/09] and BPS: 12/17). Despite the apparent advantages of simultaneous enrollment, there remains a gap in the literature concerning its varied forms and the precise impact on student outcomes.

Students may choose to simultaneously enroll for a variety of reasons. Enrolling in a course or courses at another institution may be a means of exploring whether the other institution is a better fit. Simultaneous enrollment could also increase the pool of available courses, which could improve a student's ability to select courses based on affordability or preferences for specific faculty or schedules (Wang & McReady, 2013). This greater access could reduce the challenges of enrolling in popular courses that are often subject to capacity constraints. Enrolling at multiple institutions also increases access to social networking opportunities, providing students the opportunity to engage with a wider range of peers, faculty, and staff (McCormick, 2003; Wang & Wickersham, 2014). Additionally, some community colleges offer specialized programs, facilities, or extracurriculars that may not be readily available at a student's home institution. Enrolling in a second community college may allow a student to tap into these resources while maintaining enrollment in their home institution.

However, most extant literature does not disentangle the various forms of simultaneous enrollment (e.g., lateral -- enrolling in two community colleges or vertical -- enrolling in a community college and a four-year college) and these studies leave room to more sufficiently control for all factors influencing selection into these enrollment patterns. Building on this gap in the research, our study specifically investigates lateral simultaneous enrollment, employing a methodologically rigorous approach to ascertain its true impact on student outcomes.

We find evidence that lateral simultaneous enrollment has a positive effect on some important academic outcomes. In particular, we find that a community college student's participation in lateral simultaneous enrollment for at least one term of their postsecondary career increases the chances of successfully transferring to a four-year institution and earning a bachelor's degree. These findings extend the existing understanding of the effects of the pattern.

Conceptual Frameworks

We adapt Wickersham's (2020) model, the Pathway (Re)Selection Model Among Beginning 2-Year College Students, to provide a framework for how college students make repeated enrollment decisions. Wickersham's model examines the short- and longer-term factors that community college students consider as they make decisions and navigate educational pathways: repeatedly having to decide whether to re-enroll, deciding on which courses to take and where to take them, and deciding which degree to pursue. Each of these decisions includes multiple layers of considerations that students must weigh before a final decision is made. Wickersham's model identifies five key decision-making factors. Wickersham identifies *payoff* as the most influential factor, which aligns with many students' primary impetus for attending college: the idea of anticipated gains. Such gains could be shorter time to degree, better learning outcomes, or increased long-term earnings. *Mobility* represents the personal or professional growth that students hoped to achieve. *Flexibility* is the preference for pathways that permits a student to work or attend to other responsibilities while attending college. *Transferability* is the concern as to whether one's completed units can be easily transferred to another program in the future. *Fit* is the match that students seek in terms of the institutional environment, size, and program. Lastly, *place* is the connection that a student feels to a location.

The Pathway (Re)Selection Model provides a helpful point of departure for examining students' decisions to opt into, and the effects of, simultaneous enrollment patterns. A student will likely consider whether the act of simultaneously enrolling will be a financial burden in the short term and will pay off in the long term (*payoff*), will compete with their existing responsibilities (*flexibility* & *place*), will offer them some opportunity to grow personally or professionally (*mobility* & *fit*), and/or will earn them course credits applicable towards their current and long-term goals (*transferability*). Students' perceptions of the costs and benefits related to each of these elements will influence their decision to simultaneously enroll.

The variation across students in the perceptions of costs or benefits associated with simultaneous enrollment may help us understand why a given student decides to engage in the practice. In this paper, we leverage the uneven distribution of geographic cost – depending on the density of colleges near a student, they will have more or less access to schools at which they could simultaneously enroll. If a student has the perception of easier access to the opportunity, they should be more willing to partake. In other words, we hypothesize that a reduction in geographic cost, in terms of how far they have to go to get to school, could help to explain a student's decision to participate in simultaneous enrollment.

To explain how simultaneous enrollment is related to our outcomes of interest, we draw on Bourdieu's (1984) social capital theory. Bourdieu's original concept posited that one accumulates social capital through relationships or connections through social networks. The accrual of sufficient social capital and networks is believed to provide individuals with key knowledge that can help them achieve their goals. The concept has been adopted for a number of studies seeking to understand the experience of transfer students (Laanan et al., 2011; Laanan & Jain, 2017; Lukszo & Hayes, 2020; Young & Litzler, 2013). In particular, the transfer student

capital (TSC) conceptual framework has been used to understand how students' accumulated social and networking capital helps them to navigate the complexity of the transfer experience. Applied to this study, we hypothesize that students who simultaneously enroll are more likely to accrue more knowledge related to how to navigate post-secondary educational systems and will acquire a more robust network of contacts that they can rely on for questions and support during their postsecondary career.

Literature Review

Researchers have used a number of labels to describe the wide variety of enrollment patterns postsecondary students exhibit. As enrollment patterns have become increasingly complex in the last 20 years (Goldrick-Rab, 2006), so too have the number of terms used to describe these patterns. The term *swirling* was introduced by Santos and Wright (1990) to describe the general complexity of the nonlinear pathways that postsecondary students exhibit. Such nonlinear patterns include stopping out for a period of time, dropping out of a four-year college and enrolling in a community college for a period of time, or attending multiple institutions simultaneously (Wang & McReady, 2013). In line with one of the primary goals of community college attendance, most research focuses on transfer as the primary form of multi-institution attendance, but few have focused on the distinct forms of simultaneous multi-institution attendance (Bahr, 2012; McCormick, 2003). These alternate enrollment patterns have been referred to as "double-dipping," "co-enrollment," "concurrent enrollment," "overlapping enrollment," or even "dual enrollment" (de los Santos & Wright, 1990; Peter et al., 2005). For the purposes of this paper, we refer to this general pattern of enrollment as *simultaneous enrollment* and describe our operationalization of the term in greater detail below.

Simultaneous Enrollment Patterns

The prevalence of simultaneous enrollment appears to be increasing and a number of studies have examined the relationship between these patterns and student outcomes. However, most of the existing work investigating simultaneous enrollment has grouped distinct forms into one general category, likely due to inadequate data being available to parse out the patterns (Crisp, 2013; de los Santos & Wright, 1990; Gose, 1995; Adelman, 2006; McCormick, 2003). Nonetheless, this past work is a useful point of departure in understanding how these distinct enrollment patterns may affect student outcomes.

Investigations of the impact of simultaneous enrollment on student outcomes have produced varied results. Earlier studies, such as those using data from cohorts like BPS: 96/2001, have generally shown positive effects. For example, McCormick (2003) and Peter et al. (2005) reported that students who engaged in lateral simultaneous enrollment exhibited higher first-year grades after transferring, increased persistence rates, and were more likely to earn a degree. Specifically, Peter et al. found that these students were more likely to persist and obtain a four-year degree compared to their peers who did not simultaneously enroll. On the contrary, Adelman (2006) suggested that simultaneous enrollment might actually decrease the likelihood of earning a bachelor's degree, arguing that a formal transfer from a community college to a university is more beneficial. However, Adelman noted the need for more comprehensive research to clearly define and understand the varied forms and impacts of different enrollment patterns.

Wang and McReady (2013) analyzed the relationship between simultaneous enrollment and persistence/completion with data from the BPS: 04/09 and Postsecondary Education Transcript Study (PETS: 09). Using models that controlled for observable selection into various enrollment patterns, they concluded that simultaneous enrollment did have a significant and

positive relationship with persistence and completion for students, regardless of whether they started at a community college or a 4-year institution. Similarly, Crisp (2013) used propensity score matching to compare observably similar students in the BPS: 04/09, PETS: 09, focusing on students who started at a two-year institution and were of traditional college age (less than 25 years old). She found that simultaneous enrollment was associated with increased odds that a community college student would be successful in earning a degree and/or in persisting through the sixth year of college. Both of these studies generally align with more historical work by McCormick (2003) and Peter et al. (2005) who used prior cohorts, suggesting that the measured patterns are consistent over time.

Forms of Simultaneous Enrollment

To our knowledge, the various distinct patterns of simultaneous enrollment and the potential effects thereof have only been investigated by Wang & Wickersham (2014) using the BPS: 04/09 and PETS: 09 datasets. The authors distinguish two unique simultaneous enrollment patterns: lateral and vertical. Wang and Wickersham further differentiate when students exhibited the pattern (e.g., before transfer, after transfer, or not transferred). Using multinomial logistic regression models to address observable patterns of selection, they found that vertical simultaneous enrollment had a positive and significant relationship with bachelor's attainment and persistence amongst those who started at a 4-year, while lateral had a null relationship for both groups. They explain that these students exhibiting lateral simultaneous enrollment are probably doing so for "exploratory" reasons, meaning they are simply wanting to try out different coursework rather than taking courses that are required for their current program(s) of study. To our knowledge, no prior work has investigated the specific courses that students are likely to take during periods of simultaneous enrollment.

Prior work has taught us much about these patterns, including a sense of their prevalence and estimates of their effects (e.g., Crisp, 2013; Wang & McCready, 2013; Wang & Wickersham, 2014). Since prior work has not provided conclusive findings as to the direction (positive, negative, or even neutral) of the relationship, we believe that our work will help better establish what the direction may be using an additional quasi-experimental approach accounting for the exogeneity of access.

Policies Related to Lateral Simultaneous Enrollment

Very few states have official policies to enable or promote lateral simultaneous enrollment. However, local articulation agreements, formal agreements between institutions that define transfer equivalencies for courses taken at other institutions, likely influence patterns of uptake of simultaneous enrollment (both lateral and vertical) (de los Santos & Sutton, 2012). If, for example, there are established agreements for several courses between a student's home and neighboring institution(s) a student may be more inclined to take courses at a neighboring institution (i.e., transferability). However, if there are unclear agreements and students are unsure how courses will be counted by their home institution, a student may decide against taking courses at the neighboring institution.

Apart from local or state policies, a federal policy which likely has an impact on simultaneous enrollment is financial aid; a student typically can only apply for financial aid at one institution unless the two institutions have an established consortium (Fincher & Cruse, 2019). A student having to pay additional expenses to uptake the pattern may influence their perception of the payoff of the behavior.

Selection into Simultaneous Enrollment Patterns

There is evidence of selection into simultaneous enrollment. For example, male, traditional aged, and financially dependent students are more likely to enroll in multiple institutions (Peter & Forrest Cataldi, 2005; Goldrick-Rab, 2006). This kind of selection complicates efforts to determine effects of each enrollment pattern because unobservable factors that may increase the probability that a student will simultaneously enroll, such as motivation to earn a bachelor's degree, may also similarly influence a downstream outcome like transfer. The limited literature that has examined the relationship between various enrollment patterns and student outcomes has used various analytic approaches to account for selection (Crisp, 2013; Wang & McCready, 2013; Wang & Wickersham, 2014). Many of these approaches (e.g., regression controls or propensity score matching) might not fully account for selection.

One factor which may explain selection into simultaneous enrollment patterns that has received little attention is the geographic distance between institutions (Wang & McReady, 2013; Wang & Wickersham, 2014; Wickersham, 2020).[10] Our work expands the understanding of how physical geographic distance influences such patterns by attempting to measure degrees of access.

Our work extends upon this existing body of literature in three key ways. First, we add to the descriptive knowledge base on the prevalence of simultaneous enrollment by using the most current BPS cohort available. Second, we use an approach which produces credibly causal

[10] Existing studies which used BPS have made efforts to account for geographic distance between where students live and their first school of attendance, but we argue that this measure is inadequate in the context of the current phenomenon. Two different students may live within a similar distance of their first institution, but one may live in an area where there is a high density of colleges available while the other only has one available; we argue that the student who lives near multiple colleges has a higher probability of simultaneously enrolling.

estimates of the effects of simultaneous enrollment on important academic outcomes.[11] Our final contribution is methodological. Using the detailed transcript data available in the PETS data, we increase accuracy and nuance of definitions of simultaneous enrollment.

In this paper we address the following questions:

- Is lateral simultaneous enrollment predictive of eventual degree attainment for community college students?
- Is lateral simultaneous enrollment predictive of transfer for community college students?

Data

In this study we combine restricted-use data from the National Center for Education Statistics Beginning Postsecondary Students Longitudinal Study (BPS:12/17) and student transcript files from the Post-Secondary Education Transcript Study (PETS: 12/17) to form a data set that includes student characteristics, enrollment patterns, and student-level outcomes for a cohort of students who first enrolled in college during the 2011-2012 academic year.

[11] We note that in this work we initially intended to assess the effect of both vertical and lateral patterns. However, because our analytic approach requires a relatively large sample size and vertical simultaneous enrollment is less common, we are only able to estimate the effects of lateral simultaneous enrollment on student outcomes.

Beginning Postsecondary Study:12/17

The BPS:12/17 dataset is a longitudinal study that follows a cohort of first-time college students who first enrolled in college in the 2011-2012 academic year for six-years.[12] Students in the cohort were surveyed every two years. The dataset includes both raw data as well as a number of derived variables computed by NCES researchers. The data provides the degree award outcomes and demographics for each student in the sample.

Post-Secondary Education Transcript Study: 12/17

The PETS: 12/17 data set provides detailed transcript data for the same sample of students included in the BPS:12/17 data set. This data includes granular course level information such as the institution where a course was taken, course title, enrollment dates, and course grade earned. Using the course level detail in the PETS file, we generated the variables describing simultaneous enrollment patterns (the predictor of interest), the transfer achievement outcome, and degree attainment outcomes.

Given the complex and unique enrollment patterns that many students exhibit, we take into account a number of factors when identifying patterns of simultaneous enrollment.

[12] BPS:12/17 is a nationally representative subsample of the 2011-12 National Postsecondary Student Aid Study (NPSAS:12). The original NPSAS: 12 cohort was derived from over 6,670 institutions from the 2008-09 Integrated Postsecondary Education Data System (IPEDS: 2008-09), and final participants were selected with probabilities proportional to size (PPS) using a sequential probability minimum replacement sampling algorithm (Chromy, 1979). However, the initial BPS:12/14 pool of participants included three subsamples of students: (1) first-time NPSAS:12 students who completed the survey, (2) first-time NPSAS:12 students who did not complete the survey, and (3) non-NPSAS:12 first-time students (For more details on sampling methodology, please refer to BPS:12/17 handbook [Bryan et al., 2019]).

Measures

The BPS dataset provides a "co-enrollment" indicator that captures whether a given student had overlapping attendance in two or more institutions. However, this variable is lacking in two key ways. First, the variable does not indicate which types of institutions (e.g., two community colleges or two universities) the student is simultaneously enrolled in. Second, the variable flags periods of simultaneous enrollment that are as short as one month. Because terms at different colleges might overlap (e.g., a spring quarter at one college that overlaps with a summer semester at another college), this variable might flag consecutive periods of enrollment as simultaneous enrollment. While this short period of overlap may be meaningful in its own right, we do not consider short periods of incidental overlap to be simultaneous enrollment for purposes of this study. To better answer our specific research questions, we created more precise measures of simultaneous enrollment that capture periods in which a student is enrolled at multiple institutions during the same academic period.[13]

To differentiate/distinguish whether a student was simultaneously enrolled, we first identified each student's home institution. We defined this as the institution at which a student is taking the majority of their units in a given 5-month period (e.g., January to June or August to December). Based on the identification of a home institution, we then define *lateral simultaneous enrollment* as instances where a student's home institution is a 2-year institution and the student is simultaneously enrolled at another 2-year institution in a given 5-month period. We first create a binary indicator of whether a student exhibited the pattern at least once

[13] The BPS dataset does include a number of imputed transfer outcomes, but we found that these sometimes-reflected simultaneous enrollment as transfer.

during their academic career. This indicator does not reflect the frequency of or at what point in the time frame the students exhibited the pattern, just whether a student engaged in simultaneous enrollment during their postsecondary career.

In this study, we define transfer as ending enrollment at a community college and subsequently beginning enrollment at a university, with or without a gap in enrollment. However, this definition can be complicated to operationalize given the complexity of enrollment patterns. For example, some students may take courses at a four-year institution for a term with the intention of returning to the prior campus immediately after. While this pattern fits a strict definition of transfer, it does not capture permanent transfer. Because explicitly identifying these different patterns is important for this study, we define transfer as occurring when.[14]

1. Student's home institution is a community college in the term prior to switching institutions
2. The receiving institution is a four-year university
3. The student's home institution is a community college for the majority of terms of enrollment prior to switching home institutions
4. The student's home institution is a four-year university for the majority of terms of enrollment after switching home institutions

[14] These criteria were finally decided upon after testing a number of iterations which used less stringent definitions that inevitably yielded similar results. We concluded that these provide the most rigorous criteria and should effectively capture the behavior of interest allowing us to address our current research questions.

The PETS:12/17 transcript files provide detailed information on awards granted to students. Before determining whether a student earned an award, we considered the temporal precedence of simultaneous enrollment, specifically in computing indicators for certificate or Associate's degree attainment. Students may apply and be granted these awards before transferring, so it is possible that they simultaneously enroll after the outcome of interest. Bachelor's attainment, however, is unlikely to be vulnerable to the same problem in that it is typically achieved after transferring.[15]

To explore our research question, we limited our sample to only include those students who ever had a two-year college as a home institution, had pursued either an associate's or bachelor's degree, and whose first institution was within a reasonable commuting distance (further defined in the methodology).[16] This restricted the sample to students for whom our instrument, treatment, and outcome were relevant. While we included certificate achievement as an outcome, we excluded those pursuing a certificate exclusively because certificate programs are often very unique to each school and require fewer units or courses for completion. In addition, schools may require that the majority of units for a certificate be completed in

[15] Another issue that arose in computing transfer is that certain students had no evidence of transferring but somehow earned a bachelor's degree. This is the result of potentially inaccurate transcript records, but given that very few community colleges throughout the nation offer bachelor's degrees during the time frame of interest we are confident in assuming that a CC student must have transferred at some point before earning their bachelor's degree. Ergo, any CC student who has a recorded bachelor's degree is also flagged as having successfully transferring.

[16] The requirement for one's first institution to be within commuting time was implemented in order to ensure that the instruments used are applicable to the current sample.

residence, making it unlikely that taking courses outside of the home campus would satisfy residency requirements for a certificate award.

Analytic Sample

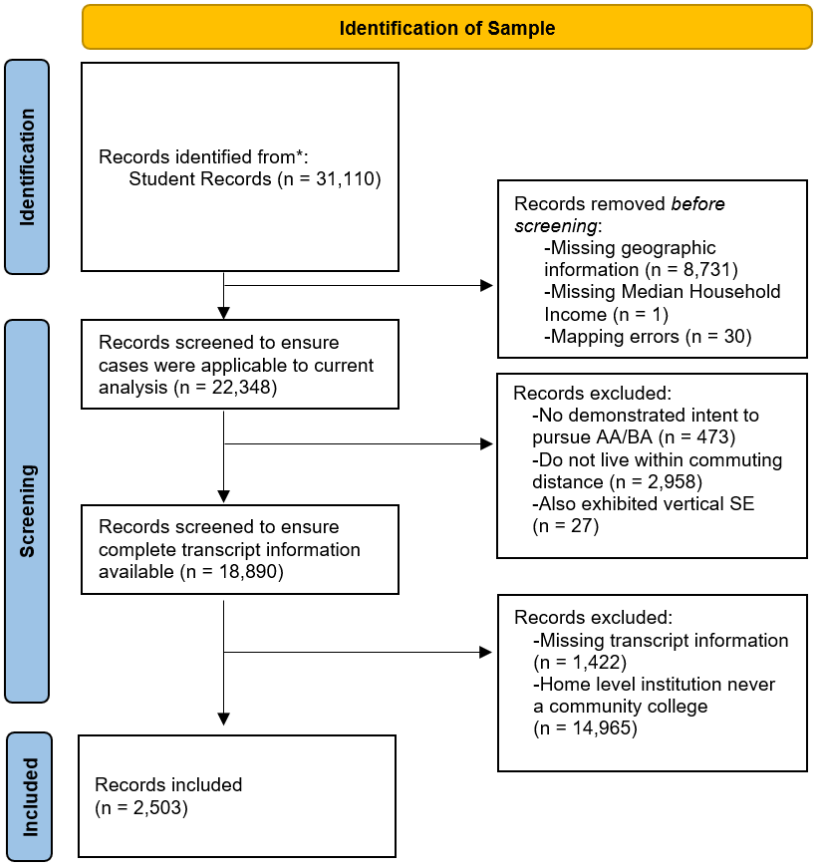
The current analysis only utilizes cases with complete data as provided by the original BPS file (See figure 3.1). The BPS data provided by NCES has already undergone a variety of imputation techniques to maximize completeness of data across the sample.[17] Of the original 6,941 students who met our initial criteria for inclusion (e.g., home campus ever a community college, pursued an associate's or bachelor's), 30 were dropped due to errors with the mapping software used.[18] Only one student was dropped due to missingness of median household income data. Next, as mentioned previously, we restricted the sample to those whose first institution was within commuting distance, reducing the sample by 2,958. The PETS data that was used to impute various crucial indicators (e.g., lateral simultaneous enrollment or transfer) has incomplete records of enrollment for many students. To reduce the chances of students being inaccurately classified as a member of the simultaneous enrollment group, the team decided to

[17] As described in the BPS:12/17 handbook (Bryan et al., 2019, p. 92), the weighted sequential hot deck method was used to replace missing data by imputing values from selected donor cases, also known as stochastic imputation. There are still many cases where the NCES researchers elected not to impute values in cases where there was not adequate data or information to do so; to address this missingness we elected not to impute these fields because of the fact that much of the values used are imputed values themselves.

[18] If a student's first institution of attendance was over an hour drive, they would perhaps be more willing to simultaneously enroll at other institutions within a similar range, and thus our current instruments would under-estimate the students' likelihood to simultaneously enroll. Therefore, we decided it would be invalid to include them in the current analysis.

only include those who had complete enrollment data. The data most likely to be missing is the enrollment dates at a given institution; there may be records of enrollment at a given institution, however, if there is no way to confidently determine their specific period of enrollment, we are concerned that we may inaccurately categorize them as simultaneously enrolled or not. This removed another 1,422 students. Lastly, we wanted to be intentional about isolating the effect of lateral specifically, so we dropped another 27 from the sample who ever vertically simultaneously enrolled, leaving a final total sample of 2,503 students.

Figure 3.1 Identification of Sample from BPS 12:17



As shown in table 3.1, descriptive statistics indicate significant differences between students who laterally simultaneously enrolled and those who did not.[19] There are significant differences in distance to the nearest public community college, distance to the nearest public university, dependency and marital status, and number of institutions accessible. These differences suggest that students who are younger, are married without dependents, and live closer to a public community college or university are more likely to engage in lateral simultaneous enrollment.

Due to these potential differences in group characteristics, it is difficult to interpret differences in outcomes as representative of the effects of lateral simultaneous enrollment (See table 3.2). These differences could be reflecting meaningful student selection into these patterns.

[19] To gauge how well the current data represents the national population, survey weights provided by NCES were applied for the descriptives exclusively. In short, we followed the recommended procedure described by NCES using STATA's "svy" function. Since we are not trying to estimate the effect of simultaneous enrollment for the entire population, we do not apply the weights for any of the subsequent analyses.

Study 3

Table 3.1 Student Demographics by Enrollment Pattern

	Ever Lateral Simultaneously Enrolled		
	No	**Yes**	**P Value**
Age as of Dec 31, 2011	20.9	20.8	$p > 0.05$
Closest Public Community College (Miles)	9.4	6.4	$p < 0.01$
Closest Public University (Miles)	16.6	12	$p < 0.01$
Expected Family Contribution (EFC) ($), Average	6,645.8	6,787.9	$p > 0.05$
Female (%)	51	43	$p < 0.05$
Race/ethnicity (%)			
White	49	37	
Black or African American	16	6	
Hispanic or Latino	26	47	
Asian	5	2	$p > 0.05$
American Indian or Alaska Native	1	0	
Native Hawaiian/other Pacific Islander	1	0	
More than one race	3	9	
Income group 2012 (%)			
Low (1)	28	19	
Low middle (2)	28	29	
High middle (3)	27	24	$p > 0.05$
High (4)	17	28	
Parents' highest education level (%)			
Do not know either parent's education level	5	6	
Did not complete high school	10	20	
High school diploma or equivalent	27	23	
Vocational/technical training	5	2	
Associate's degree	11	3	
Some college but no degree	17	13	$p > 0.05$
Bachelor's degree	14	24	
Master's degree or equivalent	8	9	
Doctoral degree - professional practice	1	1	
Doctoral degree - research/scholarship	1	0	
Grade point average in high school (%)			
Missing	8	3	
0.5-0.9 (D- to D)	0	0	
1.0-1.4 (D to C-)	2	12	
1.5-1.9 (C- to C)	6	4	
2.0-2.4 (C to B-)	20	32	$p > 0.05$
2.5-2.9 (B- to B)	13	8	
3.0-3.4 (B to A-)	35	33	
3.5-4.0 (A- to A)	15	7	
Degree of Urbanization of Student's Permanent Address, 2011-2012 (%)			
Missing	2	0	
City	41	52	
Suburb	40	39	$p > 0.05$
Town	6	7	
Rural	11	1	
Type of high school attended (%)			
Not applicable/Missing	11	15	
Public	81	82	
Private	4	0	$p > 0.05$
Attended a foreign high school	2	2	
Home schooled	2	1	
Dependency and Marital Status, 2011-12			
Dependent	72	75	
Independent, no dependents, unmarried/separated	11	5	
Independent, no dependents, married	2	13	$p < 0.05$
Independent, with dependents, unmarried/separated	9	4	
Independent, with dependents, married	5	3	
U.S. Citizen	92	96	$p > 0.05$
n	2,437	66	
Population Size	591,768	13,579	

Note. Continuous variable differences estimated using independent sample T-test; Categorical variable differences reflect F-statistic

Table 3.2 Weighted Outcomes by Enrollment Pattern

	Ever Lateral Simultaneously Enrolled		
	No	**Yes**	**Difference**
Outcomes, Success Rates (%)			
Certificate	11.2	23.4	12.1
Associate degree	24.9	24.2	-0.7
Transfer to 4-Year Institution	18.6	34.7	16.1*
Bachelor's Degree	12.9	13.4	0.5
n	2,437	66	
Population Size	591,768	13,579	

Note. Outcome rates reported are computed using survey weights. * $p < .05$, ** $p < .01$

Identification Strategy: Access

To estimate the causal effects of simultaneous enrollment on student outcomes, we employ an identification strategy leveraging plausibly exogenous variation in access to simultaneous enrollment. Specifically, we create measures of the number of colleges within a reasonable distance for commuting, and thus at which they could simultaneously enroll, for each student in our sample. The BPS dataset includes a set of geographic information for each student, including the census tract in which their permanent residence is located. To compute a measure of access, we merged navigation data for each census tract with all postsecondary institutions as captured by the Integrated Postsecondary Education Data System. Using the HERE Matrix Routing API (V8), we computed the fastest drive time, without traffic, and distance between each census tract centroid (geographic center) and each college (e.g., community college or university) within 100 geodetic miles.[20]

[20] Due to financial costs of the HERE vendor, the restriction of 100 geodetic miles was necessary to reduce the number of pairs to what is likely a more than generous range that an individual would likely be comfortable driving for school.

The last step in defining access was creating a measure of how many colleges or universities are within a certain time or distance from a student's permanent residence (described in more depth below).[21] We obtained average commute time for each census tract represented in our sample from the American Community Survey (2017). We use the upper bound of the 90% margin of error around the average commute time within census tract as more than 90% of individuals in that tract are comfortable commuting that time for work. This measure, which ranges from 12 to 71 minutes with an average of 30.7 minutes, provides a sense of the expectations and tolerance for traffic and commutes in a given area. As a robustness check, we also generated a measure of the number of institutions within a 30-minute drive time of one's census tract centroid.

Methodology

'Naive' Analysis

We first examined raw differences in degree outcomes between students who simultaneously enrolled and those who did not without controlling for any background characteristics (Equation 1).

$$Y_i = \alpha_0 + \beta_1 LateralSimEnr_{is} + \epsilon_i \quad (1)$$

In which Y_i is out outcome of interest (e.g., transferring, earning a bachelor's degree) for student *i* and $LateralSimEnr_i$ is a binary variable indicating if student *i* ever simultaneously enrolled in

[21] Since only an estimated one percent of community college students live on campus (AACC, 2016) we are confident in assuming that students are generally commuting from their listed primary residence.

two community colleges. In this model, β_1 is the estimated relationship of ever laterally simultaneously enrolling and our outcomes of interest.

Prior work (Crisp, 2013) highlights the need to account for student selection into simultaneous enrollment, as students whose backgrounds predict better outcomes (e.g., gender, race, age, and income) are more likely to select into simultaneous enrollment (Goldrick-Rab, 2006). We take a first step in accounting for potential selection biases by including a vector of student-level characteristics (X_i in Equation 2 below). Included in this vector are binary indicator variables for female gender identity, race and ethnicity, income groups, highest education level, high school grade point average categories, type of high school attended (e.g., public or private), dependency and marital status, urbanicity of census tract, and citizenship status (See appendix K). These variables control for factors that are likely related both to a student's probability of simultaneous enrolling and to their potential outcome. We also include controls for the distance to the nearest public community college and the nearest public four-year college. Comparing students who live a similar distance from a community college and university is helpful in addressing the concern that families that value higher education might live closer to colleges. We view this as a conservative approach, as past research suggests that families likely do not take community college locations into consideration when deciding where to live (Jepsen & Montgomery, 2009). We address this further in the section below in which we describe our analytic approach.

Because state higher education policies and practices are likely correlated both with a student's probability of simultaneous enrollment and their outcomes, we also include a vector of state-of-residence fixed effects (θ_s).[22]

$$Y_{is} = \alpha_0 + \beta_1 LateralSimEnr_{is} + X_{is} + \theta_s + \epsilon_{is} \quad (2)$$

β_1 is the coefficient of interest and presents the estimated relationship of ever simultaneously enrolling with our outcomes of interest, controlling for a range of observable student and geographic characteristics that we think might be correlated with both simultaneous enrollment and our outcomes.

Opportunity & Selection

Students, by virtue of where they live, have varying degrees of geographic access to post-secondary institutions. Some students may live in areas where they have multiple institutions within what they consider a reasonable distance, while others may live in an area where there are only one or no institutions in a commutable range (Hillman, 2016; Frenette, 2006). The number of schools a student has access to within this distance likely affects their probability of simultaneous enrollment. This exogenous source of variation may help to explain why students opt in or out of the pattern.

Others researchers, in education and economics, have recognized the potential of geographic variation in access and have used distance as an instrumental variable (IV) to estimate the causal effect of an educational treatment or intervention. Distance to college has been used a number of times as an instrument to estimate the returns to a college education (e.g.,

[22] Ideally, one would use more granular location fixed effects, such as county of residence, but this data set does not have adequate sample sizes to support such analyses.

Card, 1995; Dee, 2003; Liu, 2021; Long & Kurlaender, 2008; Xu & Jaggers, 2013). The basic logic supporting this method is that the proximity of colleges should affect outcomes by inducing higher enrollment rates due to a reduced costs of attendance and should not affect outcomes via any other channels. Dee (2003) used distance-to-college as an instrument in examining whether educational attainment had an effect on adult civic engagement and attitudes. He found a strong first stage, that geographic availability predicts the uptake of educational opportunities, and that additional schooling increased civic knowledge.

Liu (2021) similarly used variation in geographic access to investigate whether the specific enrollment pattern of reverse transfer (transfer from a four- to a two-year college) affects academic and employment outcomes. She leveraged variable access to community colleges and used distance to two-year colleges as an instrumental variable. She found a strong first stage result (having closer access to a community college is strongly predictive of reverse transfer), and that being induced to reverse transfer has a positive effect on both academic and employment outcomes for some groups of students.

In this study we build on this past work by leveraging the fact that geographic proximity is strongly predictive of college enrollment (Hillman, 2016; Jepsen & Montgomery, 2009; Turley, 2009). We extend prior work examining any college enrollment to examine the effects simultaneous enrollment. Specifically, we test the hypothesis that students who have greater access to multiple institutions are more likely to laterally simultaneously enroll and that this increased probability of lateral simultaneous enrollment is associated with better outcomes for these students.

To achieve this, we use the number of public colleges within a reasonable commute time (defined as either 30 minutes or the average commute time in a census tract) as our instrument.

We include only public colleges because prior research has found that students who enroll in multiple institutions largely do so at public institutions (National Student Clearinghouse Research Center, 2011).[23] The distribution of this measure of access to colleges is wide, with a mean around four and a standard deviation just above four (See table 3.3 & figure 3.2).

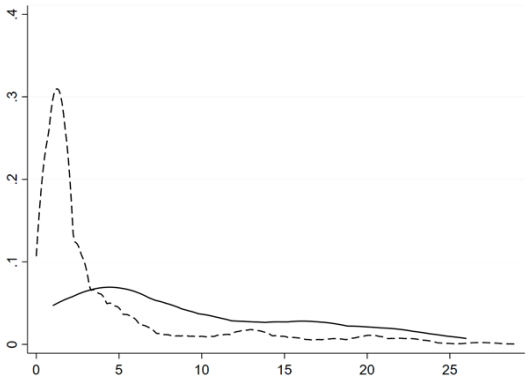
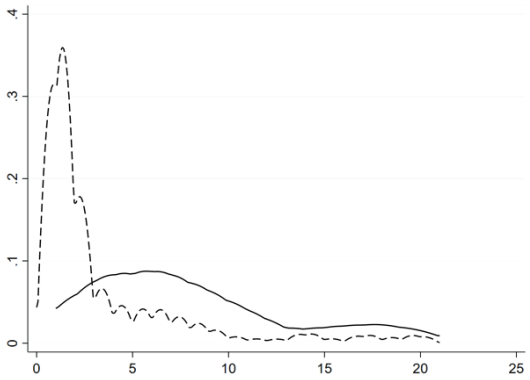
Table 3.3 Descriptives of Instruments

	Ever Lateral Simultaneously Enrolled		
Instrument	**No**	**Yes**	**Difference**
Number of Public Community Colleges, Within Commuting Time	4.0	8.1	4.1**
Number of Public Community Colleges, Within 30 Minute Drive Time	3.2	7.3	4.1**

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

[23] As a robustness check, we compared access to private institutions, and confirmed that public was consistently stronger.

Figure 3.1 Kernel Density Charts of Access to Institutions by Lateral Simultaneous Enrollment Status

Type of Access	Public Community Colleges
Commuting Distance	
30 Minute Drive Time	

Note. Dashed Line: Students who lateral simultaneously enrolled. Solid line: Students who did not lateral simultaneously enroll.

The kernel density diagrams showcase the general distribution of access to institutions under certain parameters and whether ever lateral simultaneously enrolled.

Because a student only needs one additional college to simultaneously enroll, the probability of simultaneously enrolling is not likely to increase linearly with the number of available institutions. To examine this, we created two versions of the access variable: a linear capped variation and a dummy coded variation. The linear capped variable assigns a value of how many institutions are within commuting distance and caps at four or more institutions (e.g., if a student has 10 institutions within commuting distance, they will be coded with a value of 4). The dummy code variation creates a vector of binary variables indicating whether a student has

zero, one, two, three, or four or more institutions available to them within a given proximity (e.g., if a student has two institutions within commuting distance, they will have a value of 1 recorded for the corresponding variable and 0 for the others).

We employ a two-stage least squares approach as a means of systematically carving out exogenous variation in the potentially endogenous predictor (simultaneous enrollment) to estimate a Local Average Treatment Effect (LATE). Specifically, in the first stage we predict simultaneous enrollment using our instrument, geographic access.

$$\text{1st Stage: } \hat{X}_{1is} = \alpha_0 + \alpha_1 I_{is} + \alpha_2 X_{2is} \ldots_+ \delta_i$$

We estimate this first stage with the various forms of instruments (*I*) mentioned earlier (linear capped version and vector of dummy variables) to ensure that the analytic decisions are not driving results.

In the second stage, we predict outcomes of interest (degree attainment or transfer) using the predicted value of simultaneous enrollment ($\hat{X}$) from the first stage, the vector of student-level characteristics and the state fixed effects.

$$\text{2nd Stage: } Y_{is} = \beta_0 + \beta_1 \hat{X}_{is} + \beta_2 X_{2is} \ldots. + \varepsilon_i$$

This model should provide a plausibly causal estimate of the effect of lateral simultaneous enrollment on the educational outcomes of interest.[24]

[24] We note that our outcomes of interest (transferring, earning a bachelor's degree) are binary variables, and while the linear probability model we employ above is relatively easy to interpret, it can produce estimated probabilities that are not bounded between 0 and 1 and error terms that are not normally distributed. To address these concerns, we also employ a probit estimator.

$$\Pr(Y_i = 1 | SE_{is}, X_{is}) = \beta_0 + \beta_{1i} + \beta_2 X_{2is} \ldots. + \varepsilon_i$$

This approach yields estimates that are qualitatively similar to our main models. We discuss this strategy and present the results in Appendix B.

Necessary Assumptions

For the estimates from our IV approach to approximate the causal effect of simultaneous enrollment on outcomes, the instrument must satisfy five specific assumptions (Cunningham, 2021). These assumptions stipulate that the instrument (access to schools at which a student could simultaneously enroll) should (1) be related to our endogenous variable (simultaneous enrollment), (2) be as good as randomly assigned (ignorability), (3) have no impact on any outcomes except through the exogenous variable (exclusion restriction), (4) meet the stable unit treatment values assumption (SUTVA), and (5) affects the endogenous predictor (lateral simultaneous enrollment) in the same direction for everyone (monotonicity).

The first stage of the IV method explores whether an instrument is related to our endogenous variable (assumption 1). In our case, this entails examining the extent to which geographic access (how many additional colleges are within a reasonable commuting distance) explains students' uptake of simultaneous enrollment. If the instrument does not adequately explain variation in the endogenous regressor, the IV approach will yield biased results. Lateral simultaneous enrollment is positively and significantly correlated with both the number of public community colleges within a 30-minute drive, $r(2,727) = .16$, $p < .01$, and the number within commuting time, $r(2,727) = .13$, $p < .01$.

The ignorability assumption has been a primary concern in using distance as an IV in education research. As individuals and families who place a higher value on education might choose to live closer to a postsecondary campus, the concern is that distance to a college is not as good as randomly assigned (Card, 1995; Long & Kurlaender, 2008; Rouse, 1995; Xu & Jaggars, 2014). However, we note that this is likely less of a concern in this context than in studies that have used distance to a four-year school as an instrument, as there is no strong evidence that

families select where they live based on proximity to community colleges and even more unlikely that an individual would decide where to live based on the density of community colleges in an area. To partially address this potential concern, we include a control for the distance to the nearest public community college.

To further explore whether there is evidence that the assignment of schools to simultaneously enroll in is not "ignorable", we examine if student observable characteristics are related to community college availability. Specifically, we predict our instrument (number of commutable colleges) using our vector of student-level covariates while controlling for geographic characteristics (state of residence, urbanicity, and distance to nearest community college and university). Doing so allows us to estimate the relationship between variables that are potential proxies of a family's estimated value of education (e.g., socioeconomic status, parental education) and our instruments, while holding all other covariates constant. The resulting model for the commuting distance instrument (but not 30-minute instrument) does jointly predict our instrument ($F = 26.76$, $p < .01$). While initially this might seem concerning, none of the variables of concern (median household income, expected family contribution, or parental education) are significant.

It is notoriously difficult to fully test the exclusion restriction, which stipulates that our instrument only affects the outcomes through our predictor of interest (that is, the goal is to rule out if there are mechanisms, other than simultaneous enrollment, by which access to multiple colleges could affect academic outcomes). One potential is that if there are more community colleges within a given area, it's arguably more likely that a four-year will work on transfer policies and have more transfer staff available. We argue though that most transfer policies in effect are at the state level, so the density in a given area shouldn't affect transfer policies more

broadly. Another possible concern is that if there are more community colleges in an area, they may have a greater degree of collaboration with one another, or even share resources. We believe that this is very unlikely, given that most community colleges, especially public, probably do not have superfluous resources to provide to students from other institutions. Based on our understanding of community college policies we are not greatly concerned about these threats.

The SUTVA assumption states that the outcomes of student *j* should not be affected by the treatment status of student *i*, a particularly difficult assumption to empirically rule out. Peer effects are always a consideration in education research; students are often affected by the experiences and dispositions of their peers. These potential influences are difficult for us to definitively prove or disprove with the given national sample data, but we find it unlikely that violations of SUTVA could drive results for two reasons. First, because treatment is defined geographically, students at the same community college will have similar access to treatment. We wouldn't expect students to affect the outcomes of other students beyond typical peer effects. Second, simultaneous enrollment is relatively uncommon, so the potential for such spillover is relatively low.

Monotonicity states that there should be no defiers—individuals for whom treatment assignment works in the exact opposite direction (students who do not simultaneously enroll because they have greater access or vice versa). Monotonicity is difficult to prove or disprove, but it is difficult to imagine a scenario in which this would be the case in the current study.

Results

The naive comparisons indicate that students who exhibited patterns of lateral simultaneous enrollment have no significant difference in associate's or bachelor's degree achievement but significantly higher rates of certificate achievement and transfer (See table 3.4).

Model 1 results indicate that the associate's degree ($\beta = .04$, $p > .05$) and bachelor's degree ($\beta = .01$, $p > .05$) success rates of those who laterally simultaneously enrolled were greater by one to four percentage points, though these differences are not statistically significant. Conversely, certificate ($\beta = .09$, $p < .05$) and transfer ($\beta = .16$, $p < .05$) achievement rates differences are positive and significant with simultaneous enrollment students having a nine-percentage point higher probability of earning a certificate and 16-percentage point higher probability of transferring.

Table 3.4 Relationship of Lateral Simultaneous Enrollment Predictor with Academic Outcomes, OLS Models

	Certificate		Associate's		Transfer		Bachelor's	
Model	1	2	1	2	1	2	1	2
Lateral Simultaneous Enrollment	0.09* (0.04)	0.10** (0.04)	0.04 (0.05)	0.03 (0.05)	0.16** (0.05)	0.14** (0.05)	0.01 (0.04)	-0.01 (0.04)
Comparison group mean	13.8	13.8	25.5	25.5	20.1	20.1	12.2	12.2
Controls Included		Yes		Yes		Yes		Yes
State Fixed-Effects		Yes		Yes		Yes		Yes
Observations, n	2,503							

Note. Coefficients reported are generated using models without survey weights applied. Model 1 is only inclusive of the simultaneous enrollment predictor. Controls included in Model 2: Age, Closest Public Community College, Closest Public University, Expected Family Contribution, Female, Race/ethnicity, Income group, Parental Education, High School GPA, Type of High School Attended, Citizenship, Urbanization of permanent address, and state fixed-effects. Comparison group means reported are unweighted.

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

Standard errors in parentheses

Model 2, the multivariate OLS regression model that controls for rich student-level characteristics and state fixed-effects, also shows that students who have laterally simultaneously enrolled do not have a significant difference in associate's degree (β = .03, p > .05) and bachelor's degree achievement (β = -.01, p > .05). Consistent with model 1, there is a positive significant difference in terms of certificate (β = .10, p < .05) and transfer (β = .14, p < .05) achievement controlling for a variety of characteristics.

Tables 3.5 and 3.6 present the two-stage IV models examining the effect of lateral simultaneous enrollment on outcomes. As shown in Table 3.5, the strength of the first stage models were inconsistent between instruments, with the linear capped instrument stronger than the vector of dummy variables for both the commuting distance and 30-minute drive time instruments. For the linear-capped commute time instrument, the coefficient on the instrument in the first stage was significant and positive (β = 0.01, p < .01), and the F-statistic of the excluded instrument (F = 20.85, p < .01) indicates that the instrument is not weak.[25] The dummy coded variation did have significant and positive coefficients for two (β = 0.04, p < .01), three (β = 0.05, p < .01), and four or more additional (β = 0.04, p < .01) coefficients, but the joint F-statistic indicated that the instrument is potentially weak (F = 5.89, p < .01). Likewise, the access to institutions within 30-minutes capped instrument had a relatively strong first stage with a positive and significant coefficient (β = 0.02, p < .01) and relatively strong F-statistic (F = 28.01, p < .01). The dummy coded iteration was again weaker (F = 8.65, p < .01). The second stage

[25] Stock, Wright, & Yogo (2002) provide a general rule of thumb for estimating the strength of instruments in models using one instrument. They indicate that an instrumental variable is considered weak if the F-Statistic against the null hypothesis is less than 10.

Table 3.5 Results of First-Stage IV Regressions: Probability of Lateral Simultaneous Enrollment

Measure of Access	Instrumentation Type	1	2
Commute Time	# of Community Colleges, Linear Capped	0.01**	
		(0.00)	
	# of Community Colleges, Dummy Coded		
	One additional		0.01
			(0.01)
	Two additional		0.04**
			(0.01)
	Three additional		0.05**
			(0.01)
	Four or more additional		0.04**
			(0.01)
	F-test on excluded instruments	20.85	5.89
	Prob>F	<0.001	<0.001
30 Minutes Driving	# of Community Colleges, Linear Capped	0.02**	
		(0.00)	
	# of Community Colleges, Dummy Coded		
	One additional		0.00
			(0.01)
	Two additional		0.02
			(0.01)
	Three additional		0.07**
			(0.01)
	Four or more additional		0.05**
			(0.01)
	F-test on excluded instruments	28.01	8.65
	Prob>F	<0.001	<0.001

Note. Number of observations for each model is 2,503. * $p < .05$, ** $p < .01$

Table 3.6 Instrumental Variable Estimation, Second Stage Results

Measure of Access	Instrumentation Type	Certificate	Associate's	Transfer	Bachelor's
30 minutes Driving	# of Community Colleges, Linear Capped	0.63	-0.17	1.25**	0.94*
		(0.39)	(0.48)	(0.47)	(0.40)
	# of Community Colleges, Dummy Coded	0.45	-0.33	0.96*	0.85*
		(0.35)	(0.44)	(0.42)	(0.36)
Commute Time	# of Community Colleges, Linear Capped	0.19	-0.28	1.61**	1.16*
		(0.44)	(0.55)	(0.58)	(0.48)

Note. Number of observations for each model is 2,503. All models are inclusive of controls and fixed effects. Results with weak first stages are not reported.

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

Standard errors in parentheses

results reported below only include the linear version of the instrument (for both a 30-minute drive and local average commuting distance) because of their comparative strength.

The second stage results shown in table 3.6 indicate that the instrumented predictor of interest, lateral simultaneous enrollment, has mixed relationships with our outcomes of interest. The model using the measure of access to institutions within average commuting time finds that lateral simultaneous enrollment does not have a significant relationship with certificate ($\beta = 0.12$, $p > 0.05$) or associate's ($\beta = -0.00$, $p > 0.05$) attainment. However, the same model finds that lateral simultaneous enrollment has a positive and significant effect on transfer ($\beta = 1.48$, $p < .01$) and bachelor's achievement ($\beta = 1.28$, $p < 0.05$). Robustness checks in which we use measures of access to community colleges within 30 minutes finds similar patterns, with the relationship with transfer ($\beta = 1.30$, $p < .01$) and bachelor's achievement ($\beta = 0.91$, $p < 0.05$) being positive and significant. As mentioned previously, the interpretation of the coefficients yielded is potentially problematic, in that the predictor and outcomes of interest are discrete. The reported values indicate that in some cases a student is more than 100% likely to achieve a given outcome if they laterally simultaneously enroll. For this reason, we also estimated the same models using a probit function and found a similar result (See Appendix L).

Discussion

Our naive estimates suggest that lateral simultaneous enrollment has a positive relationship with important academic outcomes among community college students. Even after controlling for a variety of demographics, prior academic characteristics, geographic characteristics, and state fixed effects, students who laterally simultaneously enrolled during their academic career have a higher likelihood of achieving a certificate or of transferring than those who did not laterally simultaneously enroll. These findings extend the only prior work

(Wang & Wickersham, 2014) investigating the impact of lateral simultaneous enrollment, which found that simultaneous enrollment had a positive, but non-significant relationship with academic outcomes.

The subsequent instrumental variable models further substantiated these naive estimates. The first stage of the IV models found that access to institutions explains uptake of lateral simultaneous enrollment. Both forms of access, number of colleges within 30-minutes and with the local average commuting time, predicted uptake of simultaneous enrollment. The second stage results provide evidence that the enrollment pattern has a strong positive effect on transfer and bachelor's attainment. The fact that the certificate and associate's achievement models demonstrate no relationship with simultaneous enrollment indicates that the enrollment pattern does not have a positive or negative effect, on average. We are not necessarily surprised to see this lack of a relationship, because it may be the case that many students who exhibited simultaneous enrollment only exhibited the pattern after they had already earned the award (i.e., Associate's). Our indicators of certificate or Associate's achievement do not account for the timing of the behavior because students can apply for awards at any time, potentially several terms after they have met the criteria for completion. In other words, a student could have simultaneously enrolled subsequent to completing the required coursework and then applied for the award prior to departing from the school.

Limitations

While the national dataset provided by NCES is robust, there are still some notable limitations to keep in mind when interpreting the findings. The transcript records do not identify whether a course was taken online or in-person. The availability of online courses could change the degree to which proximity plays a role in a student's decision to simultaneously enroll,

weakening our instrument. Unfortunately, there is nothing that can be done to address this concern with the current data but hopefully future BPS cohort data will include a course delivery categorization.

The two-stage least squares approach has some limitations that are also worth highlighting. For one, the first stage of the model can reduce variation in the predictor. As a result, the second stage estimates higher standard errors than the corresponding standard error would be in a typical OLS model. While we may be confident in the direction of the estimates, the effect may lack precision. Our hope is that future national datasets will allow for a greater sample size to limit this concern.

Our access instruments are not as precise as we would like because we are not able to use each student's address. The BPS file includes the ZIP code and census tract of the primary address for each student, but we chose to use the census tract centroid since census tracts are known to be more specific geographic values as there are approximately 50% more census tracts than zip codes (UCF, 2023). Even still, the census tract centroids are not as precise as an individual's address so it does introduce some noise into our measures.

Future Directions

Future researchers could investigate the policies regarding simultaneous enrollment across the country. The current analysis fails to adequately capture or account for the fact that certain states or municipalities may have policies that enable and/or promote some form of simultaneous enrollment. The fixed-effects included may have addressed this to some degree, but we feel that this investigation of policies will allow us to incorporate a more precise measure of available policies and will provide a great contribution to the field in terms of a descriptive understanding of what's happening across the nation.

We also recommend that future work attempts to understand what specific mechanisms may explain these relationships. The pathway selection framework suggests it could be that students who are aware through counseling, friends, faculty, or otherwise are partaking because of the anticipated benefits, or payoff. Our results suggest that there will be a long-term payoff to students in terms of degree completion, but it is unclear whether the mechanisms at work involve the transferability of coursework reducing time to degree, the exposure to social capital or skills while taking classes at other campuses, or if simultaneous enrollment improves knowledge and skills related to the institutional and logistical pathways that lead to degree completion. There is an opportunity for future work to explore these mechanisms.

There may also be a dosage effect related to the frequency of simultaneous enrollment that may influence student outcomes, or differential effects based on course type and content. Future efforts should delve further into these questions with granular level transcript data, and extend the work by parsing out the frequency of various distinct patterns of enrollment patterns, what courses are being taken, and what the eventual outcomes are for these students. This will provide practical findings for policy makers in exploring ways they can promote academic achievement on their campuses.

Further research and exploration should validate and build on these findings, but regardless we suggest that practitioners explore the practice and whether there are ways to increase participation among students.

CHAPTER 4: Summary Of Findings

The analysis of the three community college practices in this dissertation highlights promising outcomes of some, limited success of others, and areas for further exploration. The findings suggest that participation in EOPS is associated with improved academic performance, particularly in GPA, yet presents mixed results in more long-term outcomes such as transfer and bachelor's degree attainment. The embedded tutoring evaluation indicates that the program did not yield significant effects on course pass rates or retention in either subject, raising questions about its efficacy in its current form. I argue that future iterations of such programs would benefit from greater alignment between faculty and tutors, and researchers could reach more definitive conclusions about their efficacy with more detailed, granular data. The investigation into lateral simultaneous enrollment among community college students suggests potential academic benefits, though the study is limited by sample size and warrants further research to fully understand its impact. Overall, these findings provide valuable insights for policymakers, administrators, researchers, and practitioners seeking to enhance educational outcomes through targeted interventions and support services within community colleges.

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Appendix

APPENDIX A: Operationalization of Outcomes

Appendix A. Operationalization of Outcomes

Outcome	Definition	Data Source	Data Type
Completion of Transfer-Level Math/English in 1st year	Grade of A/B/C/Passing earned in an English/Math course that meets minimum requirements for UC/CSU transfer requirements within first academic year the student enrolled.	District Data	Boolean [0,1]
Grade Point Average at the end of 2nd or 4th Year	Computed grade point average earned as of the end of their 2nd or 4th year at the college.	District Data	Float [0.0-4.0]
Certificate/Associate in 2 or 4 Years	Completion of a certificate or Associate degree within first 2 or 4 years of enrollment.	District Data	Boolean [0,1]
Transfer in 2 or 4 Years	Enrollment in a 4-year institution within 6 months after the end of their second of fourth year of enrollment.	District Data & National Student Clearinghouse	Boolean [0,1]
Bachelor's Degree	Successful attainment of a bachelor's degree at any point after enrollment.	District Data & National Student Clearinghouse	Boolean [0,1]

APPENDIX B. Logit Weights, Balancing Output

Appendix B. Logit Weights, Balancing Output

	unw.tx.mn	unw.tx.sd	unw.ct.mn	unw.ct.sd	unw.std.eff.sz	unw.stat	unw.p	unw.ks	unw.ks.pval	tx.mn	tx.sd	ct.mn	ct.sd	std.eff.sz	stat	p	ks	ks.pval
cohort:2010	0.07	0.26	0.08	0.27	-0.04	2.07	0.05	0.01	0.05	0.07	0.26	0.07	0.26	0	0.02	1	0	1
cohort:2011	0.13	0.33	0.14	0.35	-0.04	NA	NA	0.01	0.05	0.13	0.33	0.12	0.33	0.01	NA	NA	0	1
cohort:2012	0.13	0.33	0.15	0.35	-0.06	NA	NA	0.02	0.05	0.13	0.33	0.13	0.33	0	NA	NA	0	1
cohort:2013	0.15	0.36	0.16	0.36	-0.01	NA	NA	0	0.05	0.15	0.36	0.15	0.36	0	NA	NA	0	1
cohort:2014	0.17	0.38	0.17	0.38	0	NA	NA	0	0.05	0.17	0.38	0.17	0.38	0	NA	NA	0	1
cohort:2015	0.18	0.38	0.15	0.36	0.06	NA	NA	0.02	0.05	0.18	0.38	0.17	0.38	0	NA	NA	0	1
cohort:2016	0.17	0.38	0.15	0.36	0.06	NA	NA	0.02	0.05	0.17	0.38	0.18	0.38	-0.01	NA	NA	0	1
female	0.59	0.49	0.5	0.5	0.17	5.64	0	0.09	0	0.59	0.49	0.59	0.49	0	-0.01	0.99	0	1
fosteryouth	0.04	0.2	0.01	0.11	0.15	5.15	0	0.03	0.28	0.04	0.2	0.04	0.2	0.01	0.24	0.81	0	1
firstgen	0.32	0.47	0.22	0.42	0.21	7.06	0	0.1	0	0.32	0.47	0.32	0.47	0	-0.05	0.96	0	1
ethnicity:American Indian or Alaska Native	0	0.04	0	0.05	-0.01	18.99	0	0	0	0	0.04	0	0.04	0	0.08	1	0	1
ethnicity:Asian	0.11	0.31	0.14	0.35	-0.1	NA	NA	0.03	0	0.11	0.31	0.11	0.32	-0.01	NA	NA	0	1
ethnicity:Black or African American	0.05	0.21	0.02	0.16	0.11	NA	NA	0.02	0	0.05	0.21	0.05	0.21	0	NA	NA	0	1
ethnicity:Hispanic / Latino	0.56	0.5	0.41	0.49	0.3	NA	NA	0.15	0	0.56	0.5	0.57	0.5	-0.01	NA	NA	0.01	1
ethnicity:Native Hawaiian or Pacific Islander	0	0.03	0	0.05	-0.06	NA	NA	0	0	0	0.03	0	0.03	0	NA	NA	0	1
ethnicity:Two or More Races	0.03	0.17	0.05	0.22	-0.14	NA	NA	0.02	0	0.03	0.17	0.03	0.17	0.01	NA	NA	0	1
ethnicity:Unreported or Unknown	0.01	0.11	0.01	0.11	0	NA	NA	0	0	0.01	0.11	0.01	0.11	0	NA	NA	0	1
ethnicity:White	0.24	0.43	0.35	0.48	-0.26	NA	NA	0.11	0	0.24	0.43	0.23	0.42	0.02	NA	NA	0.01	1
dsps	0.12	0.32	0.07	0.25	0.16	5.42	0	0.05	0.01	0.12	0.32	0.12	0.32	0.01	0.22	0.83	0	1
esl	0.08	0.27	0.02	0.13	0.22	7.57	0	0.06	0	0.08	0.27	0.08	0.27	0	0.02	0.99	0	1
latestedgoalgroup:Career	0.06	0.23	0.06	0.23	0	0.14	0.99	0	0.99	0.06	0.23	0.06	0.23	0	0.02	1	0	1
latestedgoalgroup:Degree or Certificate	0.08	0.27	0.09	0.28	-0.01	NA	NA	0	0.99	0.08	0.27	0.08	0.28	0	NA	NA	0	1
latestedgoalgroup:GED/Basic Skills	0.01	0.11	0.01	0.11	0	NA	NA	0	0.99	0.01	0.11	0.01	0.12	-0.01	NA	NA	0	1
latestedgoalgroup:Personal Development	0.03	0.18	0.03	0.17	0.02	NA	NA	0	0.99	0.03	0.18	0.03	0.18	0	NA	NA	0	1

Appendix

latestedgoalgroup:Transfer	0.77	0.42	0.77	0.42	0.01	NA	NA	0	0.99	0.77	0.42	0.77	0.42	0.01	NA	NA	0	1
latestedgoalgroup:Undecided	0.04	0.2	0.05	0.21	-0.01	NA	NA	0	0.99	0.04	0.2	0.04	0.21	0	NA	NA	0	1
latestedgoalgroup:Vocational Certificate/Transfer	0	0.04	0	0.04	0	NA	NA	0	0.99	0	0.04	0	0.04	0	NA	NA	0	1
finaidever	0.99	0.08	0.99	0.1	0.06	1.83	0.07	0	1	0.99	0.08	0.99	0.07	0	-0.13	0.9	0	1
Poppy college	0.55	0.5	0.41	0.49	0.27	8.92	0	0.14	0	0.55	0.5	0.54	0.5	0.01	0.43	0.67	0.01	1
finalhsgpa	2.61	0.65	2.66	0.63	-0.08	-2.72	0.01	0.06	0	2.61	0.65	2.61	0.64	0	0.07	0.94	0.02	0.68
age	18.36	2.48	18.11	1.51	0.1	3.38	0	0.04	0.04	18.36	2.48	18.37	2.67	0	-0.11	0.91	0.03	0.23

Note. The table shown is a standard balance table produced in R. All columns were included for any curious parties.

APPENDIX C. Demographics by EOPS Participation, Matched Sample

Demographic	Non-EOPS	EOPS	Std. Mean Difference
Age (mean)	17.8	17.8	0.0
Cohort (%)			0.0
2010	6.7	6.7	0.0
2011	13.3	13.3	0.0
2012	11.7	11.7	0.0
2013	16	16	0.0
2014	16.9	16.9	0.0
2015	17.1	17.1	0.0
2016	18.2	18.2	0.0
Female (%)	60.7	60.7	0.0
Foster Youth (%)	0	0	0.0
First Generation (%)	30.6	30.6	0.0
Ethnicity (%)			0.0
American Indian or Alaska Native	0	0	0.0
Asian	9.8	9.8	0.0
Black or African American	1.7	1.7	0.0
Hispanic / Latino	66.5	66.5	0.0
Native Hawaiian or Pacific Islander	0	0	0.0
Two or More Races	1	1	0.0
Unreported or Unknown	0	0	0.0
White	21.2	21.2	0.0
Disabled Student Programs and Services (DSPS) (%)	3.8	3.8	0.0
English as a Second Language (%)	2.5	2.5	0.0
Latest Educational Goal, Group (%)			0.0
Career	2.5	2.5	0.0
Degree or Certificate	3.8	3.8	0.0
GED/Basic Skills	0	0	0.0
Personal Development	1	1	0.0
Transfer	91.2	91.2	0.0
Undecided	1	1	0.0
Vocational Certificate/Transfer	0	0	0.0
Financial Aid Recipient (%)	99	99.4	0.0
Poppy College (%)	49.3	49.3	0.0
High School Grade Point Average (mean)	2.6	2.6	0.0
n	8,153	1,207	

APPENDIX D. TWANG Weights, Balancing Output

	Unweighted								KS								ES						
Variable	tx.mn	tx.sd	ct.mn	ct.sd	std.eff.sz	stat	pval	ks	pval	mean.ATT.tx.mn	mean.ATT.tx.sd	mean.ATT.ct.mn	mean.ATT.ct.sd	mean.ATT.std.eff.sz	mean.ATT.stat	mean.ATT.pval	mean.ATT.ks	mean.ATT.pval	mean.ATT.tx.mn	mean.ATT.tx.sd	mean.ATT.ct.mn	mean.ATT.ct.sd	mean.ATT.std.eff.sz	mean.ATT.stat	m
cohort:2010	0.07	0.26	0.08	0.27	-0.04	2.07	0.05	0.01	0.05	0.07	0.26	0.07	0.26	0	0.09	1	0	1	0.07	0.26	0.07	0.26	0	0.09	
cohort:2011	0.13	0.33	0.14	0.35	-0.04	NA	NA	0.01	NA	0.13	0.33	0.12	0.33	0.01	NA	NA	0	NA	0.13	0.33	0.12	0.33	0.01	NA	
cohort:2012	0.13	0.33	0.15	0.35	-0.06	NA	NA	0.02	NA	0.13	0.33	0.13	0.34	-0.02	NA	NA	0.01	NA	0.13	0.33	0.13	0.34	-0.02	NA	
cohort:2013	0.15	0.36	0.16	0.36	-0.01	NA	NA	0	NA	0.15	0.36	0.15	0.36	0	NA	NA	0	NA	0.15	0.36	0.15	0.36	0	NA	
cohort:2014	0.17	0.38	0.17	0.38	0	NA	NA	0	NA	0.17	0.38	0.17	0.38	0	NA	NA	0	NA	0.17	0.38	0.17	0.38	0	NA	
cohort:2015	0.18	0.38	0.15	0.36	0.06	NA	NA	0.02	NA	0.18	0.38	0.17	0.38	0.01	NA	NA	0	NA	0.18	0.38	0.17	0.38	0.01	NA	
cohort:2016	0.17	0.38	0.15	0.36	0.06	NA	NA	0.02	NA	0.17	0.38	0.17	0.38	0.01	NA	NA	0	NA	0.17	0.38	0.17	0.38	0.01	NA	
female	0.59	0.49	0.5	0.5	0.17	5.64	0	0.09	0	0.59	0.49	0.58	0.49	0.02	0.49	0.62	0.01	1	0.59	0.49	0.58	0.49	0.02	0.49	
fostergouth	0.04	0.2	0.01	0.11	0.15	5.15	0	0.03	0.28	0.04	0.2	0.03	0.18	0.05	1.39	0.17	0.01	1	0.04	0.2	0.03	0.18	0.05	1.39	
firstgen	0.32	0.47	0.22	0.42	0.21	7.06	0	0.1	0	0.32	0.47	0.31	0.46	0.02	0.65	0.52	0.01	1	0.32	0.47	0.31	0.46	0.02	0.65	
ethnicity:American Indian or Alaska Native	0	0.04	0	0.05	-0.01	18.99	0	0	0	0	0.04	0	0.04	0	0.15	0.99	0	0.99	0	0.04	0	0.04	0	0.15	
ethnicity:Asian	0.11	0.31	0.14	0.35	-0.1	NA	NA	0.03	NA	0.11	0.31	0.11	0.32	-0.01	NA	NA	0	NA	0.11	0.31	0.11	0.32	-0.01	NA	
ethnicity:Black or African American	0.05	0.21	0.02	0.16	0.11	NA	NA	0.02	NA	0.05	0.21	0.05	0.21	0.01	NA	NA	0	NA	0.05	0.21	0.05	0.21	0.01	NA	
ethnicity:Hispanic / Latino	0.56	0.5	0.41	0.49	0.3	NA	NA	0.15	NA	0.56	0.5	0.56	0.5	-0.01	NA	NA	0.01	NA	0.56	0.5	0.56	0.5	-0.01	NA	
ethnicity:Native Hawaiian or Pacific Islander	0	0.03	0	0.05	-0.06	NA	NA	0	NA	0	0.03	0	0.04	-0.03	NA	NA	0	NA	0	0.03	0	0.04	-0.03	NA	
ethnicity:Two or More Races	0.03	0.17	0.05	0.22	-0.14	NA	NA	0.02	NA	0.03	0.17	0.03	0.17	0	NA	NA	0	NA	0.03	0.17	0.03	0.17	0	NA	
ethnicity:Unreported or Unknown	0.01	0.11	0.01	0.11	0	NA	NA	0	NA	0.01	0.11	0.01	0.12	0	NA	NA	0	NA	0.01	0.11	0.01	0.12	0	NA	
ethnicity:White	0.24	0.43	0.35	0.48	-0.26	NA	NA	0.11	NA	0.24	0.43	0.23	0.42	0.02	NA	NA	0.01	NA	0.24	0.43	0.23	0.42	0.02	NA	
dsps	0.12	0.32	0.07	0.25	0.16	5.42	0	0.05	0.01	0.12	0.32	0.1	0.3	0.05	1.39	0.16	0.01	0.98	0.12	0.32	0.1	0.3	0.05	1.39	
esl	0.08	0.27	0.02	0.13	0.22	7.57	0	0.06	0	0.08	0.27	0.06	0.24	0.06	1.68	0.09	0.02	0.96	0.08	0.27	0.06	0.24	0.06	1.68	
latestedgoalgroup:Career	0.06	0.23	0.06	0.23	0	0.14	0.99	0	0.99	0.06	0.23	0.06	0.23	0	0.11	0.99	0	0.99	0.06	0.23	0.06	0.23	0	0.11	
latestedgoalgroup:Degree or Certificate	0.08	0.27	0.09	0.28	-0.01	NA	NA	0	NA	0.08	0.27	0.08	0.28	0	NA	NA	0	NA	0.08	0.27	0.08	0.28	0	NA	
latestedgoalgroup:GED/Basic Skills	0.01	0.11	0.01	0.11	0	NA	NA	0	NA	0.01	0.11	0.01	0.11	0.01	NA	NA	0	NA	0.01	0.11	0.01	0.11	0.01	NA	
latestedgoalgroup:Personal Development	0.03	0.18	0.03	0.17	0.02	NA	NA	0	NA	0.03	0.18	0.03	0.17	0.02	NA	NA	0	NA	0.03	0.18	0.03	0.17	0.02	NA	
latestedgoalgroup:Transfer	0.77	0.42	0.77	0.42	0.01	NA	NA	0	NA	0.77	0.42	0.77	0.42	-0.01	NA	NA	0	NA	0.77	0.42	0.77	0.42	-0.01	NA	
latestedgoalgroup:Undecided	0.04	0.2	0.05	0.21	-0.01	NA	NA	0	NA	0.04	0.2	0.05	0.21	-0.01	NA	NA	0	NA	0.04	0.2	0.05	0.21	-0.01	NA	
latestedgoalgroup:Vocational	0	0.04	0	0.04	0	NA	NA	0	NA	0	0.04	0	0.04	0	NA	NA	0	NA	0	0.04	0	0.04	0	NA	
finaidever	0.99	0.08	0.99	0.1	0.06	1.83	0.07	0	1	0.99	0.08	0.99	0.08	0	-0.05	0.96	0	1	0.99	0.08	0.99	0.08	0	-0.05	
Poppy College	0.55	0.5	0.41	0.49	0.27	8.92	0	0.14	0	0.55	0.5	0.53	0.5	0.03	0.91	0.37	0.01	0.99	0.55	0.5	0.53	0.5	0.03	0.91	
finalhsgpa	2.61	0.65	2.66	0.63	-0.08	-2.72	0.01	0.06	0	2.61	0.65	2.6	0.63	0.01	0.31	0.75	0.02	0.97	2.61	0.65	2.6	0.63	0.01	0.31	

Note

Appendix

APPENDIX E. Survey of Embedded Tutor Faculty, 2018-2023

Question	Answer	Average Score/Proportion
Overall Satisfaction with the Embedded Tutor's engagement [1-5]		4.9
In what ways did you utilize the embedded tutors for your class?		
	Had the student do a presentation about tutoring center early on	80%
	Encouraged Tutors to walk around the classroom and engage with students during group and solo work time	80%
	Made sure tutors had access to Canvas or emailed them	100%
	Allowed tutors to lead or contribute in small group discussions	67%
	Met with tutors as needed for assignment/lesson clarification	93%
Would you host an embedded tutor again?		
	Yes	100%
	No	0%
	Maybe	0%
	n	15

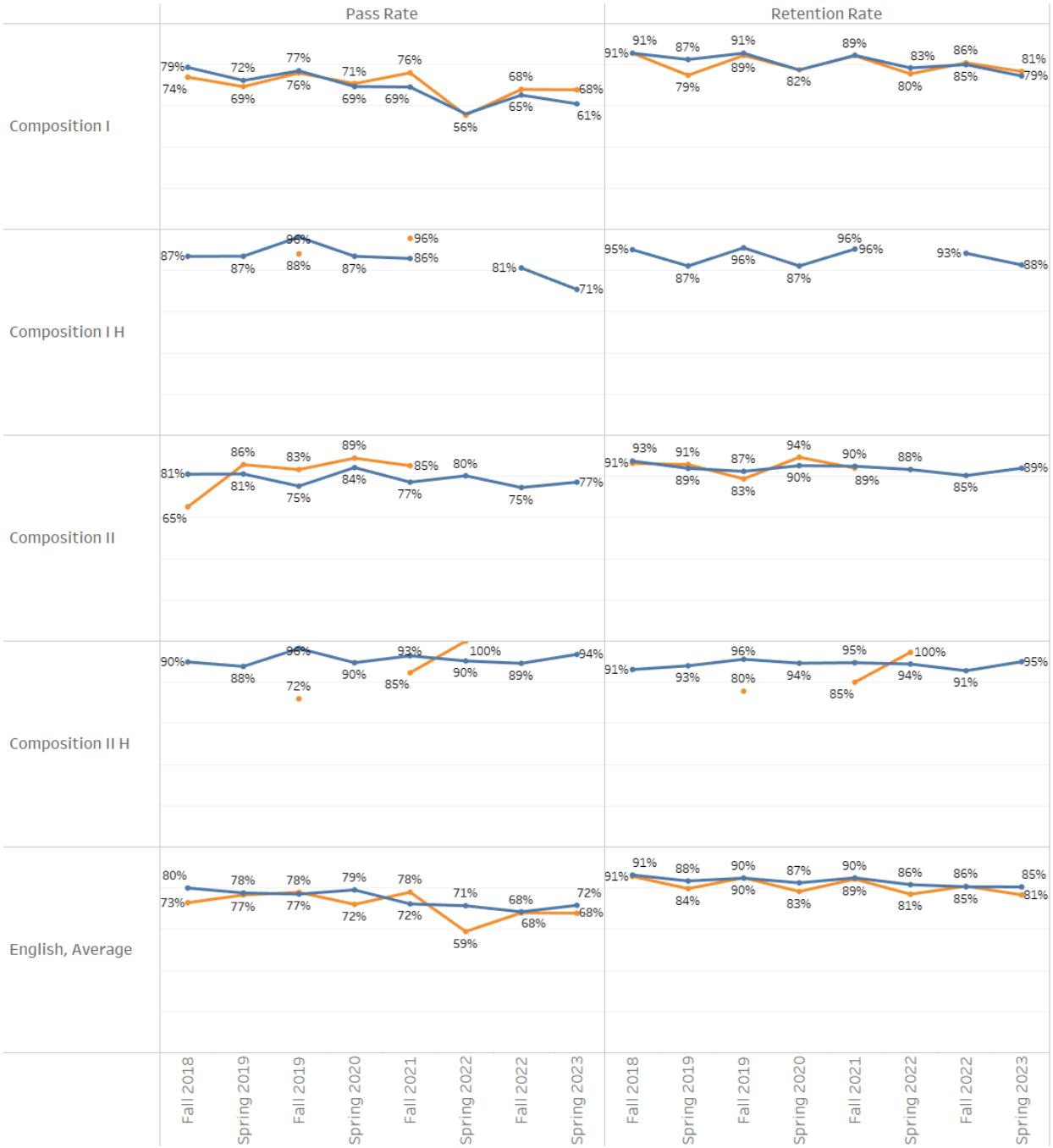
APPENDIX F. Within Group Variance By Fixed Effect Dimensions, Count of Cases

		Course ID & Term			Course ID & Term & Instructor		
Subject	Course	With Variance	W/O Variance	% with Variance	With Variance	W/O Variance	% with Variance
English							
	Composition I	13,417	0	100%	1,429	11,988	11%
	Composition I H	251	323	44%	0	574	0%
	Composition II	5,318	2,813	65%	102	8,029	1%
	Composition II H	267	550	33%	0	817	0%
	Subtotal	19,253	3,686	84%	1,531	21,408	7%
Math							
	Algebra for Calc.	769	501	61%	85	1,185	7%
	Geo. & Calc. I	1,171	1,281	48%	0	2,452	0%
	Geo. & Calc. II	1,517	0	100%	0	1,517	0%
	Pre-Calc	683	1,162	37%	0	1,845	0%
	Statistics	4,808	2,724	64%	1,215	6,317	16%
	Trig	1,988	281	88%	0	2,269	0%
	Subtotal	10,936	5,949	65%	1,300	15,585	8%
	Total	30,189	9,635	76%	2,831	36,993	7%

APPENDIX G. Controls Used

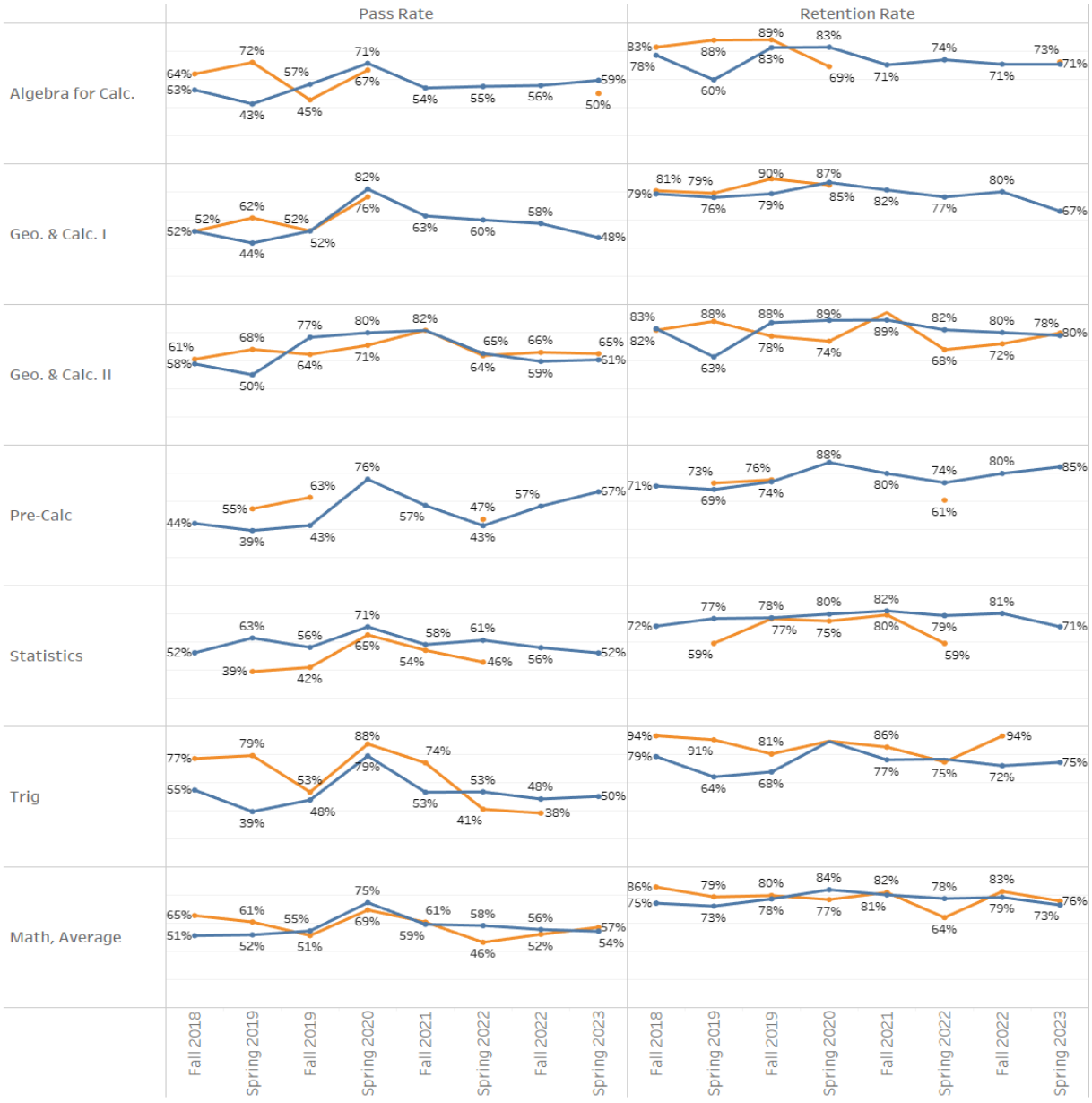
Control	Variable Name	General Definition
Student's Age	Age	Student's Age as of Term of Course
Grade Point Average	CumulativeGPAAsOfBOT	Cumulative college grade point average as of the beginning of the term
Units Earned	CumulativeUnitsEarnedAsOfBOT	Cumulative college units earned as of the beginning of the term
Enrollment Status	EnrollmentStatus	Enrollment status of the student that term
Educational Goal	EdGoal	Latest education goal of the student
High School Grade Point Average	HSGPA	High School GPA quartiles
Student's Ethnicity	Ethnicity	Self-declared ethnicity on college application
Student's Gender	Gender	Self-declared gender on college application
Instructor's Gender	InstructorGender	Gender of the instructor
Instructor's Failure Rate	InstructorFailureRate	Failure rate of a given instructor in all coursework prior to the current term
First Attempt of a Course	FirstAttempt	Flag of whether it was the first-time attempting a course.
Instructor's Historical Employment Status	OverallEmploymentStatus	Whether the faculty member was full-time or part-time, on average.
Instructor's Current Term Load	TermLoad	Whether the faculty member was full-time or part-time during the current term.
Student's Financial Aid	FinancialAid	Whether the student was receiving financial aid in the current term.
Student's Enrollment Status	FullTimeStudent	Whether the student was enrolled in 12 or more units.
Affiliated Support Section	SupportSection	Whether the section enrolled in had an affiliated support section.
First-Generation Student	FirstGeneration	Whether the student is a first-generation student, meaning their parents did not attend college.
Section Enrollment	NumberOfStudentsEnrolled	Number of students enrolled in a given section.
Instructional Method	Online	Whether the course was taught virtually or in-person.

APPENDIX H. Academic Outcomes by Year & Course, English



Appendix

APPENDIX I. Academic Outcomes by Year & Course, Math



Appendix

APPENDIX J. IV First Stage Results, Coefficient of Instrument & F-Test Value

	Pooled	Math	English
Instrument	0.12***	0.14***	0.08***
	(0.01)	(0.01)	(0.01)
F-test, Excluded Instrument	350.99***	255.8***	402.92***

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

Note. First stage predicting enrollment in an embedded tutor section. Predictors include First Attempt, Support Section, Cumulative Units Earned as of Beginning of Term (BOT), Cumulative GPA as of BOT, First-Generation, Enrollment Status, High School GPA, Online, Ethnicity, Full time status, Financial aid, and Number of Students Enrolled. Fixed effects include course ID and term code.

APPENDIX K. Lateral Simultaneous Variables, Definitions

Variable	Source/BPS Variable Name	Definition	Relevant Recoding
Age	AGE	Age as of December 31, 2011	
Expected Family Contribution (EFC)	EFC	Expected Family Contribution a	
Female	GENDER	Derived from the Gender variable, which indicates the student's sex.	
Race/Ethnicity	RACE	The student's race/ethnicity with Hispanic or Latino origin (HISPANIC=1) as a separate category.	
Income Group	INCGRP	Indicates the respondent's income group in 2012.	
Parent's Highest Education Level	PAREDUC	The highest level of education achieved by either parent of the student as of 2011-12.	
Grade Point Average in High School	HSGPA	Indicates the student's high school grade point average (GPA) as of the standardized test date, according to self-report on test questionnaire.	A dummy value was created for missing values.
Degree of Urbanization of Student's Permanent Address	LOCALEST	Degree of urbanization of the student's permanent address in 2011-12.	
Type of High School Attended	HSTYPE	Indicates the type of high school the student attended.	A dummy value was created for missing values.
Dependency and Marital Status	DEPEND5A	The student's dependency status including dependents and marital status in 2011-12.	
U.S. Citizen	CITIZEN2	The student's citizenship status in 2011-12.	
Lateral Simultaneous Enrollment	PETS (12:17) Enrollment	A flag of whether the student ever was simultaneously enrolled in two or more community colleges during the time period. Summer time frames are not included. For more details see methodology.	
Certificate Completion	PETS (12:17) Awards	A flag of whether the student ever earned at least one certificate of achievement. No time restrictions were applied.	
Associate's Completion	PETS (12:17) Awards	A flag of whether the student ever earned at least one Associate degree. No time restrictions were applied.	
Bachelor's Completion	PETS (12:17) Awards	A flag of whether the student ever earned at least one Bachelor's degree. No time restrictions were applied.	
Transfer to a 4-year University	PETS (12:17) Enrollment	A flag of whether the student ever changed their home institution from a community college to a university. There are several other considerations described in the methodology in greater detail.	

APPENDIX L. Probit Robustness Check

The probit models produced using Stata's "ivprobit" function produced results similar to the "ivreg" approach (See table 7). Using the same measures of access and instrumentation types (e.g., linear and dummy coded measures of access), the marginal effects at the means (MEMs) similarly found that the relationship between lateral simultaneous enrollment and certificate or associate's attainment is not significant in the current sample. Meanwhile, the pattern is still showing a positive and significant relationship with transfer and bachelor's attainment, with marginal effects ranging from 0.78 to 0.97. This suggests that when comparing two otherwise-average students, one who simultaneously enrolled and one who did not, the simultaneously enrolled student will have between 78 to 97 percentage points higher chance of transferring or earning a bachelor's degree. While these values are more plausible than those produced in the linear IV models, we suggest caution when interpreting the effect size. We argue that while the estimated size of the effect may be inaccurate to some degree, we are confident that the various tests producing a positive and significant estimate indicates that the pattern of enrollment does have a causal and positive impact on the academic outcomes of interest.

Table 7. Probit Models, Second Stage Margins At Means

			Lateral Simultaneous Enrollment			
Institution Type	Measure of Access	Instrumentation Type	Certificate	Associate's	Transfer	Bachelor's
Community College	Commute Time	Capped Access	0.57	0.41	0.94*	0.97*
		Dummy Coded	0.63	0.33	0.86	0.98*
	30 minutes Driving	Capped Access	0.75	0.45	0.89*	0.80*
		Dummy Coded	0.68	0.39	0.82	0.78*

Note. All models are inclusive of aforementioned controls and fixed effects.

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