Unraveling Teacher Steering and Student Sorting in Between-School Segregation's Impact on Within-School Segregation

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Abstract

This study develops a framework to analyze the impact of between-school segregation on within-school segregation. We model students' course choices as a game of incomplete information, incorporating inter-student and student-teacher interactions. Using idiosyncratic variation in student composition across cohorts in Texas high schools, we find that Black and low SES students receive less encouragement from teachers as their representation increases, suggesting weaker student-teacher interactions. Conversely, Hispanic and female students receive more encouragement with increased representation. White and academically high-performing students are less likely to enroll in college-prep courses as their representation grows, suggesting higher inter-student competition. Additionally, higher expected college-prep enrollment in a cohort discourages students from enrolling, though stronger within-group coordination incentives exist among White, Hispanic, and female students. Policy simulations using an entropy index support the segregation paradox, indicating that racial disparities in course-taking widen in integrated schools. These findings suggest merit in exploring policies like all-girls schools, race-separate courses, and SES desegregation to promote equity in course-taking.

***Keywords*: simultaneous-move game, course choice, segregation**
***JEL Codes*: I24, J15, J24**

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1 Introduction

School desegregation is a topic of immense importance, capturing the attention of policymakers and researchers alike. While desegregation efforts often focus on achieving diversity between schools, examining whether these initiatives lead to equitable outcomes within schools is crucial. In particular, equity gaps in advanced math and science in high school persist (Card and Payne, 2021). These gaps hold profound implications for the future educational and employment trajectories, with implications extending to lower college completion rates and continued under-representation in STEM majors and careers (Rose and Betts, 2004; Aughinbaugh, 2012; Todd and Wang, 2021).

While racial desegregation efforts have been associated with positive impacts on the human capital outcomes of Black students (Guryan, 2004; Johnson, 2011; Weiner, Lutz, and Ludwig, 2009), a "segregation paradox" has been observed in the context of high school course-taking. Specifically, racial gaps in enrollment in advanced math courses are wider in more racially integrated schools (Card and Rothstein, 2007; Kelly, 2009; Clotfelter, Ladd, Clifton, and Turaeva, 2021). Explanations for this paradox include behavioral disengagement due to social stigma, integration fatigue, and less strategic behavior resulting from a lack of institutional knowledge (Rothstein and Yoon, 2008; Fryer Jr and Torelli, 2010; Ackert, 2018; Casey, Cline, Ost, and Qureshi, 2018).

Contemporary segregation policies are increasingly based on socioeconomic status (Tractenberg et al., 2016; Learned-Miller, 2016; Potter, 2023). For example, the Dallas Independent School District in Texas introduced the "Transformation Schools" initiative, which uses random assignment to ensure socioeconomic diversity, aiming for a 50/50 split (Rix, 2022). Factors such as household income, parent education, and single-parent status are considered for integration. Policies like opening all-girls schools are also being implemented to improve girls' enrollment in STEM courses (Yap, 2016). The rise in single-sex schools is attributed to the 2006 Title IX regulations (Lavy and Schlosser, 2011). Recently, some schools have also started to offer math courses separated by race (Randazzo and Belkin, 2023).

This study proposes a framework to comprehensively investigate the implications of changing between-school segregation – in terms of race, gender, and socio-economic status – on within-school segregation – regarding enrollment in college-prep coursework in high school. It considers the role of student-teacher and inter-student interactions in driving the incentives behind coursework decision-making. Changes in between-school segregation affect the student body composition, which can influence inter-student interactions (such as, the information-sharing among them or students' perceptions of their abilities relative to their cohort) and student-teacher interactions (such as, teachers' perceptions of student abilities). However, desegregation initiatives often face logistical challenges such as moving costs, disruptions to educational continuity, and the need for policy, resource, and curriculum changes to foster an inclusive environment (Hanushek, Kain, and Rivkin, 2009; Reber, 2010; Johnson, 2011). Disentangling how these mechanisms mediate the implications of between-school segregation on within-school segregation can be a complex endeavor.

To this end, we conceptualize high school students' decisions to enroll in college-prep courses as a game with incomplete information. While characteristics like race, gender, socioeconomic status, and academic performance are public information within the cohort, some remains private, such as students' work habits or college aspirations. Consequently, students within a cohort engage in a simultaneous-choice game for course selection, forming beliefs about their cohort members' choices. Another influential factor, private information for students but observable to the researcher, is the nature of students' interactions with teachers regarding college preparation. Students consider whether teachers encourage them to pursue college, but they can only speculate whether their cohort members receive similar encouragement.

Our modeling framework captures three primary pathways through which changes in student composition, resulting from shifts in between-school segregation, influence course decisions. First, changes in student composition can directly impact students' choices, such as, by influencing information-sharing among cohort members – we refer to these as contextual social interactions. We allow these interactions to vary by observed characteristics such as race, gender, SES, and academic performance. For instance, female students may have better institutional knowledge about enrolling in college-prep courses in a predominantly female cohort.

Second, changes in student composition can influence student-teacher interactions or teachers' perceptions of student abilities, thereby affecting their encouragement decisions. These interactions are also allowed to vary by observed characteristics. For example, when a female student is part of a predominantly female cohort, teachers may perceive her abilities more positively, leading to increased encouragement to apply to college.

Third, changes in student composition can shape students' coordination or competition incentives when enrolling in college-prep coursework – referred to as endogenous social interactions. We allow these interactions to vary by observed characteristics. For example, female students may prefer to align with the course decisions of their female cohort members, so when the proportion of female students in their cohort increases, they may find it more beneficial to enroll in college-prep coursework.

Our analysis is based on student-level data collected from a sample of schools across Texas. Adjacent cohorts were surveyed regarding their course-taking behaviors, performance, and demographic information. Notably, the data also includes information on student-teacher interactions regarding pursuing college in the future. The availability of multiple cohorts within the same school allows us to rely on the identifying assumption of conditional random assignment, where variations in student compositions across adjacent cohorts within a school are considered idiosyncratic.

The described model of course choice is characterized by the concept of Bayesian Nash equilibrium. We propose a two-stage, three-step nested pseudo-likelihood (NPL) estimation method, combining the NPL estimator introduced by Aguirregabiria and Mira (2007) and the contraction mapping by Berry, Levinsohn, and Pakes (1993). Model parameters governing teachers' encouragement decisions are estimated using maximum likelihood estimation and plugged into students' decisions in the second stage, involving three steps.

We start with initial guesses for the model parameters governing the students' decisions and their conditional choice probabilities (CCPs). First, we update the utility parameters of the students' decision through maximum likelihood estimation. In the second step, we solve for a contraction mapping in the school fixed effects. Finally, we update the CCPs of the student decision iteratively until convergence is achieved.

Our analysis reveals several key findings regarding inter-student and student-teacher interactions and course selection. As the representation of Black and low SES students increases, they are less likely to receive encouragement from teachers. In contrast, an increase in the representation of Hispanic students and female students correlates with a higher likelihood of receiving encouragement among these groups. These patterns suggest that for Black and low SES students, higher representation leads to weaker student-teacher interactions. In contrast, for Hispanic students and female students, it leads to stronger interactions.

Additionally, we find that White students in White-majority cohorts and academically high-performing students in high-performing cohorts are less likely to enroll in college-prep courses. This may reflect weaker inter-student interactions, lower self-perceptions of abilities, or increased competition among these groups as their representation grows.

Moreover, higher expected enrollment among cohort members generally leads to decreased college-prep enrollment, suggesting a competition effect. However, within-group endogenous social interactions positively impact enrollment for White students, Hispanic students, female students, and students whose parents attended college. This indicates that there are incentives to coordinate course-taking within these groups.

We conduct several policy simulation exercises to explore the influence of changing between-school segregation on course-taking. We manipulate the level of segregation using the entropy index proposed by Theil (1972), which measures the disparity between individual school compositions and the overall student composition across the state. By randomly reassigning students across schools, we create alternative distributions of school-level compositions, resulting in different levels of segregation.

Our simulations focus on segregation based on race, gender, and socioeconomic status (SES). Using our model estimates, we re-solve the course choice model to predict teachers' and students' decisions under these alternative segregation scenarios. This approach allows us to assess how different levels of between-school segregation impact within-school enrollment in college-prep courses.

Our policy simulations reveal several critical insights into the effects of between-school segregation on student outcomes. First, racial desegregation between schools has a mixed impact. On the one hand, it positively affects teachers' encouragement of Black students to pursue college. Despite this increased encouragement, however, there is no corresponding rise in college-prep coursework enrollment among Black students. On the other hand, racial desegregation negatively impacts Hispanic students, reducing both teacher encouragement and college-prep enrollment. These patterns align with the "segregation paradox," where racial gaps in course-taking tend to widen in more racially integrated schools (Card and Rothstein, 2007; Kelly, 2009) especially for Hispanic students (Clotfelter, Ladd, Clifton, and Turaeva, 2021). These results may also explain the recent policies offering race-separate courses to mitigate these issues (Randazzo and Belkin, 2023).

SES desegregation also shows promising results, leading to higher levels of teacher encouragement and greater enrollment in college-prep coursework for low SES students. Moreover, SES desegregation has the potential to close racial gaps in course-taking, particularly when supported by counseling interventions aimed at improving students' self-perceptions relative to their cohort members.

This study contributes to three strands of literature. Firstly, it advances the literature on modeling educational decision-making, building upon previous studies that have utilized discrete choice models to explore various aspects of education, such as career choices and occupational decisions (Keane and Wolpin, 1997; Arcidiacono, 2004; De Groote, 2023). This study takes a step further by modeling course choice as a game of incomplete information, incorporating strategic coursework selections made by high school students and the role of teachers in influencing these selections into the analysis.

Secondly, it contributes to the research investigating desegregation's effects on educational decision-making (Card and Rothstein, 2007; Mookherjee, Ray, and Napel, 2010; Clotfelter, Ladd, Clifton, and Turaeva, 2021; Francis and Darity, 2021). This research contributes to a broader literature on the role of social interactions in shaping educational decisions (Zanella, 2007; De Giorgi, Pellizzari, and Redaelli, 2010; Tincani, 2018; Wu, Zhang, and Wang, 2021).

Lastly, this study aligns with the growing body of research that employs game-theoretic approaches to estimate social incentives in various contexts (Lee, Li, and Lin, 2014; Ciliberto, Miller, Nielsen, and Simonsen, 2016; Yang and Lee, 2017; Guerra and Mohnen, 2020; Lin, Tang, and Yu, 2021). By allowing for heterogeneous social incentives, proposing an efficient estimation method for the large parameter space, and proposing an innovative, optimization-based policy simulation of student reassignment, this research explores the implications of group redistribution on individual behavior in a simultaneous-move game setting.

The remainder of the paper is structured as follows: Section 2 discusses the related literature. Section 3 provides an overview of the data and institutional background. Then, Section 4 presents the modeling framework used in the analysis. The identification strategy is discussed in Section 5, followed by the estimation method in Section 6. The results obtained from the model are presented in Section 7. Section 8 explores the outcomes of counterfactual policy experiments. Finally, the paper concludes with Section 9.

2 Related Literature

This section discusses four areas of literature crucial to our study. First, we examine research on the effects of segregation based on race, gender, and SES. Second, we review methodologies used to study student body composition impacts. Third, we synthesize empirical findings on the significance of high school course-taking for future educational paths. Fourth, we discuss game-theoretic approaches, focusing on models, estimation techniques, and policy simulations.

Various court-ordered racial desegregation efforts were introduced following the historic 1954 Supreme Court ruling in Brown v. Board of Education. These initiatives have been associated with positive outcomes for Black students, including reduced high school dropout rates (Guryan, 2004), increased educational and occupational attainments (Johnson, 2011) and reduced homicide victimization and arrests (Weiner, Lutz, and Ludwig, 2009).

However, some studies have documented a "segregation paradox" in high school course-taking. Using data on SAT test-takers, Card and Rothstein (2007) document that the racial gap in enrollment in honors courses is wider when schools are more highly integrated. Kelly (2009) and Clotfelter, Ladd, Clifton, and Turaeva (2021) observed similar patterns using data from the National Education Longitudinal Study and administrative data for North Carolina public schools, respectively. Additionally, Elder, Figlio, Imberman, and Persico (2021) find that Black and Hispanic students are overidentified for special education in schools with small minority populations and underidentified in schools with large minority populations using data from Florida. A notable exception is the study by Billings, Deming, and Rockoff (2014), which finds that students are less likely to enroll in advanced courses when assigned to Black/Hispanic-majority schools.

Contemporary efforts of desegregation are based on socioeconomic factors. Recent policies such as opening all-girls schools aim to boost girls' STEM enrollment. Most studies conclude that a higher presence of female students benefits both male and female students. For instance, Mouganie and Wang (2020) find that exposure to high-performing female peers increases girls' likelihood of choosing a science track during high school. Similarly, Bostwick and Weinberg (2022) observe that women are less likely to drop out in the first year of a STEM PhD program when they have a higher proportion of women in their program. Lavy and Schlosser (2011) find that increasing the proportion of girls improves cognitive outcomes for both boys and girls, mediated through lower classroom disruption, and improved inter-student and student-teacher relationships. Contrarily, Anelli and Peri (2019) find that male students in predominantly male classes tend to opt for male-dominated college majors, while female students' choices are unaffected by class gender composition. Brenøe and Zölitz (2020) show that increased numbers of female peers reduce women's STEM enrollment but boost men's participation in STEM programs.

Research has explored the impact of exposure to high-achieving peers on educational outcomes. Lavy, Paserman, and Schlosser (2012) find that a higher proportion of low-ability peers negatively affects academic performance, teacher practices, and relationships. Conversely, Vardardottir (2013) and Kimbrough, McGee, and Shigeoka (2022) show that being assigned to a high-ability class boosts academic achievement. However, Booij, Leuven, and Oosterbeek (2017) find that low-ability students have more positive peer interactions, with no evidence of teachers adjusting their teaching. Additionally, Cools, Fernández, and Patacchini (2019) find that exposure to high-achieving boys, proxied by parent education, decreases girls' bachelor's degree attainment.

Research suggests that peers' family backgrounds can impact educational achievement. Chung (2020) find that the college attainment of peers' parents influences one's future college attainment. Additionally, Carrell and Hoekstra (2010) show that children from troubled families significantly decrease their peers' reading and math test scores and increase misbehavior in the classroom. Moreover, Gould, Lavy, and Daniele Paserman (2009) find that native children's educational attainment was adversely affected by a higher concentration of low SES immigrant children.

Studies examining the implications of segregation on student outcomes have often utilized idiosyncratic variations in student composition. For instance, Hoxby (2000) analyzed changes in gender and racial composition within school grades. Hoekstra, Mouganie, and Wang (2018) used population variation in the proportion of children from families linked to domestic violence. Similarly, Cools, Fernández, and Patacchini (2019) leveraged variation in parent education across school cohorts. Additionally, Gould, Lavy, and Daniele Paserman (2009) relied on variation in the number of immigrants across grades within the same school. Alternatively, Billings et al. (2014) use quasi-experimental evidence from the end of school busing.

The existing literature underscores the impact of high school course selection on future educational paths. Levine and Zimmerman (1995) and Rose and Betts (2004) find that increased enrollment in high school math courses correlates with higher wages and a greater likelihood of entering technical fields. Cho (2007) document that women's math and science course enrollment contributes to closing the gender gap in college enrollment. Likewise, Aughinbaugh (2012) find that students undertaking advanced math coursework are more inclined to pursue higher education at four-year institutions. Moreover, Todd and Wang (2021) demonstrate that exposure to science and math courses during high school is a crucial predictor of selecting STEM majors and careers.

We adopt a methodological approach similar to the growing literature on studying peer effects through a game-theoretic framework to model high school course-taking. Brock and Durlauf (2001) develop a discrete choice model with social interactions, where individuals form homogenous rational expectations based on group-level variables. Building on this, Lee, Li, and Lin (2014) extend the model to incorporate heterogeneous rational expectations in a general network setting. Yang and Lee (2017) further extend this by introducing asymmetric private information. More recently, Lin, Tang, and Yu (2021) allow for heterogeneous social effects and an unobserved network. Additionally, Lin, Tang, and Xiao (2023) tackle endogeneity issues in a discrete choice game by introducing a control-function approach and a nested pseudo likelihood (NPL) estimator.

In this study, we estimate a game of incomplete information with heterogeneous contextual and endogenous social interactions, incorporating asymmetric private information (student-teacher interactions are private while student characteristics are public). We utilize idiosyncratic variations in student composition within schools and employ a two-stage, three-step NPL estimation, combining the NPL estimator in Aguirregabiria and Mira (2007) with the Berry, Levinsohn, and Pakes (1993) contraction mapping to recover the school fixed effects.

Researchers have utilized these models to predict individual decision-making under hypothetical reassignment policies. Ciliberto, Miller, Nielsen, and Simonsen (2016) conduct policy simulations comparing fertility decisions under random workplace assignment versus assigning similar women to the same workplace. Badev (2021) investigates smoking tendencies under hypothetical racial segregation by randomly reassigning students between White-majority and Black-majority schools. In another context, Lin, Tang, and Yu (2021) explore students' tendencies to participate in volunteering activities under random dorm assignment policies versus assigning similar individuals to the same dorm. Our study proposes a more comprehensive policy simulation exercise, solving a nonlinear optimization problem to construct hypothetical levels of between-school segregation, measured by the Theil (1972) index.

3 Background and Data

In this section, we first provide an overview of high school course-taking in Texas and then describe the data used for the analysis in this study.

Background: High school students in Texas select a graduation program that determines the curriculum or bundle of courses they undertake during high school. They can choose from the minimum high school program, the recommended high school program, or the advanced high school program (Office of the Secretary of State, 2000).

There is considerable variation in the selection of graduation programs among high school students, which we will discuss further in the data section. As shown in Table **??**, Black and Hispanic students, students whose parents did not attend college, and students from single-parent households are less likely to enroll in the advanced graduation program. These trends align with findings from a National Science Board (2018) report, which examines high school students' participation in science and mathematics courses using data from HSLS:09, the College Board's AP program, and data collected by the Department of Education's Office for Civil Rights.

We should be concerned about these gaps because the choice of graduation program impacts a student's career for several reasons. First, only the recommended and advanced high school programs fulfill the prerequisites for admission to major four-year colleges (Cavanagh, 2005). The minimum program does not require Algebra II or a foreign language and demands only two years of science and mathematics.

Second, there are differences in rigor between the recommended and advanced programs. Students in the recommended program must take four years of English, three years of science and mathematics, and two years of a foreign language. The advanced program sets an even higher standard, requiring three years of foreign language, four years of science and mathematics, and additional options such as conducting a research project or achieving a specified score on college-prep or college entrance exams. Less rigorous courses, such as "math models" or "integrated physics and chemistry," can satisfy the requirements of the recommended program. In contrast, more rigorous courses in science and math (such as pre-calculus and physics) are necessary for the advanced program.

Third, and perhaps most importantly, only the advanced high school program guarantees eligibility for the top ten percent automatic admission policy to in-state universities. This is a vital feature of the Texas high school system since 1997 (Holley and Spencer, 1999). Students in the top ten percent of their high school class are granted admission to in-state universities. Beyond the automatic admission policy, high rank is crucial for securing college scholarships (Domina, 2007). In this study, we investigate the incentives that influence students' decisions regarding enrollment in the advanced graduation program, which we will henceforth refer to as college-prep coursework. Several factors can influence these decisions, including parents, cohort members, and teachers.

Parents can play a major role, particularly if they are well-informed or highly motivated regarding their children's education (Attanasio and Kaufmann, 2014; Giustinelli, 2016; Carlana, La Ferrara, and Pinotti, 2022). Similarly, peers within a student's cohort can impact their decisions; students might coordinate their course choices with friends or deviate based on anticipated lower relative ability (De Giorgi, Pellizzari, and Redaelli, 2010; Lavy and Schlosser, 2011; Zölitz and Feld, 2021).

The role of teachers is also crucial in this decision-making process. A substantial body of literature highlights the importance of teachers' perceptions of student abilities (Dee, 2005; Ouazad and Page, 2013; Lavy and Sand, 2018; Lavy and Megalokonomou, 2024). Students often meet with their teachers to discuss various issues, including course selection, college plans, and future employment. While there may be no explicit capacity constraint in the graduation programs, teachers may implicitly influence students' choices through their guidance and recommendations.

To investigate the incentives behind the choice of graduation plan, we require information on the students, their parents, their cohort members, and their teachers, which we will discuss next.

Data: We utilize student data from the Texas Higher Education Opportunity Project (THEOP), a research initiative managed by the Office of Population Research at Princeton University (Tienda and Sullivan, 2011). THEOP administered surveys to tenth and twelfth graders from a state-representative sample of public schools in Texas in 2002, capturing information on various aspects of their academic journey. The THEOP data has been employed in numerous recent studies on college outcomes, including those by Kapor (2020), Li, Sickles, and Williams (2020), and Akhtari, Bau, and Laliberté (2020).

Table 1. Students' Characteristics and their Coursework Decision

	(1)	(2)	(3)	(4)	(5)
			College-prep coursework		
	Mean	S.D.	No	Yes	Difference
Panel A: Demographic information					
Black/Hispanic	0.555	0.497	0.200	0.135	−0.065***
Female	0.475	0.499	0.153	0.176	0.023***
Parent attended college	0.539	0.498	0.103	0.215	0.113***
Single parent household	0.462	0.499	0.190	0.132	−0.058***
Panel B: Course Grades					
Got an A in English	0.305	0.461	0.113	0.278	0.165***
Got an A in Math	0.228	0.420	0.126	0.289	0.163***
Got an A in History	0.359	0.480	0.105	0.268	0.163***
Got an A in Science	0.278	0.448	0.118	0.282	0.164***
Panel C: Encouragement from Teacher					
Encouraged for college	0.768	0.422	0.121	0.176	0.055***
Encouraged for vocational school	0.210	0.407	0.174	0.123	−0.051***
Encouraged for apprenticeship	0.220	0.414	0.169	0.143	−0.027***
Encouraged for military service	0.197	0.398	0.173	0.126	−0.047***
Encouraged for jobs after high school	0.319	0.466	0.180	0.129	−0.051***
Panel D: What matters for College Admissions					
Course grades matter	0.714	0.452	0.136	0.175	0.039***
Coursework matter	0.535	0.499	0.128	0.194	0.066***
Class rank matter	0.485	0.500	0.132	0.197	0.065***
HS diploma matter	0.795	0.403	0.140	0.170	0.030***
Race matters	0.099	0.299	0.165	0.153	−0.012
Panel E: Friends characteristics					
Do well in school	0.688	0.463	0.118	0.184	0.067***
Plan to go to college	0.721	0.449	0.089	0.192	0.103***
Think it's important to work hard	0.469	0.499	0.132	0.199	0.067***
Participate in extra-curriculars	0.555	0.497	0.105	0.210	0.105***
Obs	24,432				

Note: This table provides student-level characteristics in Columns (1) and (2) as means and standard deviations. Each variable represents a binary indicator for a student characteristic. Columns (3) and (4), respectively, show group averages for those who take the college-prep coursework and those who do not, and Column (5) presents the t-test results. Significance levels: $p < 0.1$; $p < 0.05$; $p < 0.01$.
Data source: Texas Higher Education Opportunity Project (THEOP), Wave I, 2002.

The THEOP surveys every student from two cohorts of the sampled schools, gathering comprehensive information on students' demographics, including their gender, race, parents' education, and family structure. Additionally, the survey records the student's choice of graduation program and their grades in core courses such as English, math, science, and history.

Furthermore, the survey includes questions about students' interactions with teachers, specifically regarding academic matters such as whether the teacher encourages them to apply to college. Two pieces of information are crucial for our study: the survey of every student in a cohort and the student's interaction with the teacher. These aspects provide a distinct opportunity to examine students' educational decision-making within the same cohort and investigate the influence of teachers on these decisions. Table 1 illustrates the relationship between student characteristics and the decision to take the college-prep coursework.

In Panel A, looking at Column (1), we observe that approximately 56% of the students in the sample are Black or Hispanic, with around 48% female. This distribution is quite representative of Texas's public high school system in terms of racial/ethnic makeup. About 54% of students report that either of their parents attended college, while approximately 46% reside in single-parent households.

Looking at Columns (3) to (4), we find that Black and Hispanic students are 6.5% less likely to enroll in the college-prep coursework than White students. Female students are 2.3% more likely to enroll in the college-prep coursework compared to males. Students whose parents attended college are 11.3% more likely to enroll, while those in single-parent households are 5.8% less likely compared to two-parent households.

In Panel B, it's evident that students who received an A in English, Math, History, or Science are more likely to enroll in the college-prep coursework.

Panel C examines the relationship between teacher encouragement and coursework decisions. Students are asked in the survey to report whether they were encouraged by their teacher for college, vocational school, apprenticeship, military service, and employment. These responses are not mutually exclusive, and a student could have answered yes to being encouraged for more than one of these career options by their teacher. We observe that while being encouraged to pursue college positively correlates with the decision to enroll in the college-prep coursework, encouragement for other post-high school options shows a negative association.

The THEOP survey asked students to report how much importance they attribute to different factors in the college admissions process. In Panel D, higher importance ratings for course grades, coursework, class rank, and a high school diploma positively correlate with choosing the college-prep coursework. These patterns indicate that students who enroll in the college-prep coursework have a better understanding of what matters for college admissions.

Students' social circles also correlate with coursework decisions. In Panel E, having three or more friends who excel academically, plan to attend college, value hard work, and engage in extracurricular activities positively correlates with the probability of the student choosing the college-prep coursework. These patterns reflect that students who enroll in the college-prep coursework also have better-motivated friends.

These findings underscore the multifaceted nature of factors shaping students' coursework decisions, including family background, academic performance, teacher interactions, institutional knowledge, and social influences. Table 2 integrates these factors to examine the relationship between these factors and (1) whether a student receives encouragement to apply to college, (2) the prevalence of college plans among their cohort members, and (3) enrollment in the college-prep coursework.

In assessing individual characteristics, we consider race, gender, academic performance, parental education, and single-parent status. Contextual characteristics encompass the proportion of students with similar attributes within the cohort. Additionally, our analysis incorporates school and year fixed effects.

In Column (1), we discuss teachers' decision to encourage students to go to college. Throughout the paper, we refer to encouraging college, not other career options. In Column (2), we examine if students have friends planning to apply to college. In Column (3), we study students' enrollment in college-prep coursework.

Three patterns emerge regarding the influence of cohort composition. First, as the share of Black students increases, teachers' encouragement to pursue college decreases, possibly due to lower perceptions of their abilities or weaker student-teacher interactions. Similar patterns are observed for low SES students. Conversely, Hispanic and female students receive higher encouragement as their share increases.

Second, an increase in same-race or same-gender students is associated with having more friends who plan to go to college. This is possibly explained by homophily, where students are more likely to be friends with those of the same race or gender. A higher share of high SES students predicts a higher probability of high SES students having friends with college plans, while the opposite is true for low SES students. This may be explained by higher SES being positively associated with higher ambitions or means to pursue college. A higher share of high academic-performing students is associated with having fewer friends with college plans, possibly due to increased academic competition and weaker friendships.

Third, an increase in same-race or same-gender students is associated with higher college-prep course enrollment for Black, Hispanic, and female students, possibly due to higher self-efficacy.

Overall, changes in student composition have multifaceted implications, affecting teachers' encouragement decisions and students' coursework choices. While insightful, this analysis overlooks a key aspect: the simultaneity in students' course decisions. We address this in the next section

Table 2. Student Composition, Student-Teacher and Inter-Student Interactions, and Coursework Decisions

	Teacher encourages for college	Friends have college plans	College-prep coursework
Black	0.129	-0.054	-1.086***
	(0.128)	(0.133)	(0.190)
Hispanic	-0.370***	-0.513***	-1.028***
	(0.135)	(0.140)	(0.188)
Female	0.042	-0.123	-0.825
	(0.419)	(0.425)	(0.543)
High academic performance	0.796***	0.981***	1.712***
	(0.190)	(0.209)	(0.248)
Parent attended college	-0.702***	-0.276	0.152
	(0.256)	(0.259)	(0.393)
Single Parent	0.934***	0.860**	0.256
	(0.352)	(0.352)	(0.534)
White × White share	0.116	0.358**	-0.817***
	(0.162)	(0.175)	(0.222)
Black × Black share	-0.504**	0.691***	0.896**
	(0.243)	(0.229)	(0.403)
Hispanic × Hispanic share	0.359**	0.570***	0.876***
	(0.142)	(0.143)	(0.197)
Female × Female share	1.044**	2.466***	1.401**
	(0.531)	(0.548)	(0.686)
Male × Male share	0.868*	1.547***	-0.476
	(0.481)	(0.483)	(0.640)
Low acad × Low acad share	0.410	0.036	1.468***
	(0.330)	(0.350)	(0.468)
High acad × High acad share	-0.250	-0.853**	0.199
	(0.357)	(0.407)	(0.462)
Parent no college × Parent no college share	-0.916***	-0.635**	-0.773*
	(0.271)	(0.269)	(0.430)
Parent college × Parent college share	1.317***	1.074***	0.507
	(0.265)	(0.275)	(0.397)
Two parent × Two parent share	1.133***	1.743***	0.598
	(0.384)	(0.403)	(0.564)
Single parent × Single parent share	-1.339***	-0.936**	-0.544
	(0.402)	(0.390)	(0.622)
Mean	0.329	0.721	0.164
Obs	24,432	24,432	24,432

Note: This table presents logit regressions for the probabilities of teacher encouragement (Column 1), student's friends aspiring to go to college (Column 2), and student's choice of the college-prep coursework (Column 3). School and year fixed effects are included. Significance levels: p <0.1; p <0.05; p <0.01.
Data source: Texas Higher Education Opportunity Project (THEOP), Wave I, 2002.

by developing a model that encompasses both teachers' encouragement decisions and students' coursework choices in a simultaneous-move game framework.

4 Model

In this section, we outline how we model the teacher's decision of whether to encourage a student to apply to college and the student's decision of whether to enroll in the the college-prep coursework.

We model this as a simultaneous-move game of course choice among students in the same cohort in which the teacher's decision enters as an exogenous technology.

4.1 Student's decision

Student i in year (or, grade level) $g \in \{1, \ldots, G\}$ in school $s \in \{1, \ldots, S\}$ faces the decision whether to take the the college-prep coursework, $a_{igs} \in \{0, 1\}$. Normalizing the utility of not taking the college-prep coursework to zero, student i decides to take the college-prep coursework if:

$$
\begin{aligned}
&\beta_0 + x_{igs}\beta + \alpha b_{igs} + \epsilon_{igs} + \kappa_g + \gamma_s + \\
&\frac{1}{N_{gs} - 1} \sum_{j \in \mathcal{N}_{gs} \setminus \{i\}} \sum_{c \in \{0,1\}} \sum_{\ell=1}^{L} \psi_{\ell,c} z_{ijgs,\ell c} + \\
&\frac{1}{N_{gs} - 1} \sum_{j \in \mathcal{N}_{gs} \setminus \{i\}} \left(\lambda + \sum_{c \in \{0,1\}} \sum_{\ell=1}^{L} \lambda_{\ell,c} z_{ijgs,\ell c} \right) \mathbb{E}\left[a_{jgs} \mid x_{gs}, b_{igs}, \epsilon_{igs} \right] > 0
\end{aligned}
\tag{1}
$$

where $\mathcal{N}_{gs} \equiv \{1, \ldots, N_{gs}\}$ represents the set of students in year g in school s. We collectively define students in the same year g and school s as a cohort.

Several factors influence the student's decision to enroll in the college-prep coursework. First, this decision is shaped by the student's (observed) characteristics, $x_{igs} \equiv \{x_{igs,\ell}\}_{\ell=1}^{L} \in \mathcal{X}$, which is a vector of L binary characteristics. These characteristics are known to everyone in the same cohort.

Second, the student's decision to enroll in the college-prep coursework is shaped by whether the student is encouraged by their teacher to apply to college, denoted as b_{igs}, which is only known to the student (and observed in the data,) but not to any other student. Third, an unobserved component, ϵ_{igs}, influences the student's motivation to take the college-prep coursework. This component is known only to the student and not to their cohort members. Fourth, the student's decision is influenced by unobserved year-specific and school-specific factors, represented by $\kappa \equiv \{\kappa_1, \ldots, \kappa_G\}$ and $\gamma \equiv \{\gamma_1, \ldots, \gamma_S\}$, respectively.

Fifth, the student takes into account the student composition of their cohort. The term $z_{ijgs,\ell c} \equiv \mathbb{1}\{x_{igs,\ell} = c, x_{jgs,\ell} = c\}$ denotes that the ℓth characteristic for both students i and j equals c. If $\psi_{\ell,c} > 0$, it indicates that students whose ℓth characteristic equals c are more likely to enroll in the college-prep coursework as the share of cohort-members whose ℓth characteristic equals c

increases. Note that we are summing up these terms across characteristics and cohort-members while excluding self, i.e., $j \in \mathcal{N}_{gs} \setminus \{i\}$, and normalizing by the total number of cohort-members $N_{gs} - 1$, thus leading a cohort-level average from the perspective of student i.

Sixth, the student's beliefs about their cohort members' coursework decisions, denoted as $\mathbb{E}\left(a_{jgs} \mid x_{gs}, b_{igs}, \epsilon_{igs}\right)$, shape the student's coursework decisions. This belief is conditional on the information available to the student, $(x_{gs}, b_{igs}, \epsilon_{igs})$, where x_{gs} represents the characteristics of all students in the cohort. A positive value of λ indicates that a student is more likely to enroll in the college-prep coursework when they expect a higher share of their cohort members to enroll in the college-prep coursework. We further allow these beliefs to be heterogeneous by observed characteristics. If $\lambda_{\ell,c} > 0$, it indicates that students whose ℓth characteristic equals c are more likely to enroll in the college-prep coursework as the share of cohort-members whose ℓth characteristic equals c expected to enroll in the college-prep coursework increases.

4.2 Teacher's decision

Students do not have direct knowledge of whether their cohort members are encouraged by the teacher to apply to college (b_{igs}). Normalizing the utility of not encouraging a student to apply to college to zero, the teacher encourages student i in year g in high school s to apply to college if:

$$\delta_0 + x_{igs}\delta + \eta_{igs} + \xi_g + \zeta_s + \frac{1}{N_{gs} - 1} \sum_{j \in \mathcal{N}_{gs} \setminus \{i\}} \sum_{c \in \{0,1\}} \sum_{\ell=1}^{L} \rho_{\ell,c} z_{ijgs,\ell c} > 0, \tag{2}$$

where η_{igs} is a student-specific unobserved factor that affects the teacher's decision in addition to the student's observed characteristics x_{igs}. The decision also depends on year-specific and school-specific unobserved factors, captured by $\xi \equiv \{\xi_1, \ldots, \xi_G\}$ and $\zeta \equiv \{\zeta_1, \ldots, \zeta_S\}$, respectively. Additionally, the teacher takes into account the composition of the cohort. If $\rho_{\ell,c} > 0$, it indicates that the teacher is more likely to encourage a student whose ℓth characteristic equals c to apply to college as the share of cohort-members whose ℓth characteristic c increases.

4.3 Equilibrium

Consider student k in year g in high school s. This student forms a belief about their cohort-member i taking the college-prep coursework given their information set $(x_{gs}, b_{kgs}, \epsilon_{kgs}, \eta_{kgs})$:

$$\Pr\left(a_{igs}=1 \mid x_{gs}, b_{gs}, \epsilon_{kgs}, \eta_{kgs}\right)=$$
$$\mathbb{E}\left(\mathbb{1}\left\{\beta_0+x_{igs}\beta+\alpha b_{igs}+\epsilon_{igs}+\kappa_g+\gamma_s+\frac{1}{N_{gs}-1}\sum_{j\in\mathcal{N}_{gs}\setminus\{i\}}\sum_{c\in\{0,1\}}\sum_{\ell=1}^{L}\psi_{\ell,c}z_{ijgs,\ell c}+\right.\right.$$
$$\left.\left.\frac{1}{N_{gs}-1}\sum_{j\in\mathcal{N}_{gs}\setminus\{i\}}\left(\lambda+\sum_{c\in\{0,1\}}\sum_{\ell=1}^{L}\lambda_{\ell,c}z_{ijgs,\ell c}\right)\mathbb{E}\left[a_{jgs}\mid x_{gs}, b_{igs}, \epsilon_{igs}\right]>0\right\} \mid x_{gs}, b_{kgs}, \epsilon_{kgs}, \eta_{kgs}\right). \tag{3}$$

In other words, this is the conditional probability of student i choosing the college-prep coursework from their cohort-member k's perspective. However, a lot of information that student k has may tell them nothing about student i. For instance, $epsilon_{kgs}$ is the unobserved utility for student k from choosing the college-prep coursework. This could be something like the student's motivation to attend college or the number of hours they put into their work. This may say nothing about ϵ_{igs} i.e., how motivated student i is or how much time they put into work. Therefore, it is reasonable to make some simplifying assumptions at this point.

We assume that ϵ_{igs} and η_{igs} are independent and identically distributed within and across cohorts and independent from x_{gs}. This assumption implies that the information available privately to student k, i.e., $(b_{kgs}, \epsilon_{kgs}, \eta_{kgs})$, does not provide any additional insight into student i's coursework decision or the teacher's decision to encourage student i to apply to college. In other words, student k forms beliefs about student i's being encouraged to apply to college and choose the college-prep coursework based solely on publicly available information x_{gs}. Now, the probability of student i taking the college-prep coursework based on the information available to student k is

$$\begin{aligned}
&\Pr\left(a_{igs}=1 \mid x_{gs}\right)=\\
&\mathbb{E}\left(\mathbb{1}\left\{\beta_0+x_{igs}\beta+\alpha b_{igs}+\epsilon_{igs}+\kappa_g+\gamma_s+\frac{1}{N_{gs}-1}\sum_{j\in\mathcal{N}_{gs}\setminus\{i\}}\sum_{c\in\{0,1\}}\sum_{\ell=1}^{L}\psi_{\ell,c}z_{ijgs,\ell c}+\right.\right.\\
&\left.\left.\frac{1}{N_{gs}-1}\sum_{j\in\mathcal{N}_{gs}\setminus\{i\}}\left(\lambda+\sum_{c\in\{0,1\}}\sum_{\ell=1}^{L}\lambda_{\ell,c}z_{ijgs,\ell c}\right)\mathbb{E}\left[a_{jgs}\mid x_{gs}\right]>0\right\} \mid x_{gs}\right).
\end{aligned} \tag{4}$$

Now, $\Pr\left(a_{igs}=1 \mid x_{gs}\right)$ represents the probability that student i decides to take the college-prep coursework from the perspective of their (identity-agnostic) cohort members. In equilibrium, this is student i's best response to their beliefs regarding the decisions of other students in their cohorts. Let σ_{igs} be a short-hand representation of $\Pr(a_{igs} = 1 \mid x_{gs})$. A pure-strategy Bayesian-Nash equilibrium of this simultaneous-move game of course choice among students within a year g in high school s is defined by a vector of conditional choice probabilities denoted as $\sigma_{gs} \equiv \{\sigma_{1gs}, \ldots, \sigma_{N_{gs}gs}\} : \mathcal{X}^{N_{gs}} \to \{0,1\}^{N_{gs}}$.

Section 5 will establish conditions that guarantee the uniqueness of the equilibrium. These conditions ensure that the best response function, represented by Equation (4), exhibits properties of a contraction mapping. By examining the estimation results, we will determine whether we can rule out the possibility of multiple equilibria while refraining from imposing constraints on the parameter space.

5 Identification

In this section, we discuss the strategy to identify the parameters associated with the teacher's decisions regarding encouraging students to apply to college, $\theta_1 \equiv (\delta, \xi, \zeta, \rho)$ and students' decisions regarding taking the college-prep coursework, $\theta_2 \equiv (\beta, \alpha, \kappa, \gamma, \psi, \lambda)$. Below, we outline the assumptions that underpin our analysis.

Assumption 1. *We assume that ϵ_{igs} and η_{igs} are independent and identically distributed across cohorts and independent of x_{gs}. They are also assumed to be drawn from a type I extreme value distribution with a location parameter of 0 and a scale parameter of 1.*

This assumption implies random assignment conditional on observable student factors and school and year fixed effects, which has been employed in various studies (Hoxby, 2000; Gould, Lavy, and Daniele Paserman, 2009; Caetano and Maheshri, 2017; Hoekstra, Mouganie, and Wang, 2018; Cools, Fernández, and Patacchini, 2019). This is akin to taking variations in student composition across cohorts within the school to be idiosyncratic variations.

Assumption 2. *We assume* $\max_i \frac{1}{N_{gs}-1} \sum_{j \in \mathcal{N}_{gs} \setminus \{i\}} \mid \lambda + \sum_{c \in \{0,1\}} \sum_{\ell=1}^{L} \lambda_{\ell,c} z_{ijgs,\ell c} \mid \leq 4.$

This condition constrains the strength of the endogenous social interactions in the model, ensuring that the best response function in Equation (4) is a contraction mapping. This a standard tool employed to establish the uniqueness of equilibrium in Bayesian games (Lin, Tang, and Yu, 2021).

It is important to note that we do not impose Assumption (2) on the parameter space. We verify whether this condition holds after the estimation of the model. We derive this condition by considering the gradient of the vector of choice probabilities and its maximum row sum. We consider the vector of choice probabilities in a generic graduating class and high school, omitting the subscripts g and s: $\sigma = (\sigma_1, \ldots, \sigma_N)$. The gradient $\frac{\partial \sigma}{\partial \sigma'}$ is given by

$$\begin{pmatrix} 0 & \frac{1}{N-1}\sigma_1(1-\sigma_1)(\lambda + \sum\limits_{c,\ell} \lambda_{\ell,c} z_{12,\ell c}) & \ldots & \frac{1}{N-1}\sigma_1(1-\sigma_1)(\lambda + \sum\limits_{c,\ell} \lambda_{\ell,c} z_{1N,\ell c}) \\ \vdots & \ddots & \vdots & \\ \frac{1}{N-1}\sigma_N(1-\sigma_N)(\lambda + \sum\limits_{c,\ell} \lambda_{\ell,c} z_{N1,\ell c}) & \frac{1}{N-1}\sigma_N(1-\sigma_N)(\lambda + \sum\limits_{c,\ell} \lambda_{\ell,c} z_{N2,\ell c}) & \ldots & 0 \end{pmatrix} \tag{5}$$

Let $\|.\|_\infty$ denote the maximum row sum of a square matrix. A sufficient condition for equation (4) to be a contraction mapping is that $\left\|\frac{\partial \sigma}{\partial \sigma'}\right\|_\infty < 1$. Note that under the Assumption (1) that ϵ's are drawn from a type I extreme value distribution, $\sigma_i(1-\sigma_i)$ has a maximum value of $\frac{1}{4}$. Therefore, it follows that σ is a contraction mapping with respect to the $\|.\|_\infty$ norm if

$$\begin{aligned} &\max_i \frac{1}{N-1}\sigma_i(1-\sigma_i)\sum_{j\neq i} \mid \lambda + \sum_{c,\ell} \lambda_{\ell,c} z_{ij,\ell c} \mid \leq 1 \\ &\max_i \frac{1}{N-1}\sum_{j\neq i} \mid \lambda + \sum_{c,\ell} \lambda_{\ell,c} z_{ij,\ell c} \mid \leq 4 \end{aligned} \tag{6}$$

Assumption 3. *We assume that* $E\left[\mathrm{Var}\left(V\right)\right]$ *is non-singular where we define*

$$\begin{aligned} V = \Bigg(& 1, x_{igs}, b_{igs}, \left\{ \frac{1}{\mid \mathcal{N}_{gs} \mid -1} \sum_{j \in \mathcal{N}_{gs}\setminus\{i\}} \sum_{c\in\{0,1\}} z_{ijgs,\ell c} \right\}_{\ell=1}^{L}, \\ & \left\{ \frac{1}{\mid \mathcal{N}_{gs} \mid -1} \sum_{j \in \mathcal{N}_{gs}\setminus\{i\}} \sum_{c\in\{0,1\}} z_{ijgs,\ell c} \mathbb{E}\left[a_{jgs} \mid x_{gs}\right] \right\}_{l=1}^{L}, \\ & \frac{1}{\mid \mathcal{N}_{gs} \mid -1} \sum_{j \in \mathcal{N}_{gs}\setminus\{i\}} \mathbb{E}\left[a_{jgs} \mid x_{gs}\right] \Bigg) \end{aligned} \tag{7}$$

This condition is a standard regularity condition that rules out pathological cases of linear dependence. Recall that $\mathbb{E}\left[a_{jgs} \mid x_{gs}\right]$ solves a nonlinear fixed-point equation in Equation (4) hence it is generally nonlinear in x_{gs} (Yang and Lee, 2017; Lin et al., 2021). This assumption is testable given that the conditional choice probabilities can be consistently estimated (Xu, 2018).

Together, these assumptions imply that after ruling out collinearity between regressors and imposing sufficient within–group variation on choices and characteristics, the structural parameters are identified up to some normalization.

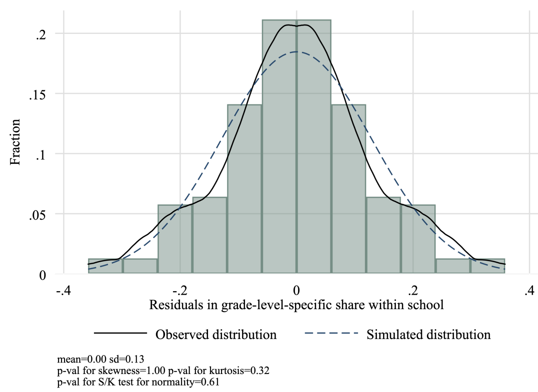
A potential threat to identification is the non–random sorting of students into cohorts, ruled out by Assumption (1). To test this assumption, we regress the cohort-level share of characteristic-ℓ students on the school and year fixed effects and plot the distribution of the residuals of this regression in Figure 1. We also include a simulated normal distribution with the same standard deviation. As we see in Figure 1 (a), the variation in share of White students after controlling for school and year fixed effects resembles a normal distribution. Similarly, cohort-specific shares regarding gender, academic performance, and parent education within school appear to be random. However, we reject the hypothesis that conditional on school and years fixed effects, the share of single parents is normally distributed.

This indicates that there may be a non-random change in single-parent status across years within some schools, which may be more than a macro event. This could be because of a change in the availability of child care or after-school activities or home prices. In this case, ignoring non-random sorting would be a concern if these factors also play a role in students' decision to enroll in the college-prep coursework, for instance. Similarly, there could be correlated effects created by common unobserved information shocks that hit the cohort. Within a school, there might be changes in the staff or the neighborhood amenities between the two years. Unfortunately, cohort-level unobservables are not identified in this framework (Blume, Brock, Durlauf, and Ioannides, 2011).

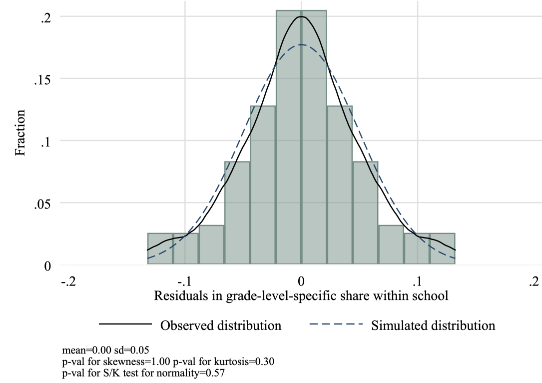
In the study of social interactions, the identification is further complicated by the simultaneity problem, also known as the reflection problem (Manski, 1993). However, the non–linear functional form given by the discrete choice model breaks this simultaneity problem (Brock and Durlauf, 2001; Blume, Brock, Durlauf, and Ioannides, 2011).

We summarize the intuition behind the identification below. We have five sets of identifications: conditional probabilities, school and year fixed effects, individual characteristics, contextual social interactions, and endogenous social interactions.

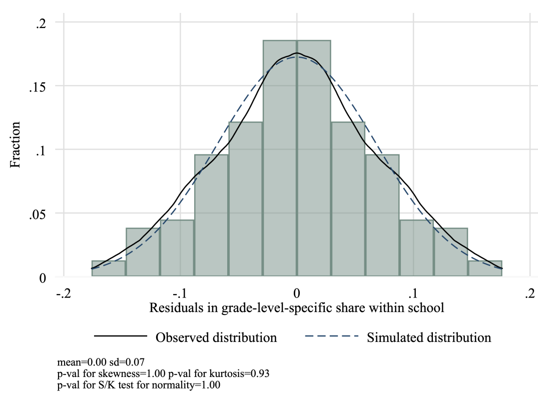
Figure 1. Distribution of Characteristic Shares within School



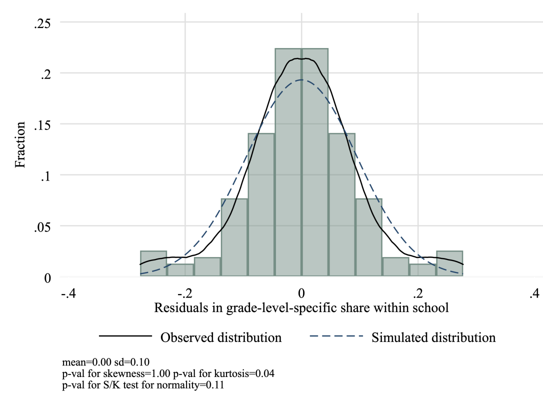
(a) Race



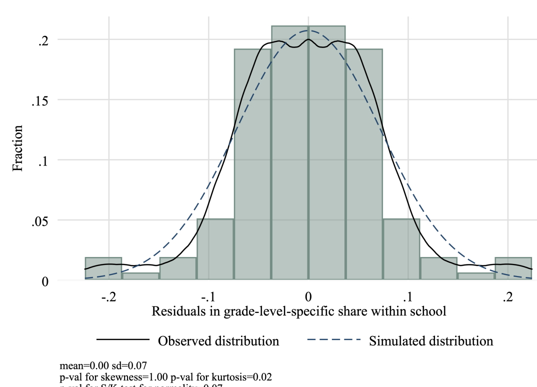
(b) Gender



(c) Academic Performance



(d) Parent Education



(e) Single Parent

Note: This figure shows the distribution of the residualized variation in the share of characteristic-ℓ across years within a school. It includes a simulated normal distribution with the same standard deviation.
Data source: Texas Higher Education Opportunity Project (THEOP), Wave I, 2002

First, the conditional probabilities of a teacher encouraging the student to apply to college and of a student taking the college-prep coursework are identified by examining the sample moments from the data.

Second, the parameters ζ and γ capture the school-specific unobserved heterogeneity in the encouragement and enrollment rates, respectively. They are identified by studying variations in the encouragement and enrollment rates, respectively, across schools. We normalize $\zeta_1 = 0$ and $\gamma_1 = 0$. To ensure the consistency of the estimates, it is necessary to have a sufficiently large number of students in each school (Lee, Li, and Lin, 2014). Therefore, the analysis is based on high schools with at least 100 students. The parameters ξ and κ are associated with year-specific unobserved heterogeneity in encouragement and enrollment rates, respectively. They are identified by studying variations in the encouragement and enrollment rates, respectively, across grade levels. Each high school in the sample has two grade levels: tenth and twelfth. We normalize $\xi_1 = 0$ and $\zeta_1 = 0$.

Third, the parameters δ and β govern the utility of encouragement and enrollment, respectively, is associated with the student-specific observed characteristics. They are identified by analyzing variations in encouragement and enrollment rates across student characteristics.

Fourth, the contextual social interaction parameters ρ's and ψ's and ψ's capture how the utility of encouragement and enrollment are associated with the share of same-characteristic students in the cohort. For example, $\rho_{gender,1}$ captures how the probability that a female student is encouraged by their teacher to apply to college is associated with the share of female cohort members in the cohort. This parameter is identified by studying the variations in the encouragement decisions for female students across variations in the share of female cohort members.

Fifth, the (homogenous) endogenous social interaction parameter λ captures how the utility of enrollment is associated with the enrollment rate among cohort members. It is identified by studying the variations in the enrollment rates across variations in the average enrollment rate in the cohort. The (heterogenous) endogeneous social interaction parameters λ's capture how the utility of enrollment is associated with the enrollment rate among same-characteristic cohort-members. For example, $\lambda_{gender,1}$ captures how the probability of a female student enrolling in college-prep coursework is associated with the enrollment rate among female cohort members. This parameter is identified by studying the variations in the enrollment decisions for female students across variations in the enrollment rate among female cohort members.

6 Estimation

In this section, we outline the estimation procedure for the parameters associated with the teacher's decision, $\theta_1 \equiv (\delta, \xi, \zeta, \rho)$, and the student's decision, $\theta_2 \equiv (\beta, \alpha, \kappa, \gamma, \psi, \lambda)$. The estimation approach involves two stages: in the first stage, we recover θ_1 using a maximum likelihood estimation approach,. In the second stage, we recover θ_2 using a three-step nested pseudo likelihood estimation.

The utility specification includes vector x_{igs} that consists of binary variables representing various characteristics of student i. These characteristics include the student's race, gender, academic performance, parents' education, and single-parent status. These L binary variables define the state space $\mathcal{X} \equiv \{0,1\}^L$, representing all possible combinations of these characteristics. As a result, we can define students as 2^L observed types. The student's type $t \in \{0,1\}^L$ allows for the mapping the best response function in the state space 2^L, considerably increasing the computational efficiency.

6.1 First stage: Teacher's decision

The log-likelihood of student i of type t in year g of high school s getting encouraged to apply to college is:

$$\mathcal{L}_{itgs}(\theta_1) = \mathbb{1}\{b_{itgs} = 1\} \log(\phi_{itgs}(x_{gs}; \theta_1)) + (1 - \mathbb{1}\{b_{itgs} = 1\}) \log(1 - \phi_{itgs}(x_{gs}; \theta_1)) \tag{8}$$

where b_{itgs} represents the teacher's (observed) decision whether to encourage student i of type t for college and $\phi_{itgs}(x_{gs}; \theta_1)$ represents the probability of the teacher encouraging student i to apply to college, given the candidate parameter value θ_1. Under the assumption that η_{igs} follows a type I extreme value distribution with a location parameter of 0 and a scale parameter of 1, this probability is:

$$\phi_{itgs}(x_{gs}; \theta_1) = \frac{\exp\left(\delta_0 + x_{tgs}\delta + \xi_g + \zeta_s + \sum_{t'} w_{tt'gs} \sum_{c,\ell} \rho_{\ell,c} z_{ijgs,\ell c}\right)}{1 + \exp\left(\delta_0 + x_{tgs}\delta + \xi_g + \zeta_s + \sum_{t'} w_{tt'gs} \sum_{c,\ell} \rho_{\ell,c} z_{ijgs,\ell c}\right)}, \tag{9}$$

where $w_{tt'gs} = \frac{N_{t'gs} - \mathbb{1}\{t'=t\}}{N_{gs}-1}$ represents the share of cohort-members of type t' from the perspective of a student of type t in yea g of high school s. We can think of $w_{tt'gs}$ as a term in a matrix representing the social network of year g and high school s. To illustrate this, we can define a $N_{tgs} \times N_{tgs}$ matrix, denoted as $w^*_{tt'gs}$, with elements $w^*_{tt'gs} = N_{t'gs}$ if $t' \neq t$ and $w^*_{tt'gs} = N_{t'gs} - 1$ if $t' = t$. This matrix represents the social network, where each student of type t knows $N_{tgs} - 1$ cohort-members of the same type (excluding themselves) and $N_{t'gs}$ students of type t'. By row-normalizing this matrix, we obtain the values of $w_{t'tgs}$. In this context, a student of type t assigns a weight of $\frac{N_{tgs}-1}{N_{g}s-1}$ to their same-type cohort-members and $\frac{N_{t'gs}}{N_{gs}-1}$ to cohort-members of type t'. These weights change when a policy alters the student composition within a cohort.

Due to the assumption that the unobserved random components η's are independent and identically distributed within each cohort, the likelihoods of individual outcomes are independent of each other, conditional on the observed characteristics. This assumption allows for the summation of likelihoods across students within each cohort. We estimate the parameters θ_1 by maximizing the sum of the log-likelihoods across all cohorts and student types:

$$\hat{\theta}_1 = arg \max_{\theta_1} \sum_{s=1}^{S} \sum_{g=1}^{G} \sum_{t=1}^{T} \sum_{i=1}^{N_{tgs}} \mathcal{L}_{itgs}\left(\theta_1\right). \tag{10}$$

6.2 Second stage: Student's decision

The log-likelihood function is:

$$\begin{aligned} \mathcal{L}_{itgs}(\hat{\theta}_1, \theta_2) = {} & a_{itgs} \log\left[\sigma_{itgs}\left(x_{gs}; \hat{\theta}_1, \theta_2\right)\right] \\ & + (1 - a_{itgs}) \log\left[1 - \sigma_{itgs}\left(x_{gs}; \hat{\theta}_1, \theta_2\right)\right]. \end{aligned} \tag{11}$$

where a_{itgs} represents the (observed) coursework decision of student i of type t in year g in school s, and $\sigma_{tgs}(\hat{\theta}_1, \theta_2)$ denotes the estimated conditional choice probability of a type-t student in year g in school s, based on the estimated first-stage parameter vector $\hat{\theta}_1$ and a candidate parameter vector θ_2.

For each candidate vector θ_2, we solve for the vector of choice probabilities $\sigma_{itgs}\left(x_{gs}; \hat{\theta}_1, \theta_2\right)$ that satisfy

$$\begin{aligned} \sigma_{itgs}\left(x_{gs}; \hat{\theta}_1, \theta_2\right) = {} & \sigma_{itgs}\left(x_{gs}, 0; \theta_2\right)\left(1 - \phi\left(x_{gs}; \theta_1\right)\right) \\ & + \sigma_{itgs}\left(x_{gs}, 1; \theta_2\right)\phi\left(x_{gs}; \theta_1\right) \end{aligned} \tag{12}$$

where $\sigma_{itgs}\left(x_{gs}, b; \theta_2\right)$ is the probability of the student taking the college-prep coursework conditional on the teacher's encouragement decision b:

$$\sigma_{itgs}\left(x_{gs}, b; \theta_2\right) = \frac{\exp\big(\beta_0+x_{tgs}\beta+\alpha b+\kappa_g+\gamma_s+\sum_{t'} w_{tt'gs}\big(\lambda\sigma_{t'gs}+\sum_{c,\ell} z_{tt'gs,\ell c}(\psi_{\ell,c}+\lambda_{\ell,c}\sigma_{t'gs})\big)\big)}{1+\exp\big(\beta_0+x_{tgs}\beta+\alpha b+\kappa_g+\gamma_s+\sum_{t'} w_{tt'gs}\big(\lambda\sigma_{t'gs}+\sum_{c,\ell} z_{tt'gs,\ell c}(\psi_{\ell,c}(\psi_{\ell,c}+\lambda_{\ell,c}\sigma_{t'gs}))\big)\big)}. \tag{13}$$

One way to estimate θ_2 would involve an iterative procedure that nests a fixed-point solution for σ by solving for Equation (13) inside maximum likelihood estimation (Rust, 1987). However, this method can be computationally costly. We can instead rely on a nested pseudo-likelihood estimation method (Aguirregabiria and Mira, 2007; Lin, Tang, and Xiao, 2021). Another concern is the number of school-specific fixed effects. Define the second-stage parameters $\theta_2 \equiv (\beta, \alpha, \kappa, \psi, \gamma, \lambda)$ governing the student's decision to enroll in the college-prep coursework as two sub-groups $\theta_{21} \equiv (\beta, \alpha, \kappa, \psi, \lambda)$ and $\theta_{22} \equiv \gamma$, the latter being the school-specific fixed effects. We propose a three-step nested pseudo likelihood method in which instead of searching for θ_{22} in the same way as search for θ_{21}, we solve for θ_{22} through a contraction mapping as described by Berry, Levinsohn, and Pakes (1993):

$$\theta_{22,s}^{(h+1)} = \theta_{22,s}^{(h)} + \log\left[\frac{1}{N_s}\sum_i a_{igs}\right] - \log\left[\frac{1}{N_s}\sum_i \sigma_{itgs}\left(x_{gs}; \hat{\theta}_1, \theta_{21}, \theta_{22}^{(h)}\right)\right] \tag{14}$$

The idea is that we start with a guess for the mean utility specific to school s, $\theta_{22,s}$, and iterate over it until the observed share of students enrolled in the college-prep coursework in school s is sufficiently close to the predicted share of students enrolled in the college-prep coursework in school s. Now, the search space for θ_{21} is much smaller.

Let p_{tgs} define the conditional choice probability of type t student of year g of school s taking the college-prep coursework. Let p denote the collection of all p_{igs} for all i, g, s.

We define the pseudo log-likelihood function as:

$$\begin{aligned}\mathcal{L}_{itgs}(\hat{\theta}_1, p_{gs}, \theta_{21}, \theta_{22}) = a_{itgs} \log\left[\sigma_{itgs}\left(x_{gs}; \hat{\theta}_1, p_{gs}, \theta_{21}, \theta_{22}\right)\right] \\ + (1 - a_{itgs}) \log\left[1 - \sigma_{itgs}\left(x_{gs}; \hat{\theta}_1, p_{gs}, \theta_{21}, \theta_{22}\right)\right]\end{aligned} \tag{15}$$

and the conditional choice probability mapping

$$\sigma_{itgs}\left(x_{gs}, b; p_{gs}, \theta_{21}, \theta_{22}\right) = \frac{\exp\left(\beta_0 + x_{tgs}\beta + \alpha b + \kappa_g + \gamma_s + \sum_{t'} w_{tt'gs}\left(\lambda p_{t'gs} + \sum_{c,\ell} z_{tt'gs,\ell c}(\psi_{\ell,c} + \lambda_{\ell,c} p_{t'gs})\right)\right)}{1 + \exp\left(\beta_0 + x_{tgs}\beta + \alpha b + \kappa_g + \gamma_s + \sum_{t'} w_{tt'gs}\left(\lambda p_{t'gs} + \sum_{c,\ell} z_{tt'gs,\ell c}(\psi_{\ell,c} + \lambda_{\ell,c} p_{t'gs})\right)\right)}. \tag{16}$$

Algorithm 1 Three-Step Nested Psuedo Likelihood Algorithm

Require: Initial guess $(p^{(1)}, \theta_{21}^{(1)}, \theta_{22}^{(1)})$ and first-stage estimate $\hat{\theta}_1$
Ensure: $\max(|p^{(h+1)} - p^{(h)}|) < tol$
  Initialize $h \leftarrow 1$
  while $\max(|p^{(h+1)} - p^{(h)}|) \geq tol$ **do**
    Step 1
    $\theta_{21}^{(h+1)} \leftarrow \arg\max_{\theta_{21}} \sum_i \mathcal{L}_i(\hat{\theta}_1, p^{(h)}, \theta_{21}, \theta_{22}^{(h)})$ in Equation (17)
    Step 2
    $\theta_{22,s}^{(h+1)} \leftarrow \theta_{22,s}^{(h+1)} + \log\left[\frac{1}{N_s}\sum_i a_i\right] - \log\left[\frac{1}{N_s}\sum_i p_i^{(h)}\right] \forall s$ in Equation (14)
    Step 3
    $p_i^{(h+1)} \leftarrow \sigma_i(x; \hat{\theta}_1, \theta_{21}^{(h+1)}, \theta_{22}^{(h+1)}) \forall i$ in Equation (12)
    $h \leftarrow h + 1$
  end while=0

We start with the sample moments as the initial guess $p^{(0)}$, i.e., the share of type t students in year g in school s enrolling in the college-prep coursework. We also make initial guesses for θ_2. In Step 1, we solve for θ_{21} through a maximum likelihood approach given $p^{(h)}$ and $\theta_{22}^{(h)}$:

$$\hat{\theta}_{21}^{(h+1)} = arg\max_{\theta_{21}} \sum_{s=1}^{S}\sum_{g=1}^{G}\sum_{t=1}^{T}\sum_{i=1}^{N_{tgs}} \mathcal{L}_{itg}(\hat{\theta}_1, p^{(h)}, \theta_{21}, \theta_{22}^{(h)}). \tag{17}$$

Then in Step 2, we update θ_{22} by solving for the contraction mapping in Equation (14), and then in Step 3, we update p using the conditional choice probability mapping in Equation (16). We keep repeating Steps 1-3 until $||\ p^{(h+1)} - p^{(h)}\ ||$ is small enough. We summarize this method in Algorithm 1.

7 Model Estimates

This section presents the estimation results derived from the model outlined in the course choice game described in Section 4, which examines the decision-making processes of both teachers and students regarding college preparation. Our analysis incorporates a range of individual characteristics,

Table 3. Comparing Means in Entire vs Representative Samples

	(1) Entire Sample	(2) Representative Sample
Black	0.146	0.145
Hispanic	0.409	0.410
Female	0.475	0.474
High Academic Performance	0.383	0.382
Parent attended college	0.539	0.539
Single parent	0.462	0.461
Teacher encouraged for college	0.329	0.332
Obs	24,432	1,001

Data source: Texas Higher Education Opportunity Project (THEOP), Wave I, 2002

including the student's race, gender, academic performance, parent's education, and single-parent status, alongside cohort-level shares of these attributes. We also include school and year fixed effects.

In addition to estimating the parameters outlined in Section 4, we analyze the marginal effects. To derive the average marginal effects, we construct a representative sample that mirrors the average shares of each characteristic, as illustrated in Table 3. We elaborate on the construction of these marginal effects in more detail below.

7.1 Teacher's decision

Table 4 presents the estimated parameters regarding the teacher's decision to encourage students to apply to college. The first column displays the estimates of the parameters in Equation (9). The second column provides the associated standard errors. In contrast, the third column presents the marginal effect of a unit change in each individual and contextual characteristic on the average encouragement rate in the representative sample.

We construct the marginal effect of characteristic ℓ on whether the student is encouraged to apply to college by comparing the predicted encouragement rate when all students' characteristic ℓ equals one to that when all students' characteristic ℓ equals zero while holding all other characteristics constant. When constructing the marginal effects of individual characteristics, the parameters associated with contextual characteristics are set to zero.

The results suggest that holding other factors constant, teachers are approximately nine percentage points less inclined to encourage Hispanic students to apply to college in a representative cohort than a White student. Teachers are more inclined to encourage low-SES students to apply to college. They are 14 percentage points less inclined to encourage students whose parents attended college, and about 18 percentage points more likely to encourage students residing in single-parent households. An academically high performing student is 11 percentage points more likely to receive encouragement to pursue college.

We also examine the contextual incentives of teachers to encourage students to apply to college. To calculate the average marginal effect of an increase in the share of same-characteristic cohort members for a student whose characteristic-ℓ equals $c \in \{0, 1\}$, we compare the predicted encouragement rate with contextual social interactions enabled versus disabled, while all students' characteristic ℓ equals c, and all other characteristics remain unchanged.

Teachers exhibit varying tendencies in encouraging students based on contextual factors. As the share of Black students increases by a unit, teachers are ten percentage points less likely to encourage Black students. Conversely, they are seven percentage points more likely to encourage Hispanic students as the share of Hispanic students increases by a unit. Moreover, teachers are 18 percentage points more inclined to encourage male students and 21 percentage points more inclined to encourage female students as the respective shares of male and female students increase by a unit.

Furthermore, teachers' encouragement patterns are influenced by family SES – their encouragement of low SES students decreases as the cohort becomes more low SES and their encouragement of high SES increases as the cohort becomes more high SES. They are 17 percentage points less likely to encourage students whose parents did not attend college as the share of such students increases by a unit, while 29 percentage points more likely to encourage students whose parents attended college under the same circumstances. Additionally, teachers are 23 percentage points more likely to encourage students from two-parent households as the share of students in such households increases by a unit but 24 percentage points less likely to encourage students from single-parent households as the share of students in such households increases by a unit.

Overall, these results indicate that while teachers may show less encouragement toward Hispanic students, they do positively encourage students from low-SES families.

However, this encouragement decreases as the representation of low SES students increases, suggesting that student-teacher interactions become weaker as the cohort becomes more low SES. A similar pattern is observed for Black students. Conversely, encouragement for Hispanic students,

Table 4. Model Estimates: Teacher's Decision

	(1) Estimate	(2) S.E.	(3) Marginal Effect
Constant	-1.95	0.46	-
Individual Characteristics			
Black	0.13	0.13	0.03
Hispanic	-0.37	0.13	-0.09
Female	0.06	0.41	0.01
High Academic Performance	0.59	0.31	0.11
Parent attended college	-0.74	0.25	-0.14
Single parent	0.90	0.35	0.18
Contextual Social Interactions			
White	0.12	0.16	0.01
Black	-0.51	0.24	-0.10
Hispanic	0.36	0.14	0.07
Male	0.89	0.48	0.18
Female	1.03	0.52	0.21
Low Academic Performance	0.45	0.33	0.08
High Academic Performance	0.18	0.37	0.04
Parent did not attend college	-0.95	0.27	-0.17
Parent attended college	1.36	0.26	0.29
Two Parents	1.10	0.39	0.23
Single Parent	-1.31	0.40	-0.24
Log-likelihood		-14644.64	
Number of students		24,432.00	
Number of cohorts		156.00	

Note: This table presents the estimation results for the model characterizing teachers' decision to encourage a student to pursue college in the future, as described in Equation (2). Column (3) presents the average marginal effects for a representative cohort.
Data source: Texas Higher Education Opportunity Project (THEOP), Wave I, 2002

male students, female students, and high SES students increases with their representation.

7.2 Student's decision

Table 5 presents the estimated parameters regarding the student's decision to enroll in college-prep coursework. The first column displays the estimates of the model Equation (12). The second column provides the associated standard errors. In contrast, the third column presents the marginal effect of a unit change in each variable on the average enrollment rate in the representative cohort.

Black students are nine percentage points less inclined to enroll in college-prep coursework than their counterparts. Similarly, Hispanic students show a two percentage point lower tendency to enroll. Students with high academic performance exhibit a four percentage point higher tendency to enroll in such coursework. Moreover, students who receive encouragement from their teachers to apply to college demonstrate a five percentage point higher tendency to enroll.

Regarding contextual social interactions, White students show a nine percentage point lower inclination to enroll in the college-prep coursework as the share of White students increases by a unit.

Similarly, students with high academic performance display a 13 percentage point lower inclination to enroll in such coursework as the share of students with high academic performance increases by a unit. These patterns may reflect lower self-efficacy driven by higher academic competition.

Regarding endogenous social interactions, students are six percentage points less inclined to enroll in college-prep coursework as the expected share of students who enroll in such coursework increases by a unit. This is likely to reflect a higher academic competition. When students expect a higher enrollment in the college-prep coursework, they may expect to not do well in this coursework and hence decide not to enroll in it. On the other hand, we observe positive within-group endogenous social interactions, suggesting coordination incentives. White and Hispanic students demonstrate a 17 percentage point and a 14 percentage point higher tendency to enroll as the expected share of same-race students who enroll in college-prep coursework increases by a unit. Similarly, female students display a 13 percentage point higher tendency to enroll as the expected share of female students who enroll in such coursework increases by a unit. Moreover, students whose parents attended college show a ten percentage point higher tendency to enroll as the expected share of such students to enroll in the college-prep coursework increases by a unit.

Summary of Results: Black students are less likely to receive encouragement from teachers to pursue college as their representation increases. They exhibit positive within-race contextual social interactions but negative within-race endogenous social interactions. Low SES students are also less likely to receive encouragement from teachers to pursue college as their representation increases. They have negative within-group contextual social interactions but positive, albeit small, within-group endogenous social interactions. Their college-prep enrollment is predicted to be lower as their representation increases due to weaker inter-student and student-teacher interactions.

Hispanic students, conversely, are more likely to receive encouragement from teachers to pursue college as their representation increases. Despite having negative within-race contextual social interactions, they benefit from positive within-race endogenous social interactions. Their college-prep enrollment is likely to increase with stronger inter-student and student-teacher interactions as their representation grows. Similar patterns are observed for female students.

Table 5. Model Estimates: Student's Decision

	(1) Estimate	(2) S.E.	(3) Marginal Effect
Constant	-0.98	1.10	-
Individual Characteristics			
Black	-0.85	0.19	-0.11
Hispanic	-0.71	0.19	-0.00
Female	-0.71	0.56	-0.09
High academic performance	2.13	0.62	0.26
Parent attended college	0.21	0.45	0.04
Single parent	0.51	0.57	0.04
Teacher encouraged for college	0.43	0.04	0.05
Contextual Social Interactions			
White	-0.72	0.14	-0.09
Black	0.39	0.32	0.04
Hispanic	-0.11	0.16	-0.01
Male	-0.55	0.40	-0.07
Female	-0.08	0.43	-0.01
Low academic performance	0.63	0.41	0.04
High academic performance	-0.76	0.38	-0.13
Parent did not attend college	-0.34	0.28	-0.03
Parent attended college	-0.16	0.24	-0.02
Two Parents	0.26	0.34	0.03
Single Parent	-0.41	0.37	-0.05
Endogenous Social Interactions			
Homogenous	-0.60	0.29	-0.06
White	2.28	0.57	0.17
Black	-2.62	5.05	-0.03
Hispanic	3.21	0.81	0.14
Male	0.99	1.53	0.05
Female	3.18	1.30	0.13
Low academic performance	1.90	1.53	0.02
High academic performance	1.59	1.26	0.23
Parent did not attend college	0.04	1.44	0.00
Parent attended college	1.95	0.75	0.10
Two Parents	1.43	1.25	0.04
Single Parent	0.81	1.80	0.03
Log-likelihood		-9187.81	
Number of students		24,432.00	
Number of cohorts		156.00	

Note: This table presents the estimation results for the model characterizing students' decision to enroll in the college-prep coursework, as described in Equation (1). Column (3) presents the average marginal effects for a representative cohort.
Data source: Texas Higher Education Opportunity Project (THEOP), Wave I, 2002

8 Implications of Changing Between-School Segregation

The landmark 1954 Supreme Court decision in Brown v. Board of Education declared "separate but equal" schooling unconstitutional. In response, several court-ordered school desegregation initiatives were implemented. These initiatives authorized the use of busing and the redrawing of school zones to achieve racial balance in schools.

Scholars have connected these racial desegregation initiatives with increased educational attainment, higher income, and decreased rates of homicide victimization and arrests for Black students (Guryan, 2004; Weiner, Lutz, and Ludwig, 2009; Reber, 2010; Johnson, 2011).

However, several studies have documented a "segregation paradox" in high school course-taking.

Card and Rothstein (2007), Kelly (2009), and Clotfelter, Ladd, Clifton, and Turaeva (2021) find that within-school segregation in terms of enrollment in the college-prep courses is higher in more integrated schools. Elder, Figlio, Imberman, and Persico (2021) find that Black and Hispanic students are overidentified for special education in schools with relatively small minority populations and are substantially underidentified in schools with large minority populations.

In the 1990s, racial desegregation initiatives were deemed illegal because they used race as an explicit criterion for student assignment. Today, integration policies implemented by school districts aim to address disparities in student outcomes and promote diversity through changes in attendance boundaries or lottery-based enrollment, considering factors like socioeconomic status (Tractenberg et al., 2016; Learned-Miller, 2016; Potter, 2023). For instance, the Dallas Independent School District in Texas introduced the "Transformation Schools" initiative, which utilizes random assignment to ensure socioeconomic diversity, aiming for a 50/50 split (Rix, 2022). Factors such as household income, parent education, and single-parent status are considered for integration. Another set of policies involves opening all-girls schools to improve girls' enrollment in STEM courses (Yap, 2016). In general, there is an increasing trend in the number of single-sex schools as a response to the new Title IX single-sex regulations released in 2006, which give communities more flexibility in offering single-sex classes and permit school districts to provide single-sex schools (Lavy and Schlosser, 2011). Recently, some schools have begun to offer courses separated by race (Randazzo and Belkin, 2023).

In this section, we conduct policy simulation exercises to analyze the implications of changes in between-school segregation and within-school segregation in terms of enrollment in the college-prep coursework. This involves two steps. First, we randomly reassign students across schools to construct a desired level of between-school segregation. Segregation is measured using the entropy index proposed by Theil (1972). We treat student reassignment as a non-linear optimization problem, strategically redistributing students to generate alternative entropy index values. In the second step, using the new distribution of students and the model estimates from Section 6, we re-solve the model from Section 4 to determine the new levels of within-school segregation in enrollment in the college-prep coursework. We explore between-school segregation regarding race, gender, parent education, and single-parent status. By examining these dimensions, we aim to comprehensively understand the interplay between different forms of segregation and their impact on educational equity.

8.1 Measuring segregation: Entropy Index

The Theil (1972) index is particularly suitable for capturing how the diversity across individual schools diverges from the overall diversity at the state level. It can handle more than two groups, which aligns with the focus of our investigation. Additionally, the index adheres to the principle of transfers, accurately reflecting the effects of reassigning individuals and providing realistic insights into the impact of changes in school composition.

We first discuss how we construct the Theil (1972) index for each student characteristic,: race, gender, academic performance, parent education, and single parent status. First, we define the state-wide entropy score for characteristic ℓ:

$$\bar{H}_{\ell} = -\sum_{c} \ln\left(w_{\ell,c}^{w_{\ell,c}}\right), \tag{18}$$

where $w_{\ell,c}$ represents the share of students in the state whose characteristic-ℓ equals c. Now, we define the school-specific entropy score for characteristic ℓ:

$$\bar{H}_{\ell s} = -\sum_{c} \ln\left(w_{\ell s,c}^{w_{\ell s,c}}\right). \tag{19}$$

where $w_{\ell s,c}$ represents the share of students in school s whose characteristic-ℓ equals c. Finally, we define the Theil (1972) entropy index for characteristic ℓ, which is the weighted average deviation of the school-level entropy scores from the state-wide entropy score:

$$H_{\ell} = -\sum_{s} w_s \frac{\bar{H}_{\ell s} - \bar{H}_{\ell}}{\bar{H}_{\ell}}, \tag{20}$$

where w_s represents the share of the student population in school s relative to the entire student population in the state. The entropy index ranges from zero to one, with zero indicating minimum segregation (when all schools have the same student composition as the state) and one indicating maximum segregation (when schools consist exclusively of a single student group).

8.2 Student Reassignment

To explore alternative segregation scenarios and achieve specific values of the entropy index, we formulate an optimization problem that involves redistributing students across schools. Each student is characterized by a set of observed characteristics, denoted by their type $t \in \{1, \ldots, T\}$. There are T observed student types, encompassing all possible combinations of the L individual discrete characteristics, as detailed in Section 6. The objective is to find a school-specific student composition, $\{w^*_{ts}\}_{\{t,s\}}$, that closely resembles the observed student composition $\{\hat{w}_{ts}\}_{\{t,s\}}$, in order to achieve a desired value of the characteristic-ℓ entropy index, denoted as H^*_ℓ. To accomplish this, we formulate an optimization problem:

$$\{w^*_{ts}\}_{t,s} = arg \min_{\{w_{ts}\}_{t,s}} \frac{1}{S} \sum_{s=1}^{S} \sum_{t=1}^{T} (w_{ts} - \hat{w}_{ts})^2 \text{ subject to} \tag{21}$$

$$\sum_{t \in \{1,\ldots,T\}} w_{ts} = 1 \; \forall \; s \in \{1, \ldots, S\} \tag{21a}$$

$$\sum_{s=1}^{S} w_{ts} n_s = \hat{w}_t n \; \forall \; t \in \{1, \ldots, T\} \tag{21b}$$

$$\sum_{s} w_s \frac{H_{\ell s} - \bar{H}_\ell}{\bar{H}_\ell} = H^*_\ell \tag{21c}$$

where $\bar{H}_\ell$ and $\bar{H}_{\ell s}$ are defined in Equations (18) and (19). The optimization problem aims to minimize differences between the constructed and observed school-specific student compositions while considering multiple constraints. First, the shares of students of each observed type within each school must add up to one, maintaining the overall capacity of each school. Second, the population of each observed type across all schools should match the state-wide population. Third, the constructed entropy index, which measures the level of segregation, should align with the target value. In other words, to build a hypothetical level of segregation along characteristic ℓ, students are randomly assigned to new schools so that the new school-level shares of all characteristics remain as close to the old shares as possible while achieving the desired level of segregation along characteristic ℓ.

8.3 Teachers' and Students' Decisions

To evaluate the impact of student reassignment on teachers' recommendation and students' coursework decisions', we consider the alternative student composition, $\{w^*_{ts}\}_{\{t,s\}}$, resulting from the student reassignment process described in Equation (21) and re-solve the model described in Section 4 given the parameters estimated in Section 6 for these alternative values of student composition.

Figure 2 presents how the predicted encouragement and enrollment rates change as the state desegregates in terms of characteristic ℓ i.e., as $(1 - H_\ell)$ increases. In Figure 2 (a), we observe that Black students are more likely to receive encouragement from their teachers to apply to college in a racially desegregated state compared to a racially segregated state, where schools have a majority of one race. But there is no change in their course enrollment. Hispanic students, on the other hand, are less likely to receive encouragement from their teachers to apply to college and enroll in the college-prep coursework as the state becomes more racially desegregated. Female students are less likely to receive encouragement from their teachers to apply to college and enroll in the college-prep coursework as the state becomes more gender desegregated. Low SES students (in terms of parent education and single parent status) are more likely to receive encouragement from their teachers to apply to college and enroll in college-prep coursework as the state becomes more racially desegregated.

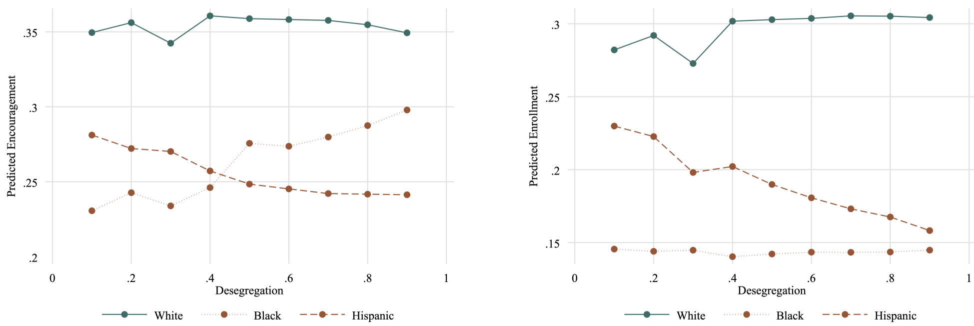
Figure 3 presents how teachers' and students' decisions vary by group (Black students, Hispanic students, female students, students whose parents did not attend college, and students who reside in single-parent households) for four policies: racial desegregation, all-girls schools, desegregation in terms of parent education, and desegregation in terms of single-parent status.

Figure 3 (a) examines teachers' decisions to encourage students to pursue college. Figure 3 (b) examines student enrollment in college-prep coursework. Figure 3 (c) examines whether students enroll in college-prep coursework, assuming no endogenous social interactions among students (i.e., students do not consider how likely others are to enroll). Figure 3 (d) examines whether students enroll in college-prep coursework, assuming encouragement from teachers to pursue college plays no role in students' course decisions.

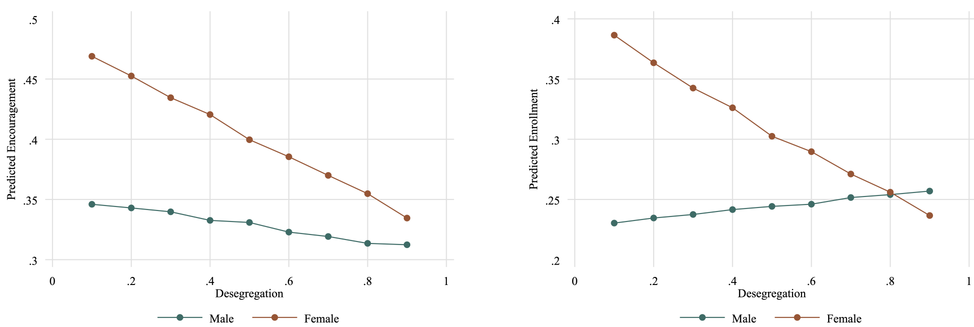
Our analysis indicates several key findings regarding the influence of cohort composition on teachers' encouragement and students' enrollment in college-prep coursework.

Figure 2. Counterfactual

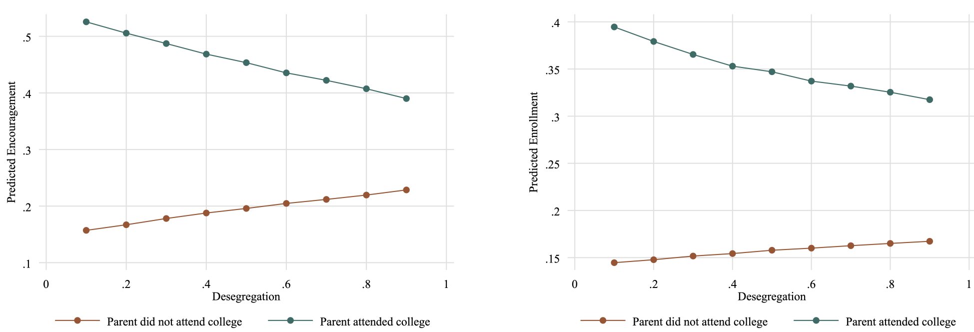
(a) Race



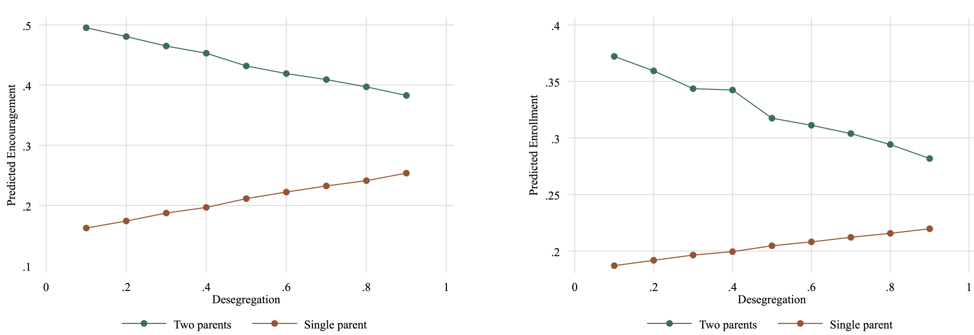
(b) Gender



(c) Parent Education



(d) Single Parent



Note: This figure presents how the predicted encouragement and enrollment rates vary at different levels of between-school segregation. The x-axis shows an increasing desegregation, i.e., $(1 - H)$ where H is the entropy index, as defined in Equation (20). The y-axis shows the predicted rate of (1) teachers encouraging students to pursue college in the future and (2) students enrolling in the college-prep coursework.

First, racial desegregation has mixed effects. Teachers are 29% more likely to encourage Black students for college in desegregated settings but are 14% less likely to encourage Hispanic students. Racial desegregation does not benefit college-prep enrollment for any group and leads to decreased enrollment among under-represented groups, particularly Hispanic students, who see a 31% decrease. This decline is primarily driven by the loss of coordination incentives among same-race cohort members when moving to a racially integrated school. These results highlight the segregation paradox in course-taking, where desegregation leads to unintended adverse outcomes for course-taking among minority students (Card and Rothstein, 2007; Kelly, 2009; Clotfelter, Ladd, Clifton, and Turaeva, 2021).

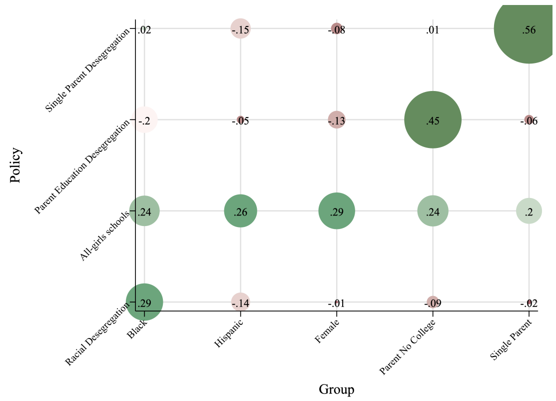
This phenomenon is particularly pronounced for Hispanic students, whose course enrollment lags in racially desegregated schools, as also documented by \citet*{clotfelter2021school} in their analysis of public high school classrooms in North Carolina. Overall, these results suggest there might be merit in recent policies being explored in some school districts that offer race-separate courses(Randazzo and Belkin, 2023).

Second, transitioning to all-girls schools increases teacher encouragement and college-prep enrollment across all groups, with the highest benefits observed for female students (39%). The literature on improved achievement in female-majority cohorts for all students due to lower classroom disruption and improved inter-student and student-teacher relationships supports the observations in Figures 3 (c) and (d) that positive endogenous social interactions among same-group students and higher encouragement to pursue college from teachers enhance the positive association between gender segregation and college-prep enrollment (Hoxby, 2000; Lavy and Schlosser, 2011; Oosterbeek and Van Ewijk, 2014).

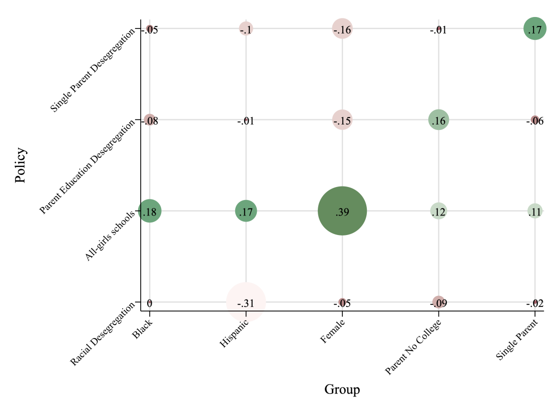
Third, SES desegregation significantly boosts encouragement from teachers for low SES students, with a 45% increase for those whose parents did not attend college and a 56% increase for those from single-parent households. This policy also positively impacts college-prep enrollment for low SES students. Furthermore, when social interactions are controlled, SES desegregation increases college-prep enrollment among Black and Hispanic students. Positive inter-student interactions and student-teacher interactions contribute equally to the benefits of SES desegregation.

These results suggest merit in exploring SES desegregation policies, such as the "Transformation School" initiative in Dallas (Rix, 2022). These policies might even help close racial gaps if accompanied by complementary efforts to counsel students regarding their self-efficacy while making course choices.

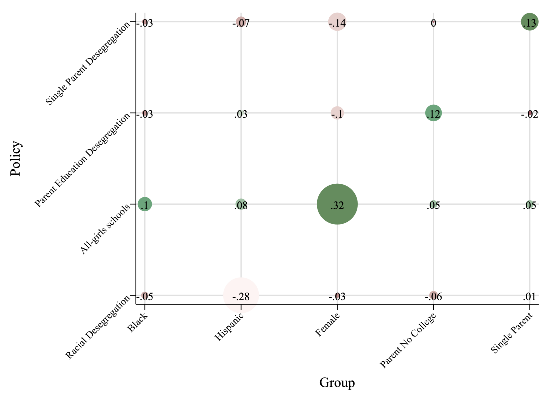
Figure 3. Teacher and Student Decisions, Categorized by Student Group and Segregation Policy



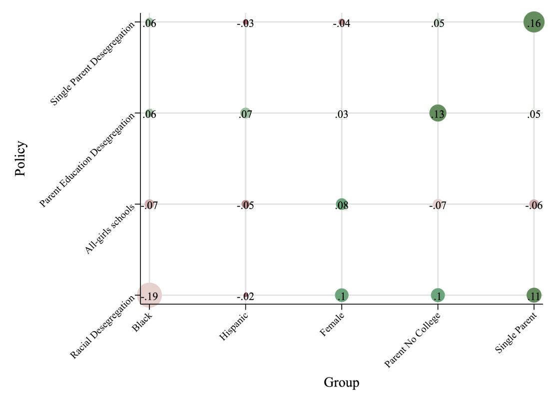
(a) Teacher Decision



(b) Student Decision



(c) Student Decision, Teacher Encouragement Disabled



(d) Student Decision, Endogenous Social Interactions Disabled

Note: This figures shows the percentage change in the predicted encouragement and enrollment rates moving from pre-policy to post-policy levels of between-school segregation, plotted separately for five groups – Black, Hispanic, female, parent did not attend college, and single-parent household – and four policies – racial desegregation, all-girls schools, desegregation based on parent education, and desegregation based on single-parent status.

9 Conclusion

This study investigates the effects of changing between-school segregation, focusing on race, gender, and socioeconomic status (SES), on within-school segregation in terms of enrollment in college-prep coursework. Employing a game-theoretic framework, we model high school students' course decisions, considering the role of inter-student and student-teacher interactions and incorporating heterogenous contextual and endogenous social interactions. Bayesian Nash Equilibrium characterizes our model. We utilize student-level data from a sample of Texas schools, capturing demographics, course choices, performance, and interactions with teachers regarding college aspirations. By leveraging variations in student compositions across adjacent cohorts within schools, we employ a nested pseudo-likelihood estimator to estimate the model parameters.

Our findings reveal significant disparities in teacher encouragement and course enrollment across demographic groups. Black and low SES students receive less encouragement as their representation increases, contrasting with Hispanic and female students who experience heightened encouragement and enrollment with increased representation. White and academically high-performing students show decreased enrollment in college-prep coursework as their representation rises, suggesting competitive pressures or lower perceived abilities within these groups. Additionally, higher expected enrollment in college-prep courses reduces individual enrollment, reflecting a competition effect. Yet, positive within-group social interactions encourage enrollment among White, Hispanic, female, and college-educated parent groups.

Policy simulations indicate mixed outcomes for racial desegregation efforts. While Black students receive more encouragement in desegregated settings, this does not translate into higher enrollment. Conversely, racial desegregation adversely affects Hispanic students, reducing both encouragement and enrollment. These findings align with the segregation paradox observed in racially integrated schools, particularly concerning White-Hispanic disparities in course-taking. The efficacy of recent policies that offer race-separate math courses is discussed in light of these findings.

Moreover, policies promoting all-girls schools positively impact female students, increasing encouragement and enrollment in college-prep coursework. This result may explain the recent popularity of all-girls schools as a tool to foster academic engagement and performance among girls. Similarly, SES desegregation policies show promise, enhancing encouragement and enrollment among low SES students and potentially mitigating racial disparities in course-taking with targeted counseling interventions.

In conclusion, this study offers a comprehensive framework to understand the complex nature of between-school segregation's impact on within-school educational outcomes. Our methodological approach provides insights for policymakers seeking to promote diversity and equity in academic settings. Future research should explore the long-term effects of recent segregation policies and conduct ex-post evaluations to validate model predictions in various local contexts.

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