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An Examination of K-12 Discipline Disparities

and the College Process.

A dissertation submitted in partial satisfaction of the

requirements for the degree Doctor of Philosophy

in Sociology

by

Paul Martinez

2021

ABSTRACT OF THE DISSERTATION

The Educational Pipeline:

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Paul Martinez

Doctor of Philosophy in Sociology

University of California, Los Angeles, 2021

Professor Vilma Ortiz, Chair

This dissertation further investigates predominant issues in the educational pipeline, that is, both the higher education and K-12 context. In particular, I first attempt to answer why post-secondary enrollment at U.S. colleges and universities has increased among all students, but racial/ethnic and gender inequalities persist in the college experience. That is, Latinx and Black students continue to be less likely to graduate from post-secondary institutions and women are underrepresented in science, technology, engineering, and mathematics (STEM) fields. Second, I further contextualize suspensions and the criminalization of students of color in schools today. Today, many schools rely heavily on police and security officers to maintain

discipline. Therefore, in part, this dissertation explores this phenomenon and investigates how the type of staff (e.g., support vs. policing) may contribute to the days of lost instruction time due to out-of-school suspensions. Overall, to investigate the issues proposed, my dissertation uses social network methods to examine college-level educational trajectories at the institutional level and, using quantitative methods, I examine discipline disparities using national data.

The dissertation of Paul Martinez is approved.

Jennie Elizabeth Brand

Cecilia Rios Aguilar

Ka Yuet Liu

Vilma Ortiz, Committee Chair

University of California, Los Angeles

2021

To my family, friends, and mentors
who kept me grounded and helped me believe in myself.

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Cecilia. Cecilia is one of the most brilliant scholars I have met and yet is extremely humble. Her encouragement and devotion in my work is something I could never repay and will forever be humbled by it. At times, I feel like I received the "Cecilia Rios-Aguilar's Fellowship" because she provided funding opportunities for me since the day I met her. While that funding provided financial stability in my life, it also provided opportunities to explore my intellectual curiosity, research skill development and growth, and many awesome datasets to work with. *Muchas gracias por todo*!

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Biographical Sketch

The author graduated from Point Loma High School in 2011. Soon thereafter, Paul Martinez attended Sonoma State University and graduated in 2014 with a B.A. in Sociology Magna Cum Laude with Distinction. Proceeding to attend the University of California, Los Angeles for graduate school, in 2016, Paul received a Master of Arts in Sociology, and in 2021 he earned his Doctor of Philosophy in Sociology. During his time at the University of California, Los Angeles, Paul gained extensive work experience as a research analyst working for research centers including The Center for Civil Rights Remedies at the UCLA Civil Rights Project, Higher Education Research Institute (HERI), and the Los Angeles Education Research Institute (LAERI). His dissertation research uses both quantitative and social network analysis methods to examine race/ethnicity, gender, class inequities in K-12 and higher education settings.

INTRODUCTION

This dissertation further investigates predominant issues in the educational pipeline, that is, both the higher education and K-12 context. In particular, I first attempt to answer why post-secondary enrollment at U.S. colleges and universities has increased among all students, but racial/ethnic and gender inequalities persist in the college experience. That is, Latinx and Black students continue to be less likely to graduate from post-secondary institutions (Bowen, Chingos, and McPherson 2009; Desilver 2014; Krogstad and Fry 2014), and while women have been earning bachelor's degrees at a higher rate than men in recent years (Buchmann and DiPrete 2006), they are underrepresented in science, technology, engineering, and mathematics (STEM) fields (Dickson 2010; Ma and Liu 2017; National Science Board 2016).

Second, I further contextualize suspensions and the criminalization of students of color in schools today. Over time there has been a shift that resulted in many public schools having environments that resemble those of high-crime neighborhoods or prisons (Noguera, 2003), consequently these schools rely heavily on police and security officers to maintain discipline (Lyons & Drew, 2006; Simon, 2007). In part, this dissertation explores this phenomenon and investigates how the type of staff (e.g., support vs. policing) may contribute to the days of lost instruction time due to out-of-school suspensions.

To investigate these issues my dissertation uses social network methods to examine college-level educational trajectories at the institutional level and, using quantitative methods, I examine discipline disparities using national data. At the theoretical level, the entire dissertation forefronts the importance of understanding how race, gender, and class are persistent in determining disparities regardless of grade level or the many issues pertaining to the educational pipeline.

The first article, “Academic Tracking in Higher Education? An Examination of Curricular Course-Taking as Emergent Structures.”, explores a mechanism that may contribute to the degree attainment gap and STEM underrepresentation among racial/ethnic and gender groups. Using social network analysis, I examine a university cohort’s (N=1,414) shared course-taking patterns (41,206 courses) over five years. I use community-detection methods to explore important questions about higher education group disparities. I specifically argue that the courses students take can create student groupings over time that reflect different and unequal social positions.

The second article, “Using Directed Networks to Examine College Major Outcomes by Race/Ethnicity and Gender.”, uses social network analysis to examine the process of choosing a college major and the outcomes of that choice. More specifically, I map longitudinal data from a higher education institution onto directed network graphs for several different subgroups. Using data from a complete network, I map five years of the college major process—major selection, change of major, and major at graduation. This study asks, to what extent do racial/ethnic and gender differences exist in the college major process? Do specific majors lead to specific academic outcomes (e.g., dropping out or graduating) among racial/ethnic and gender groups?

Lastly, the third article, “Criminalization vs. Support: How the Type of Staff Matters in Days of Lost Instruction Time Due to Out-of-School Suspensions in U.S. Public Schools.”, uses the

2015-16 Civil Rights Data Collection (CRDC) survey and other secondary data sources to explore the school level factors that may contribute to days of lost instructional time due to out-of-school suspensions in all U.S public schools. In particular, this study explored the relationship between staff-to-student ratios (among other school-level indicators) and days of lost instruction time due to out-of-school suspensions at the national level.

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Academic Tracking in Higher Education? An Examination of Curricular Course-Taking as Emergent Structures

Abstract

In this article, I explore a specific mechanism that may contribute to the degree attainment gap and STEM underrepresentation among certain racial/ethnic and gender groups. Using social network analysis, I examine a university cohort's (N=1,414) shared course-taking patterns (41,206 courses) over five years. I use community-detection methods to explore important questions about higher education group disparities. I build on the framework of "tracks as emergent structures," which argues that the courses students take can create student groupings over time that reflect different and unequal social positions. In this study, I examine the extent to which emergent structures differentiate students by demographic characteristics (e.g., race/ethnicity and gender) and academic outcomes (e.g., persistence and graduation rates). Having found different social positions within the university, I argue that these emergent structures help further understanding of group differences in higher education and allude to some degree to a mechanism that may perpetuate these differences.

Introduction

Post-secondary enrollment at U.S. colleges and universities has increased among all students. However, racial/ethnic and gender inequalities persist in the college experience. Latinx and Black students continue to be less likely to graduate from post-secondary institutions (Bowen, Chingos, and McPherson 2009; Desilver 2014; Krogstad and Fry 2014), and while women have been earning bachelor's degrees at a higher rate than men in recent years (Buchmann and DiPrete 2006), they are underrepresented in science, technology, engineering, and mathematics (STEM) fields (Dickson 2010; Ma and Liu 2017; National Science Board 2016). The choice of college major has strong implications for students' career prospects and contributes to the wage gap among college-educated men and women (Brown and Corcoran 1997; Shauman 2006). Overall, completing a bachelor's degree yields substantial economic returns (Attewell et al. 2007; Autor, Katz, and Kearney 2008), better health, longevity, happiness (Ross and Mirowsky 1999; Rowley and Hurtado 2003; Pallas 2000), and the potential to alleviate intergenerational education gaps and effects (Brand and Xie 2010; Hout 1988, 2012; Torche 2011).

Researchers who study this phenomenon have attributed several factors to the degree attainment gap and STEM underrepresentation. These factors tend to range from inequities in academic preparation in high school, financial resources, academic performance in college, and/or parental involvement (Montmarquette, Cannings, and Mahseredjian 2002; Paglin and Rufolo 1990) to factors such as campus climate, lack of program resources, professor quality, and difficulty of and/or experience in curricular courses (Feagin and Sikes 1995; Seymour and Hewitt 1997). However, these perspectives have primarily relied on explaining disparities in higher education using individual and institution-level frameworks. Thus I ask, to what extent is it possible that structural factors (e.g., academic tracking) exist at the college level?

Academic tracking is defined as the system of assigning students to a particular curriculum based on their purported interest and abilities (Gamoran and Mare 1989). Tracking in the U.S. K-12 school system was developed to create conditions in which teachers could efficiently target instruction to students' needs (Gamoran 2009). Despite this intended benefit, tracking has been criticized for widening the achievement gap and for assigning students to tracks based on race/ethnicity and social class, which has led to economically and/or racially segregated classrooms (Gamoran 2009; Oakes, Gamoran, and Page 1992; Lucas and Berends, 2002).

Moreover, scholars have found that the types of classes taken, the teaching environments, and the relationships formed in those classes affect student attitudes, achievement, future aspirations, and attainment (Braddock and Slavin 1993; Friedkin and Thomas 1997; Garet and Delany 1988; Oakes et al. 1992). Building on the importance of course-taking, Heck, Price, and Thomas (2004, 327) posit that academic tracking can actually be understood and measured as emergent structures, which they define as structures that emerge "from a series of student encounters with courses and reflecting social positions defined by the student groupings created within those courses." That is, the student groupings that emerge from shared course-taking patterns can reflect different social positions within a school. If differences in social demographics and background characteristics are present, these emergent student groupings can then be examined. Applying this framework in this article, I argue that emergent structures in higher education result from student groupings created within a series of courses and from experiences in those courses that go beyond choosing a major or taking required courses.

Mechanisms of choice and agency have been the predominant frameworks in our understanding of college major choice and course-taking. However, we have little understanding of the extent to which counselors, professors, peers, the racial/ethnic and gender demographics of college majors, course-taking experiences, and established group notions and expectations influence the college major choice and curricular course-taking processes. While I focus in this study only on the shared curricular course-taking patterns that arise at the institutional level, I attempt to uncover a systemic and structural mechanism that may contribute to between-group differences in higher education: academic tracking. Using complete longitudinal data from a public university, I use social network methods to model the complex student groupings that develop over time and examine differences by social demographics and background characteristics.

Background

Educational Inequities and Course-Taking

While the underrepresentation of racial/ethnic and gender groups at U.S. universities has declined over the years, educational inequalities persist. In 2012, college enrollment rates among 18- to 24-year-old Latinx high school graduates surpassed that of Whites by 48 percent (Krogstad and Fry 2014). Despite these changes, Latinx and Black students are still less likely to graduate from universities than their White and Asian counterparts (Desilver 2014; Krogstad and Fry 2014). In 2012, Whites accounted for 69 percent of young adults with bachelor's degrees and Asians for 11 percent, while Latinx and Blacks together only accounted for 18 percent (Krogstad and Fry 2014). When examining gender inequities, Ma and Liu (2017) found that women are more underrepresented in physical STEM fields (computer, math, physical science, and engineering) than life STEM fields (agriculture, biology, and life sciences). They found further that, among all students with an initial major in STEM, women were slightly more likely than their counterparts in all racial groups to complete the degree. Asian women had the highest persistence rate among all racial groups, followed by Asian men.

Many factors contribute to the degree attainment gap and STEM underrepresentation for certain racial/ethnic and gender groups. Given the theoretical and methodological framework used in this study, my discussion here centers around inequities and experiences in college courses and how this shapes students' educational trajectories. Scholarship examining this phenomenon has found that women who declare a major in STEM often experience daily rudeness from male peers, and undergraduate instructors demonstrate classroom inequality through their disattention to and overt discrimination against women (Seymour and Hewitt 1997). Faculty have been found to convey their lower expectations for women; for instance, women students' whose educational preparation is equal to that of men are prompted to lower their academic and career ambitions and thus to underachieve (Hall and Sandler 1982, 1984, 1986; Seymour and Hewitt 1997). Consequently, researchers posit that some women eventually lose confidence in their ability to persist in a STEM major, regardless of their actual academic performance (Seymour and Hewitt 1997).

Latinx and Black students often experience similar isolation and lack of support in the classroom, along with racism, internalization of stereotypes, discrimination and stigma, and inadequate support (Hanson 2009; Feagin and Sikes 1995; Seymour and Hewitt 1997). As a result, they doubt their ability to complete their academic requirements and, when experiencing academic difficulty, they often do not ask questions or seek help (Seymour and Hewitt 1997). These findings also reflect the high school experiences of students of color. For instance, research has shown that there are no differences in preference or academic preparedness in math and science course-taking among Black women in comparison to their peers' in middle school and high school (Hanson 2009; Riegle-Crumb and King 2010). However, Hanson (2009) argued that White women are more likely than Black women to report that teachers are interested them, to have won an academic honor, to have received recognition for good grades, to attend a private school, and to be in a college-prep program in their middle or high school. Consequently, Black women considering a STEM major often feel discouraged by their lack of preparation in high school, the isolation and discrimination they experience in their science classes, and poor teaching (Hanson 2009).

Academic Tracking

Understanding how academic tracking functions at the high school level helps us understand how this mechanism, while unique in each context, can also be relevant at the university level. While scholarship on the effects of academic tracking is varied, some studies have shown an advantage for Black students who are tracked, after controlling for social class and prior achievement (Garet and DeLany 1988), while others have shown no racial differences after controlling for the same factors (Gamoran and Mare 1989; Lucas and Gamoran 2002). On the other hand, ethnographic evidence suggests that Latinx and Black students are systematically steered into lower-track classes (e.g., Lareau and Horvat 1999; Oakes 1985; Ochoa 2013). Some scholarship has also found that racially diverse schools are more likely to have pronounced tracking systems and to place high-achieving Blacks in low-track classes (e.g., Braddock 1990; Lucas and Berends 2002). On the other hand, high-achieving Black students who attend racially segregated schools are more likely to enter a college-preparatory track (Lucas and Berends 2002). It remains unclear which factor—race/ethnicity, class, and/or prior achievement—is the primary determinant of track placement. Although some scholars note that Latinx and Black students are more likely to be socioeconomically disadvantaged and/or to have lower grades (Lucas and Berends 2002), academic tracking contributes nonetheless to educational inequality by systematically placing students into unequal learning environments based on their personal characteristics and background (Gamoran 2009; Gamoran and Mare 1989).

Different findings in the academic tracking scholarship have been attributed to the abundance of measurements, analytic strategies, and methodological limitations (Gamoran 2009). Research conducted in the 1970s and 1980s often relied on students' self-reported curricular programs (e.g., academic/college-prep, vocational, or general). However, scholars argued that this indicator did not represent students' actual learning opportunities (Gamoran 2009). Today, academic tracking is difficult to assess based on students' self-reported perceptions, given that schools claim they do not track students. Oakes (1985, 3) states that "it is . . . rare [that a] school that has no mechanism for sorting students into groups that appear to be alike in ways that make teaching them easier." Thus, researchers today have developed innovative methods to assess the extent to which students are academically tracked. For instance, using a structural measure of track location, Lucas (1999) used transcripts of the courses students had taken to identify tracks (i.e., college-prep vs. non-college-prep tracks). He found that students from high socioeconomic backgrounds are more likely to be placed in college-preparatory classes, which yield higher achievement tests scores and promote college admission.

Researchers also have implemented social network analysis techniques to identify tracks through the configuration of courses (i.e., emergent structures) (Friedkin and Thomas 1997; Heck et al. 2004). Friedkin and Thomas (1997) found that low-socioeconomic students were more likely to be on a vocational than an academic pathway. Similarly, in study conducted in a Hawaiian high school, Heck et al. (2004) found that Hawaiian, Samoan, and low-socioeconomic students were in the lowest academic curricular tracks, and were the least likely to attend college and to graduate from a four-year university.

While the higher education setting and context are completely different from the K-12 system, there are some similarities in how specific racial, gender, and class groups end up in specific academic tracks (e.g., STEM-focused courses vs. STEM majors). A major difference between higher education and K-12 is that in college there are no “lower” or “higher” tracks per se; thus the differences lie in what group chooses which majors and/or which group is more likely to drop out of college. An important aspect of K-12 tracking is based on the systemic placing of students in particular courses, whereas students in higher education have greater choice and agency when selecting courses or when choosing their major. However, I argue in this article that the decision to change majors is influenced by various factors at both the individual and the institutional level, and may be how academic tracking operates in this context. In the next section, I discuss emergent structures as a framework for measuring academic tracking and how it can be applied in the higher education model.

Emergent Structures

Few studies have conceptualized academic tracks as emergent structures. Using transcript data, Lucas (1999) used course-taking patterns to place students in track locations. Heck et al. (2004) argued, however, that this measure depends on the researcher’s construction of categories to represent course patterns. This makes it difficult to assess the reliability or validity of the measure in terms of how it reflects the sociocurricular structure of the schools. Friedkin and Thomas (1997) were the first to develop a theoretical rationale for viewing tracks as a type of social position in students’ relations with particular teachers and courses during their high school years. Building on Friedkin and Thomas, Heck et al. (2004) analyzed students’ course-taking profiles in a high school and found that the curricular positions identified were associated with students’ characteristics (i.e., socioeconomic status, race, and gender) and academic achievement.

Moreover, Heck et al. (2004) posited that academic tracks tend to be analyzed as formal structures that differentiate students. However, they argued that academic tracks can also be conceptualized as emergent structures that result from a series of student encounters with courses and reflect social positions defined by the student groupings created within those courses. The researchers noted that this approach makes minimal assumptions about what the structure might look like ahead of time. Emergent structures is able to identify actual patterns by considering each student's complete course-taking patterns, rather than relying on students' self-descriptions of their curricular tracks. Therefore, examining the composition of emerging student groupings helps to determine the degree to which any such emergent positions serve to differentiate them based on status characteristics and academic achievement.

The present study extends the work of Friedkin and Thomas (1997) and Heck et al. (2004) by analyzing students' course-taking patterns at the university level. In this study, I apply for the first time the theoretical rationale used in examining high school studies to examine the social positions that emerge from students' relations with particular courses at the university level. This study can identify group patterns by considering each student's complete course-taking patterns, rather than relying only on their choice of major. I examine in particular what emergent structures exist among students at the university level and how these emergent structures differentiate students based on demographic characteristics (e.g., race/ethnicity and gender) and academic outcomes (e.g., persistence and graduation rates).

Data and Methods

Data used in this study come from a public university in the southwestern U.S. Given the racial/ethnic makeup of the university—that is, a certified enrollment that is at least 25 percent

Latinx—it is designated a Hispanic-Serving Institution by the U.S. Department of Education. The university is divided into three schools: Engineering (ENGR), Natural Sciences (NS), and Social Sciences, Humanities, and Arts (SSHA). In addition to the courses each school offers, the university has a program called College One responsible for overseeing the general education. This program requires all first-year students to take courses designed to introduce students to faculty, the institution's research, and a wide range of academic fields.

Sample Selection

In this study, I focused on the university's 2012-2013 freshman academic cohort (N=1,415). I selected these students in order to have five years of longitudinal data that would enable me to examine their complete educational trajectories. Detailed course-level data were available for all student participants. Table 1 illustrates the independent variables I used in this study, which include demographic characteristics (e.g., race/ethnicity, gender, class, and others) and educational background (e.g., high school GPA and age when entering school).

Variables

The race/ethnicity variable I used in this study reflected students' self-identification as Latinx, Black, Asian, White, or Multiracial/Other. The Asian category includes Pacific Islander students because of the minimal number of cases. The Multiracial/Other category includes Native Americans and anyone who self-identified as multiracial. I categorized International (not a race or ethnicity) students and Unknown as missing. I coded gender 1 for women and 0 for men. For this study, I combined race/ethnicity and gender to understand between-group differences. First-generation college student is coded 1 for yes and 0 for no. Pell Grant eligibility in the first term was used as a proxy for income; receiving it is coded 1, and not receiving it is coded 0. GPA scores were created using the average formula, where the total of semester GPA scores was divided by the number of semesters. I created total course units taken by summing units taken across student's semesters considered.

To determine persistence in school, I considered students' enrollment each semester. I measured first-year persistence by whether or not students enrolled in their third semester (Returning 2nd Year). Similarly, for second-year persistence, I considered whether or not students enrolled in their fifth semester (Returning 3rd Year). The major change variable refers to any student who changed their major once (coded 1) or more than once (coded 2), or did not change it (coded 0). If a student went from undeclared to a chosen major, it was not counted as changing majors. The "entering major" variable refers to the initial major declared by a student in a specific school. For instance, if a student declared a sociology major, it was categorized in the school of SSHA. "Major in 8th Semester" indicates that the school the major was declared at the start of a student's fourth year.

Analysis Strategy

To examine linkages between actors (i.e., students) and events (i.e., courses), I first implemented a bipartite analysis also referred to as a two-mode network model. A bipartite model is a matrix, $H = [h_{ij}]$, with N actors and k events in which h_{ik} is the status of the relationship between actor i and event k. The value of h_{ik} may be binary (indicating the presence or absence of a link) or a continuous measure of the strength of the linkage (Wasserman and Faust 1994). In the present study, the value of h_{ik} is binary (0,1); that is, a student either did or did not take a particular course.

Using the bipartite matrix, I used community-detection methods to identify student groupings (i.e., clusters). Generally, community-detection methods are used to simplify and highlight important network structures that are essential to comprehending their organization. In this study, I used community-detection methods to identify specific clusters of students who shared similar course-taking patterns. It is important to reiterate that this methodological approach offers minimal assumptions about what the structure might look like ahead of time. It identifies the actual patterns by only considering each student's complete course-taking patterns. I used several community-detection methods for this analysis, located in the *igraph* package in R (e.g., spin-glass algorithm, map-equation algorithm, and fast-greedy community algorithm), and determined that the fast-greedy community algorithm detection method developed by Clauset, Newman, and Moore (2004) was preferred. For example, when comparing the map-equation algorithm results with the fast-greedy community algorithm results, the clusters that formed within the map-equation algorithm were not all meaningful.[1] [2]When cross-referencing the results with the type of courses taken and majors chosen, the fast-greedy community algorithm was preferred. That is, most student groupings generally fell under a particular school within the university (i.e., Engineering, Natural Sciences, and Social Sciences, Humanities, and Arts).

Furthermore, the fast-greedy community algorithm uses a hierarchical approach and optimizes modularity in a greedy manner. Initially, every vertex belongs to a separate community, and communities are merged iteratively such that each merge is locally optimal (i.e., it yields the largest increase in the current value of modularity). The algorithm stops when it is

[1] A total of 66 student groupings were found, yet the university only offers 23 majors in three broader schools (e.g., School of Natural Science, etc.). The 66 student groupings are possible by the fact that many students change their major multiple times, drop out at different points in time, are undeclared, or repeat courses multiple times, all factors that would result in unique curricular course-taking patterns. However, like Clauset, Newman, and Moore (2004), this study focused on the broader emerging structures.

[2]

no longer possible to increase the modularity. For a detailed explanation of the algorithm, please see Clauset et al. (2004).

Limitations

There are limitations to this study. First and foremost, having detailed financial data would have been ideal. Instead, I used Pell Grant eligibility as proxy for income, which is only available for a student's first term. Other variables that would have been ideal include whether or not a student was working (and if so, part-time or full-time), family income, parental education level, and socioeconomic status. Moreover, I only looked at one university, therefore this study cannot generalize about the university system in the United States or even in the Southwest. In fact, emerging structures may look different based on the region, type of university, majors available, and the racial/ethnic, gender, and class composition of a university. A larger sample size also would be ideal for modeling student groupings over time while taking into account the semester and professor of each course. Lastly, the fast-greedy community algorithm is known to suffer from a resolution limit (i.e., communities below a given size threshold will always be merged with neighboring communities) (Rosvall and Bergstrom 2008).

Findings

In this study, student groupings emerged from course-taking patterns at the university level, which were differentiated by major choice, race/ethnicity, gender, financial aid availability, and academic achievement. The community-detection method used revealed four distinct curricular pathways among students' course-taking patterns over five years (see Table

2).[3] Names were assigned to each student grouping based on the predominate coursework students completed in a particular school. Table 2 shows the student grouping's courses taken, by each school. In the first student grouping, labeled (1) SSHA Path (n=15,129 courses), 76 percent of courses were taken at the school of Social Science, Humanities, and Arts; the second group, labeled (2) NS Path (n=13,757 courses), was composed of students who took 66 percent of their courses in the school of Natural Sciences; the third group, labeled (3) ENGR Path (n=11,669 courses), was composed of students who took 30 percent of their courses in the Engineering school; and the fourth group, labeled (4) Undecided Path (n=471 courses), included students who took courses across multiple schools.[4]

To examine further whether the student groupings identified were differentiated by demographic characteristics and academic achievement, I analyzed summary measures of these variables for each of the four student groupings. Tables 3-5 summarize each of the student groupings and their demographic and academic characteristics (i.e., race/ethnicity and gender, first-generation college student status, Pell Grant eligibility, entering major and major changes, high school and college GPA, units taken, and dropout or graduation status). As seen in the tables, students in each of the four emerging groups are drastically different, in particular women of color, first-generation college students, and low-income students, who are predominantly in the SSHA Path. Students in the Undecided Path have the lowest GPAs, and as a result the fewest number of units taken by the end of their first year. In fact, nearly all students in the Undecided Path drop out by the start of third year, while students in the ENGR Path have the highest

[3] The fast-greedy community algorithm was the preferred tool to capture the curricular positions (see appendix Table 7). The fifth position was not considered, given that it only captured 0.1 percent of the sample.

[4] Students in the engineering program take all math courses in the school of Natural Sciences. Hence, this is why the ENGR Path has 30 percent of courses taken in the school of Natural Sciences and 30 percent in the school of Engineering.

persistence. Interestingly, a large portion of students in the ENGR Path change their major to a one in the SSHA Path.

When examining race and ethnicity, differences between the emerging student groupings are clear. Descriptive statistics in Table 3 reveal that, among Latinx women, 61 percent are in the SSHA Path. This pattern is similar among Black women, 53 percent of whom are also in the SSHA Path, in contrast to only 14 percent of Asian men. The majority (41 percent for both) of first-generation students and students who received the Pell Grant in their first term were also in the SSHA Path. Of the students who entered the university as undeclared, 48 percent eventually entered the SSHA Path. As for the NS Path, 53 percent of Asian women were in this emerging group, along with 37 percent of White women and 39 percent of Asian men. The majority of White men (47 percent) were in the ENGR Path, as were both Asian and Latinx men (42 percent and 38 percent, respectively).

Regarding educational outcomes, Table 4 shows that students in the Undecided Path had the lowest likelihood of persisting. In fact, only 1.4 percent of students in the Undecided Path returned by the start of third year, and no student in that path graduated within five years. In contrast, those in the ENGR Path had the highest likelihood of persistence (77 percent) by the third year. However, those in the SSHA Path had the highest graduation rate (70 percent) by the end of their fifth year, which may be influenced by the fact that a small proportion of students take more than five years to complete their bachelor's degree. When looking at GPA, those in the Undecided Path had the lowest scores, with a mean of 1.60 by the end of their first year and 2.05 by the end of their second year (see Table 5). Table 5 also shows that those in the SSHA Path had the highest GPA scores, with a mean of 2.61 by the end of the first year, 2.72 by the second year, and 2.82 by the fourth year. As for major changes, those in the NS Path had the lowest change rates (67 percent did not change majors), whereas 96 percent of students on the Undecided Path did not change majors; however, this is due to the fact that only 1.4 percent made it to the third year. Another interesting finding shown in Table 5 is that 23 percent of students in the ENGR Path ended up with a major in the SSHA in their fourth year. This implies that many students on this path took the majority of courses in their chosen fields but then decided to change to a major in SSHA.

Why is it that students in the Undecided Path almost all drop out by the start of their third year? A plausible explanation has to do with their low GPAs at the end of their first year. To examine this group further, I looked at the type and number of courses they failed. In general, the type of courses failed by students on the SSHA, NS, and ENGR paths were not substantially different from those in the Undecided Path (see Table 6). Table 6 reveals that the top three courses failed by all the student groupings were Introduction to Psychology, Introduction to Sociology, Academic Writing, Preparatory Chemistry, Calculus I, and Introduction to Computing I. When looking at the total number of courses failed by student groupings, Figure 1 shows that 35 percent of students in the Undecided Path failed at least four courses over a two-year period, whereas only 12 percent of students in the SSHA, NS, and ENGR paths failed four courses over a five-year period. It is important to note the magnitude course taking, since more than 72 percent of students in the SSHA, NS, and ENGR paths persisted beyond their second year, as compared to 1 percent in the Undecided Path, which means that students in the SSHA, NS, and ENGR paths had taken many more courses. Meaning that, students in the Undecided Path were more likely to fail entire semesters, which leads to the obvious question of why this is so. Demographically, the majority of students in the Undecided Path were Latinx (39 percent men and 21 percent women), had an average 3.38 high school GPA, and 38 percent had undeclared majors, more than any other group. It is plausible that this group experienced a lack of counseling and guidance, as well as academic assistance and tutoring. However, additional data is needed to understand fully why this group failed so badly.

In sum, the wide variation in student characteristics between the emerging student groups indicate that some type of stratification occurred. While the university doesn't have a tracking system per se, this stratification likely occurred due to a combination of decision processes at the university and individual levels. Regardless, it is clear that a student's racial/ethnic background and gender (among other factors) increases their likelihood of having particular course-taking patterns. Latinx and Black women in particular are more likely than all others to be on the SSHA Path. These findings have important implications, as other research has shown that women, Latinx, and Black students are underrepresented in STEM degree attainment.

Discussion

Many underrepresented students continue to experience disparity gaps in the college experience. For instance, students of color are less likely to persist and graduate from post-secondary institutions, and women are less likely than men to graduate with a STEM degree (Bowen et al. 2009; Desilver 2014; Krogstad and Fry 2014; National Science Board 2016). In this article, I implemented the framework of emergent structures (Friedkin and Thomas 1997; Heck et al. 2004) at the university level for the first time to examine the student groupings that emerge from course-taking with peers, and to illustrate that the differences between these groupings may contribute to the disparities that persist in the college experience (i.e., major choice, graduation rates). Without knowing what the structure might look like ahead of time, I used students' complete course-taking patterns to identify these student groupings. I found that the emergent positions served to differentiate students according to status characteristics and academic achievement. That is, women of color, first-generation college students, and low-income students were predominantly in the non-STEM groups, while other emergent positions revealed very low persistence and graduation rates for some.

I argue that these emergent structures show that some type of stratification occurred at the college level. While the university system doesn't have a formal tracking system per se, the stratification likely occurred due to a combination of processes at the structural, institutional, and individual levels. In this study, I criticized the frameworks of individualism (i.e., choice and agency) that are used predominantly to explain college major choice and outcomes. While this study only focused on the shared curricular course-taking patterns that arise at the institutional level, I attempted to uncover a systemic and structural mechanism that may contribute to between-group differences in higher education. That is, the extent to which counselors, professors, peers, racial/ethnic and gender demographics of college majors, course-taking experiences, and previously established notions and expectations may be influential in the college major choice, course-taking process, and graduation outcomes. Like the K-12 system today, U.S. colleges and universities do not recognize any sorting of students into specific academic tracks on the basis of race/ethnicity, gender, or class. Yet, when we examine major and graduation outcomes, it is clear that a racialized and gendered process does exist on higher education campuses.

Scholars have shown that selection of college major is not an entirely individual choice but one that is influenced by parents' socioeconomic status, counselors, teachers, friends, academic track in high school, and even media (Hanson 2009; Ma 2009; May and Chubin 2003; Montmarquette et al. 2002). However, future research needs to further understanding of the entire college process and how it operates at the individual, institutional, and structural levels. Critical factors in the college process at the individual level include students' personal interactions, the way they are treated in class by other students and the professor, parental guidance or lack thereof, their perception of self-worth and potential, academic preparedness, perceptions of racism, internalization of stereotypes, discrimination and stigma, and inadequate support (Hanson 2009; Feagin and Sikes 1995; Seymour and Hewitt 1997). At the institutional level, students' experiences with counseling (if any was received), availability and quality of tutoring services, course availability, professor quality and pedagogical practices may all shape students' college academic trajectories. At the structural level, for instance, Bonilla-Silva's (1997, 2001) theoretical framework alludes to the importance of the long history of U.S. educational institutions being part of a racialized social system, which means that students experience a form of hierarchy that produces definite social relations and puts them in a specific position based on their social identities and background characteristics. I argue that the emergent structures found in this study are caused by a combination of all these factors at the individual, institutional, and structural levels, and that they may further perpetuate and reproduce educational inequities.

Conclusion

Closing the racial/ethnic and gender academic gaps in higher education should be a priority for colleges and universities around the nation. To do so, institutions must recognize the many ways they perpetuate and reproduce these inequities. The emergent structures found in this study are contrary to the belief of social mobility and freedom of choice. If student choice is the prominent factor operating at the university level, then why did course-taking patterns reflect social stratification on the basis of race/ethnicity, gender, and class? The results found in this study demonstrate that students' academic and educational trajectories at the university were both racialized and gendered.

Regarding future research, the framework of emergent structures at the university level is a promising avenue for comparative case studies. This micro-level analysis enables understanding of the organizational differences within and between schools. That is, a comparison of one university's actual differentiation structure could be compared with another university's structure in order to understand the effects of differences in context (e.g., racial/ethnic composition, institutional differences, educational outcomes, etc.). In addition, while this method provides a thorough mapping of course-taking patterns that develop over time, it cannot identify specific mechanisms that may lead to differential patterns between groups, such as differential treatment and expectations between groups in the classroom or differences in how students are counseled. Therefore, further research on course-taking experiences, on how and why students change majors, and their experiences in those majors is important.

Additional methods are needed to expand beyond the traditional way of examining social networks (Gonzáles Canché and Rios-Aguilar 2015; Small 2017) such as the traditional model of understanding how a small group of friends or family influences the choice of major and/or course-taking patterns. The framework of emergent structures is one example of how to begin not with the network (i.e., how friends and family influence curricular course-taking patterns) but with a focus on the action (i.e., the courses taken), and on the student groupings that result from those actions. I argue that more methods using this theoretical framework are needed so that we can expand our concept of "the network" to holistically capture and understand network outcomes (Small 2017), and to show how context and structure affect underrepresented students' access, persistence, and success in higher education (Gonzáles Canché and Rios-Aguilar 2015).

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Table 1 Descriptive Statistics for the 2012-2013 Academic Cohort (N=1,414 Students)

	Freq.	Percentage
Race/Ethnicity & Gender		
Latinx Men	299	21.2
Latinx Women	346	24.5
Black Men	31	2.2
Black Women	57	4.0
Asian Men	215	15.2
Asian Women	150	10.6
White Men	117	8.3
White Women	67	4.7
Multiracial Men	37	2.6
Multiracial Women	25	1.8
Missing	70	5.0
Total	1,414	100.0
First-Generation		
No	487	34.4
Yes	927	65.6
Total	1,414	100.0
Pell-Eligible 1st Year		
No	527	37.3
Yes	887	62.7
Total	1,414	100.0
Entering Major		
Undeclared	258	18.3
Engineering	321	22.7
Natural Science	505	35.7
Social Science	330	23.3
Total	1,414	100.0
High School GPA		
Mean	3.47	
Std. Dev.	0.32	

Table 2 Student Grouping's Course-Taking Patterns for Each School (N=41,206 Courses)

	SSHA Path (n=15,129)	NS Path (n=13,757)	ENGR Path (n=11,669)	Undecided Path (n=471)
College One Courses	4.9%	4.1%	4.1%	2.6%
Engineering Courses	1.7%	4.5%	30.2%	4.5%
Natural Sciences Courses	17.5%	66.4%	31.5%	36.9%
Social Sci., Hum., and Arts Courses	76.0%	25.0%	34.2%	56.1%
Total	100.0%	100.0%	100.0%	100.0%

*SSHA Path-Social Science, Humanities, and Arts group, NS Path-Natural Science group, ENGR Path-Engineering group, Undecided Path-Undecided group.

Table 3 Student Groupings by Demographic Characteristics (N=1,414 Students)

	SSHA Path (n=515)	NS Path (n=456)	ENGR Path (n=371)	Undecided Path (n=72)	Total (n=1,414)
Race/Ethnicity & Gender					
Latinx Men (n=299)	26.1	26.4	38.1	9.4	100.0
Latinx Women (n=346)	61.0	27.5	7.2	4.3	100.0
Black Men (n=31)	35.5	19.4	32.3	12.9	100.0
Black Women (n=57)	52.6	35.1	8.8	3.5	100.0
Asian Men (n=215)	14.4	39.1	42.3	4.2	100.0
Asian Women (n=150)	30.0	52.7	14.0	3.3	100.0
White Men (n=118)	25.6	23.9	47.0	3.4	100.0
White Women (n=67)	40.3	37.3	20.9	1.5	100.0
Multiracial Men (n=37)	18.9	35.1	40.5	5.4	100.0
Multiracial Women (n=25)	40.0	44.0	12.0	4.0	100.0
Missing (n=70)	50.0	22.9	25.7	1.4	100.0
First-Generation					
No (n=487)	26.5	39.0	32.0	2.5	100.0
Yes (n=927)	41.6	28.7	23.2	6.5	100.0
Pell-Eligible 1st Year					
No (n=527)	28.8	36.6	31.9	2.7	100.0
Yes (n=887)	40.9	29.7	22.9	6.5	100.0
Entering Major					
Undeclared (n=258)	48.5	19.8	21.3	10.5	100.0
Engineering (n=321)	9.7	17.1	68.2	5.0	100.0
Natural Science (n=505)	19.6	66.1	10.5	3.8	100.0
Social Science (n=330)	78.8	4.9	13.3	3.0	100.0
High School GPA					
Mean	3.44	3.51	3.48	3.38	
Std. Dev.	0.31	0.32	0.31	0.29	
Total	36.4	32.3	26.2	5.1	100.0

*SSHA Path-Social Science, Humanities, and Arts group, NS Path-Natural Science group, ENGR Path-Engineering group, Undecided Path-Undecided group.

Table 4 Student Groupings by Educational Outcomes (N=1,414 Students)

	SSHA Path (n=515)	NS Path (n=456)	ENGR Path (n=371)	Undecided Path (n=72)
Returning 2nd Year				
No	15.7	15.1	7.8	87.5
Yes	84.3	84.9	92.2	12.5
Total	100.0	100.0	100.0	100.0
Returning 3rd Year				
No	26.2	27.6	22.9	98.6
Yes	73.8	72.4	77.1	1.4
Total	100.0	100.0	100.0	100.0
Graduated by 4th Year				
No	43.1	76.1	70.4	100.0
Yes	56.9	23.9	29.7	0.0
Total	100.0	100.0	100.0	100.0
Graduated by 5th Year				
No	30.1	42.8	39.4	100.0
Yes	69.9	57.2	60.7	0.0
Total	100.0	100.0	100.0	100.0

*SSHA Path-Social Science, Humanities, and Arts group, NS Path-Natural Science group, ENGR Path-Engineering group, Undecided Path-Undecided group.

Table 5 Student Groupings by Educational Outcomes Continued (N=1,414 Students)

	SSHA Path (n=515)	NS Path (n=456)	ENGR Path (n=371)	Undecided Path (n=72)
Major Change				
None	47.2	66.7	49.6	95.8
Once	46.4	30.0	46.1	4.2
More than Once	6.4	3.3	4.3	0.0
Total	100.0	100.0	100.0	100.0
Major in 8th Semester				
Not Enrolled	34.4	33.1	29.4	100.0
Undeclared	0.4	0.7	0.5	0.0
Engineering	0.4	6.4	43.1	0.0
Natural Science	1.0	58.6	4.3	0.0
Social Science	63.9	1.3	22.6	0.0
Total	100.0	100.0	100.0	100.0
GPA 1st Year	2.61	2.84	2.82	1.60
GPA 2nd Year	2.72	2.77	2.75	2.05
GPA 4th Year	2.81	2.74	2.74	-
Units 1st Year	29	28	29	20
Units 2nd Year	54	53	56	22
Units 4th Year	119	116	118	-

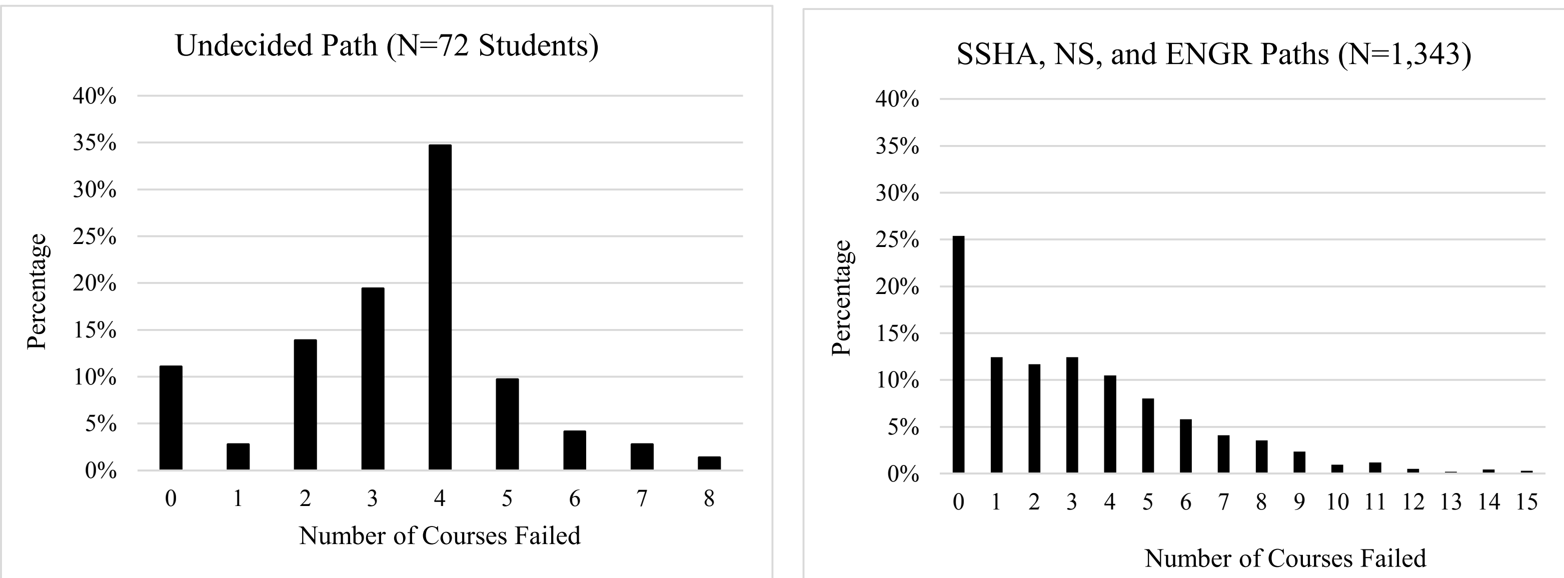
*SSHA Path-Social Science, Humanities, and Arts group, NS Path-Natural Science group, ENGR Path-Engineering group, Undecided Path-Undecided group.

Table 6 Top 3 Most Common Failed Courses by School for the Student Groupings

SSHA, NS, and ENGR Paths		Undecided Path	
Courses	Freq.	Courses	Freq.
Social Sci., Hum., and Arts			
Introduction to Psychology	267	Academic Writing	31
Introduction to Sociology	107	Introduction to Psychology	31
Academic Writing	89	Introduction to Sociology	7
Natural Science			
Preparatory Chemistry	228	Preparatory Chemistry	32
General Chemistry I	213	Pre-Calculus	22
Calculus I	200	Calculus I	19
Engineering			
Statics and Dynamics	76	Introduction to Computing I	7
Introduction to Computing I	42		
Introduction to Materials	30		

* The "most common" threshold is defined as a course that was failed or not passed more than 30 times in the SHHA, NS, and ENGR Paths or more than 4 times for the Undecided Path. This includes students who might have failed a class more than once. Failed grades only take into account Not passed, Ds, and Fs.

Figure 1 Number of Failed Courses by Student Groupings



*SSHA Path-Social Science, Humanities, and Arts group, NS Path-Natural Science group, ENGR Path-Engineering group, Undecided Path-Undecided group.

Appendix

Table 7 Fast-Greedy Community Detection Algorithm

Path	Freq.	Percentage
1. SSHA Path	515	36.4
2. NS Path	456	32.23
3. ENGR Path	371	26.22
4. Undecided Path	72	5.09
5. Dropped Path	1	0.07
Total	1,415	100
Modularity	0.36	

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Using Directed Networks to Examine College Major Outcomes by Race/Ethnicity and Gender

Abstract

Using social network analysis, this study examines the process of choosing a college major and outcomes of that choice. More specifically, I map longitudinal data from a university onto directed network graphs for different subgroups. Using data from a complete network, I map five years of the college major process—major selection, change of major, and major at graduation. This study asks, to what extent do racial/ethnic and gender differences exist in the college major process? Do specific majors lead to specific academic outcomes among racial/ethnic and gender groups? The findings align with previous research showing that Latinx and Black men are the least likely to graduate and that women are more likely than men to graduate from a non-STEM field. This micro-analysis provides new insights into how the choice of major contributes to specific outcomes. The study further contextualizes mobility between majors and major outcomes for all subgroups.

Introduction

Research has shown that the choice of college major has strong implications for career prospects, contributes to the wage gap among college-educated men and women, and is a gendered and racialized process (Brown & Corcoran, 1997; Shauman, 2006; Seymour & Hewitt, 1997). Racial/ethnic and gender discrepancies are found in particular among those who choose science, technology, engineering, and mathematics (STEM) majors. Ma and Liu (2017) found that women, Latinx, and Black students are less well represented in the physical STEM fields (i.e., computer science, math, physical science, and engineering) than in life STEM fields, (i.e., agriculture, biology, and life sciences).

What factors lead students to choose a particular major? At the individual level, scholars have argued that the choice of college major is influenced by students' precollege academic background (Montmarquette, Cannings, & Mahseredjian, 2002; Paglin & Rufolo, 1990), and by attitudes toward different subjects and life goals (Eccles, 1994; Hyde, Fennema, & Lamon, 1990). Other studies have highlighted the importance of social context, such as the influence of parental socioeconomic status (SES; Ma 2009), gender-role socialization (Bridges, 1989; Herzog, 1982; Lueptow, 1980; Marini et al., 1996), and how extensively racism and sexism are experienced in the classroom and/or on campus (Feagin & Sikes, 1995; Seymour & Hewitt, 1997). While individual-level factors and social context are both critical in analyzing college major choices, only minimal research has employed social network theory and methods to explain major outcomes.

While the traditional model of social network analysis relies on understanding how a small group of friends or family influences students' choice of major and the resulting outcomes, this study uses the theoretical framework proposed by Small (2017), Martinez (2020), and others to examine this process at the university level. Small (2017) argues that our concept of "the network" needs to be far more expansive than commonly defined in order to holistically capture and understand network outcomes. He posits specifically that social network analysis should not begin with the network but with actions that "reconstruct decisions after they take place, and that try to understand the context in which people interact with others" (p. 158). In the context of the major process, this analysis does not begin with a focus on the network (i.e., how friends and family influence choice of major) but on the action (i.e., choice of entering major, switching majors, and major outcomes). Martinez (2020) used a similar network approach to examine social structure. Without knowing what the structure might look like ahead of time, Martinez examined students' shared links to courses they had taken at the university level and identified distinct student groupings that arose from similar course-taking patterns. These clusters served to differentiate students by status characteristics and academic achievement. In a fashion similar to Martinez (2020), this study aims to understand students' shared links to majors and the patterns that emerge over time.

Using complete longitudinal data from a public university in the southwestern United States, this study examines the major process over time (i.e., entering major, change of major, and major outcomes) and illustrates this process in a directed network for several racial/ethnic and gender subgroups. The study findings show distinct patterns for different subgroups relative to race/ethnicity and gender. While choice of entering major is equitable to a certain extent across these subgroups, graduation becomes unachievable, for some students, students of color in particular.

Background

The Major Process

According to Leu (2017), about 30 percent of undergraduate students change their major at least once within three years of initial enrollment. While this pattern suggests that making decisions about choice of major is an ongoing process, we know that many students face racial and gender inequities, STEM majors in particular. While Black and Latinx students are as likely as their White counterparts to enter college with majors in STEM fields, racial gaps exist in actual STEM degree attainment (Dickson, 2010; Hanson, 2006; Ma, 2009; Riegle-Crumb & King, 2010; Ma & Liu, 2017). Moreover, research shows that switching majors is more frequent among women who originally chose STEM majors than among those who chose majors in the humanities and social sciences (Seymour & Hewitt, 1997). Recent scholarship has found, however, that women in all racial groups with an initial major in STEM were slightly more likely than their male counterparts to complete the degree. Asian women had the highest STEM persistence rate, followed by Asian men (Ma & Liu, 2017).

Extensive scholarship has tried to explain why these inequities persist in the college major process. As previously noted, scholars have argued that differences in precollege academic experiences, such as mathematical ability (Montmarquette et al., 2002; Paglin & Rufolo, 1990), and attitudes toward different subjects and life goals (Eccles, 1994; Hyde et al., 1990) are key factors in determining major outcomes. Recent scholarship, however, suggests that differences in academic preparation and attitudes explain only a small part of the variation in choice of major by race/ethnicity and gender. Dickson (2010) found that women whose SAT scores and class ranks are equivalent to men's are less likely to major in engineering. Also, Black students who attend predominantly White colleges are less likely to choose natural and technical science majors than Blacks who attend predominately Black colleges (Thomas, 1991). Price (2010) found similarly that Black students are more likely to persist in a STEM major if they take a STEM course taught by a Black instructor. Therefore, individual perspectives alone are inadequate in explaining race/ethnicity and gender discrepancies in the college major process.

When considering this process, it is critical to account for the role of social context. For instance, some scholars suggest that gender role socialization leads women to work in helping professions, whereas men are inclined toward business and high-tech jobs. This stems from the theory that women place the most importance on intrinsic, altruistic, and social job rewards while men put greater importance on extrinsic rewards, such as money and prestige (Bridges, 1989; Herzog, 1982; Lueptow, 1980; Marini et al., 1996). While this theory highlights a sexist feature of our society, it ignores the institutional inequities that also exist (e.g., sexism in STEM classrooms), and parental background. Recent scholarship found that, to maximize monetary returns (Ma 2009), students (including women) from lower SES families choose technical, life/health science, and business majors—all well-paying fields—over humanities and social science/education majors. Ma's findings suggest that parental SES has a critical influence on choice of major. Although Ma only considered initial choice of major and did not follow students over time, Seymour and Hewitt (1997), in their book *Talking about Leaving: Why Undergraduates Leave the Sciences,* found that students of color in STEM often internalize stereotypes, experience ethnic isolation and racism in the classroom, and have inadequate support in their program. As a result, these students doubt their ability to complete their academic requirements and, when they do experience difficulty, they often don't ask questions or seek help. Similarly, female students in STEM experience rudeness daily from their male peers, along with classroom inequalities such as lack of attention from professors and overt discrimination. For instance, women who are as academically well-prepared as the men in their classes are often prompted by their professors to lower their academic and career ambitions—in short, to under-achieve (Hall & Sandler, 1982, 1984, 1986; Seymour & Hewitt, 1997). Consequently, Seymour and Hewitt (1997) argue that some women eventually lose confidence in their ability to persist in a STEM major, regardless of their actual academic performance, due to schools' failure to provide faculty support or correctly interpret their performance, and to male peers' lack of acceptance.

In addition, some research suggests that the low number of Black and Latinx students with degrees in the STEM fields may be due to the small number who graduate from college (Dickson, 2010). For instance, in 2012, although Latinx college-enrollment rates among 18- to

24-year-old high school graduates surpassed those of Whites by 48 percent (Krogstad & Fry, 2014), Latinx and Black students are less likely than their White and Asian counterparts to graduate from a university (Desilver, 2014; Krogstad & Fry, 2014). In 2012, Whites accounted for 69 percent of young adults with a bachelor's degree, Asians for 11 percent, and Latinx and Blacks together only 18 percent (Krogstad & Fry, 2014). It is clear, therefore, that students' major outcomes are driven by many factors at both the individual and the institutional level, and that racial/ethnic and gender inequities persist throughout the entire process (i.e., choice of major, change of major, and major outcomes). I now discuss the important role social network analysis plays in examining the college major process.

The Role of Social Network Analysis

Social network analysis provides important theoretical frameworks and methods for overall understanding of the college major process and university outcomes. That is, social network theory enables us to determine that a university is composed of clusters of individuals joined by a variety of links that involve either people, such as students and faculty, or events, such as choice of major. Network analysis involves modeling these relationships among students to depict the structure of the group (Smelser, 1988). By analyzing relational ties within a university, its social structure can be seen as patterns in relationships among interacting units (Tichy & Fombrun, 1979; Wasserman & Faust, 1994). However, few studies have used social network theory and methods to examine the college major process. Although studies have used social network analysis to examine college majors, they lack a theoretical framework that accounts for the importance of both institutional and structural inequities. Many also have relied on a small sample size to make generalizations about specific subgroups and the university system as a whole.

For example, in "Understanding College Students' Major Choices Using Social Network Analysis," Baker (2018) examined the desired major of 297 students at a community college. She found that Asian students and male students had relatively high homophily (i.e., they tend to prefer similar majors), while Latinx, White, and women students had low homophily (i.e., preferred major varied). Baker argued that such preferences in the choice of major may later be driving factors in the segregation and inequalities experienced in certain majors. While her analyses of preferred majors are innovative, Baker does not follow students over time to understand how those preferences play out during the entire college major process or question why these preferences were formed.

In a similar study using social network analysis, Raabe, Boda, and Stadtfeld (2019) examined students' favorite subjects in middle and high school and argued that those preferences could determine students' educational and occupational careers. They concluded the study by arguing that the STEM gender gap persists because both boys and girls are influenced to like what their friends like and, given that students have mostly same-sex friends, the gender-specific tendencies of those influences emerge (i.e., boys tend to prefer STEM). However, Raabe and colleagues failed to understand and critically examine the unique ways race, gender, and class influence social relationships. For example, they did not question how homophily is affected by ideologies (e.g., racism, sexism, and classism), historical policies (e.g., school segregation), or institutional inequities (e.g., academic tracking). While these two recent examples of how scholarship uses social network analysis to examine the college major process are innovative and informative, more theoretically grounded work is needed that takes into account the importance of social network analysis in this context.

The analysis presented in this study is guided by the theoretical frameworks and the methodology of several scholars who, I argue, account for the importance of both institutional and structural inequities in social network analysis. For instance, González Canché and Rios-Aguilar (2015) argued that we must move toward a critical social network analysis to examine how an actor's place in a network affects how they form connections and the associated opportunities for social mobility. They argued in particular that we must move from a deficit perspective of students (and organizations) to an "understanding of how context and structures affect underrepresented students' opportunities in terms of access, persistence, and success in higher education" (p. 78). Individualistic social network analysis has dominated much of the educational and social scientific research over the past century; critical social network analysis allows us to move beyond this framework (Biancani & McFarland, 2013).

Small (2017) argued that our concept of the network needs to be redefined—specifically, that it needs to be more expansive (i.e., beyond the traditional framework of friends and family) in order to holistically capture and understand network outcomes and the context in which people interact with others. An example of this type of work is Martinez (2020), which accounts for students' relational ties with courses taken at a university over a period of five years. Martinez found that emergent structures stratified students along the lines of race/ethnicity, gender, and class at the university level. This study did not begin with the network (i.e., how friends and family influence choice of major or curricular course-taking patterns), focusing instead on the action (i.e., courses taken by college students), and found that distinct student groupings emerged and were differentiated by background characteristics and educational outcomes. This type of research can be understood as a network approach to social structure (Friedkin, 1998; Friedkin & Thomas, 1997; Heck, Price, & Thomas, 2004)—that is, different positions are revealed by the patterns of relations between students, and differentiated social structure are defined by the different positions students occupy in a network of social relations. This study uses the theoretical frameworks and methodological approach of social network analysis to investigate the following questions: To what extent do racial/ethnic and gender differences exist in the college major process? Do specific majors lead to specific academic outcomes (e.g., dropping out or graduating) among racial/ethnic and gender groups?

Methods

Data

For this study, I use data from a public university in the southwestern US. My sample is the university's 2012-2013 freshman academic cohort (N=1,415). I selected these students in order to have five years of longitudinal data I could use to examine completed major outcomes. Table 8 illustrates the demographic characteristics (e.g., race/ethnicity, gender, class, etc.) and educational background (e.g., high school GPA) of the sample examined. As seen in Table 8, the largest student groups in the sample analyzed are Latinx (46 percent), first generation to attend college (66 percent), Pell Grant eligible (63 percent), and have an average 3.47 high school GPA.

The university offers a total of 23 majors housed in three different schools: the School of Social Sciences, Humanities and Arts (SSHA); the School of Natural Sciences (NS), and the School of Engineering (ENGR). SSHA majors include anthropology, cognitive science, critical race and ethnic studies, economics, English, global arts studies, history, management and business economics, political science, psychology, public health, sociology, and Spanish. NS offers majors in applied mathematical sciences, biological sciences, chemical sciences, earth systems science, and physics. ENGR majors include bioengineering, computer science and engineering, environmental engineering, materials sciences and engineering, and mechanical engineering. Given the interest of this study, part of the descriptive analysis combines NS and ENGR to broadly examine all STEM majors.

Analysis Strategy

To study the major process (i.e., initial choice of major, change in major, and final major) over time, I first provide descriptive statistics to contextualize each stage for each racial/ethnic and gender subgroup, and then use weighted directed networks to show the entire process over time.[5] According to Wasserman and Faust (1994), a directed graph $\mathcal{m}_d(\mathcal{N}, \mathcal{L})$ consists of two sets of information: a set of nodes, $\mathcal{N} = \{n_1, n_2, \dots., n_g\}$, and a set of arcs, $\mathcal{L} = \{l_1, l_2, \dots., l_L\}$. Each arc is an ordered pair of distinct nodes; $l_k =< n_i, n_j >$ is directed from n_i (the origin) to n_j (the terminus). When a directed graph is presented as a diagram, the nodes are represented as points and the arcs are represented as directed arrows. The arc $< n_i, n_j >$ is represented by an arrow from the point representing n_i to the point representing n_j. For example, if a student in his first semester declares a major in economics (i) then changes his major in his second semester to sociology (j), there would be an arc originating at i and terminating at j. If that student graduates with a major in sociology (i) in their eighth semester, there would be secondary arc originating with sociology (i) and terminating at graduated (j).

Results

The overall results reveal that, among the 2012-2013 academic cohort, the entering choice of major for the majority of students, regardless of race/ethnicity and gender, was STEM related

[5] Note that, in the descriptive statistics section, more focus is given to STEM differences, given that it is where the majority of racial/ethnic and gender differences exist.

(see Table 9). However, when that is broken down by the specific type of STEM major, Table 10 shows that between-group differences are present. For example, all women, and women of color to a slightly greater extent, predominantly declared a major in biological sciences. When examining changes in major over time, we find that the students who changed their major most often from one field to another are those who initially declared a major in STEM; however, most students do not change their major.

By the start of the students' fourth academic year, STEM representation was no longer equal among all students. Latinx and Black women had the highest rate of change from a STEM-related major to an SSHA major, and they had the least representation in STEM of all other groups. Another important finding highlights major discrepancies due to dropping out. Latinx and Black men have the highest dropout rate of all subgroups in the cohort. Interestingly, STEM remains the preferred major among the Latinx and Black men who do persist. In sum, the descriptive statistics reveal the importance of accounting for differences over time by racial/ethnic and gender groups, and for the inequities that arise among them.

Table 9 shows students' entering choice of major for each field. Descriptive statistics reveal that more than 40 percent chose a major in STEM. The groups with the highest percentages among those entering the university with a STEM major were Asian men and women (72% and 68%, respectively), while those with the lowest percentages were Latinx, White, and Black women (41%, 52.2%, and 52.6%, respectively). These percentages were still relatively high when compared to those who chose other fields or were undeclared majors. The highest percentage among those entering with majors in SSHA were, as expected, Latinx women (37%), White women (31%), and Black women (26%). Only 12 percent of Asian men entered with a major in SSHA, making them the least likely group to do so. In fact, more Asian men (15.8%) entered the university with no declared major than with a major in SSHA.

Table 10 examines the differences in choice of STEM majors between racial/ethnic and gender groups. The results show that the majority of women enter with a biological sciences major; at 80 percent, Black women had the highest rate for this major, White women 66 percent. The men's majors are spread out across STEM fields but were predominantly in biological sciences, computer science and engineering, and mechanical engineering. In fact, at 25 percent, Black men had the highest representation in mechanical engineering. While these rates show the entering major, how did it look over time? Table 11 examines the changes over time for students who entered with a STEM major. Latinx women (32.4%) and Black women (33.3%) had the highest rates of change, from a STEM major to a major in SSHA. In other words, out of the 136 Latinx women who initially selected a major in STEM, about 44 of them switched to a non-STEM major; of the 30 Black women in STEM, about 10 changed their major. The groups with the greatest persistence in a STEM major were Asian men (90.5%) and multiracial men (100%); at 85.3 percent and 85.1 percent, respectively, Latinx men and White men also had high persistence rates in the STEM majors.

The next group examined is students who chose majors in SSHA. What do their changes look like over time as compared to other majors? Table 12 reveals that few groups changed their SSHA major to a STEM major. In fact, not one of the Black students who entered with an SSHA major switched to a STEM-related major. Asian women (11.1%) and White men (22.7%) were the groups with highest rate of change into STEM. These changes of course lead to differences in what the major outcomes look like between groups. Therefore, at the start of the cohort's fourth year we see discrepancies we did not see in their initial choice of major. These discrepancies are due to the fact that students switched majors, and because many students dropped out (see Table 13). Latinx and Black women have the lowest participation rates in STEM majors (19.7% and 31.6%, respectively) in comparison to their SSHA major counterparts. All other groups have higher participation rates in STEM than in SSHA, except for White women, who have equal representation in STEM and SSHA. While this is also true for Latinx and Black men, they experience higher dropout rates (42.1% and 51.6%, respectively) than all other groups. These dropout rates continue to increase until the end of the cohort's fifth year (see Table 14). By the end of fifth year, Latinx men have a dropout rate of 50.8 percent, Black men 54.8 percent, which means that more than half of the entering men of color dropped out. These high dropout rates hold true even after looking at the different graduation rates between those who initially chose STEM or SHHA majors.

Directed Networks

The directed network analysis allows us to understand the major process over time for each racial/ethnic and gender subgroup. More specifically, the figures presented show how common the average major is for each subgroup and what pathway (e.g., no change of major, changing majors, dropping out, or graduating) is most common for that major. As stated in the methods section, each node represents either the chosen major, being undeclared, dropping out, not being enrolled for a particular semester, or graduating. Each edge (also known as a link) represents a transition from point A to point B. The directionality can be seen by the arrow in each edge. The thickness of the edges depends on the weight—the thicker the edge, the more common the particular path. The size of the nodes depends on their eigen vector centrality, which allows us to see what end points are most common. As seen in the descriptive statistics, the figures reflect the overall underrepresentation of women in STEM, and demonstrate that Latinx and Black men are the most likely to drop out. We also can see that, for Latinx students, men in particular, being undeclared led to dropping out more than any choice of major. Black women had smallest node in dropping out, which suggests that they were most likely to graduate, as the descriptive statistics reveal. The few Black women who did not graduate were primarily biological sciences majors or undeclared.

I next describe in detail the racial/ethnic and gender differences seen in the directed network analysis. In Figure 2, which illustrates the major process for White men, we can see that their most common paths include graduating with a major in biological sciences, mechanical engineering, or management and business economics. Having a major in computer science and engineering or being undeclared are the paths that led most commonly to dropping out or not being enrolled. The graduated node for White men has an in-degree of eight—that is, eight majors (4 from SSHA, 2 from NS, and 2 from ENGR) led directly to graduation. There are significantly fewer paths for White women students than for White men (see Figure 3). In fact, White women students have four common paths to graduation: having a major in management and business economics, psychology, cognitive science, or biological sciences. Of the 28.4 percent of White women who did not graduate within five years (see Table 14), many dropped out from a biological sciences major or were undeclared. Asian men, on the other hand, have many common paths—changing majors, graduating, or dropping out (see Figure 4). Like White men, common paths for Asian men include graduating with a major in biological sciences, mechanical engineering, and management and business economics; however, the most common paths include graduating from computer science and engineering, economics, and psychology. The most common paths for Asian men who drop out include majors in mechanical engineering, computer science and engineering, and biological sciences. Asian men tend to switch majors more often than other groups. For instance, some who declared a major in computer science and engineering had three paths that led switching into a different major, which were math, management and business economics, or mechanical engineering.

Asian women, like White women, have fewer paths in their major transitions. The most common paths are graduating with a major in biological sciences or in psychology (see Figure 5). A common path for those who drop out starts with biological sciences; however, this path is bidirectional. Hence, Asian women students drop out/take leave, and then re-enroll as biological sciences majors. Latinx men had more major paths leading to dropping out than all other groups (an in-degree of 10; see Figure 6), primarily including students who were undeclared or had a major in biological sciences, mechanical engineering, or computer science engineering. It is important to note that there also are common paths to graduating from biological sciences and mechanical engineering majors. The most common path among Latinx women is graduating from a psychology major (see Figure 7); biological sciences, sociology, political science, management and business economics, and cognitive science are also common pathways for these women. Their most common paths for dropping out are being undeclared or a biological sciences major. Black men have the smallest eigenvector centrality for the graduating node (see Figure 8), which means that graduating within a five-year period was a least common outcome for Black male students than for all other racial/ethnic and gender groups. The most common outcome for Black male students was dropping out while being undeclared; however, this relationship was bidirectional. Black women, in contrast, had the smallest eigenvector centrality for the dropping out node, which means that graduating was a common outcome for Black women, primarily from psychology and biological sciences majors (see Figure 9).

In sum, it is critical to note that the eigenvector centrality for the not enrolled/dropping out node is significantly larger for Latinx and Black men than for all other groups. This reflects the fact that more than 50 percent of Latinx and Black men drop out. Being undeclared was another common path leading to dropping out for Latinx men and women, and for Black men. This suggests that the uncertainty of not knowing what major to choose or a lack of guidance may add an additional barrier to persistence. The fact that biological sciences is a common path for dropping out across all racial/ethnic and gender groups may be due to the fact that this is a popular major. Nevertheless, identifying which major is causing students to drop out most often is an important finding and something all institutions should be aware of. Course requirements for biological sciences at this institution should be examined further in order to identify and address these achievement gaps.

Discussion

Racial/ethnic and gender inequities continue to be a problem in colleges and universities around the United States. Latinx and Black men are less likely than all other groups to graduate with a bachelor's degree and, while women today have higher graduation rates than ever before, gaps in graduation remain in the majors they choose. In this study, I used both descriptive statistics and social network analysis to examine inequities in the college major process (i.e., entering choice of major, changing major, and major at graduation/dropout) for an academic cohort over a period of five years. The findings in this study confirm what we know about racial/ethnic and gender inequities and uncovered new insights as well. For instance, Ma and Liu (2017) found that women, Latinx, and Black students are more underrepresented in the physical STEM fields (i.e., computer, math, physical science, and engineering) than in life STEM fields (i.e., agriculture, biology, and life-science related), whereas this study finds that Latinx and Black women are less likely than any other group to study in a STEM-related field. While women from all groups enter the university with a life STEM major, the women of color tend to change to an SSHA major. In this case study, neither Latinx nor Black men were underrepresented in STEM. In fact, they had a higher percentage of representation in STEM-related majors by the start of their fourth year than in SSHA majors. This finding may be due to the fact that this university is a Hispanic-Serving Institution; note that Thomas (1991) found that Black students who attended predominantly White colleges were less likely to choose natural and technical science majors than those who attended predominately Black colleges. This institution being a Hispanic-Serving Institution may similarly influence the STEM representation of both Latinx and Black men.

In addition, Ma (2009) found that students (including women) from lower SES families choose technical, life/health science, and business majors—fields that pay more—over humanities and social science/education majors in order to maximize economic returns. However, this doesn't appear true for the women of color in this case study. While this study doesn't test for SES differences due to data restrictions, as mentioned, Latinx and Black women are the groups least likely to choose a STEM-related major. Moreover, women's social science participation is not predominantly in business-orientated majors. Ma's findings may be influenced by the fact that the study only considered the initial choice of major and did not follow students over time. Future work should examine the entire college major process while taking the intersections of race/ethnicity, gender, and class into account more closely.

Understanding discrepancies in choice of major requires understanding graduation rates. While the initial choice of major is important and informative, it is only one of several stages and a long process of decision-making, counseling (or lack thereof), coursework, classroom experiences, and financial and mental (in)stability, all factors that help determine whether a student changes majors, drops out, or graduates. Dickson (2010) argued that the low number of Latinx and Black students with degrees in STEM fields may be due to their low college graduation rates. This is true to a certain extent for the Latinx and Black men in this case study, who experienced the highest overall dropout rates. However, the majority of Latinx and Black women simply graduate from a non-STEM major. Once we account for both race/ethnicity and gender, we can see that there are different reasons for the discrepancies in STEM major outcomes.

In addition, this study used social network analysis to examine the entire college major process. This method allowed for further contextualization of each major and the specific outcomes of those majors at a subgroup level. The findings reveal that choosing certain majors or being undeclared were clear pathways to dropping out. Therefore, these findings suggest that identifying which major(s) are causing students to drop out most often is an important finding and something all institutions should be aware of in order to identify and address achievement gaps. Also, unlike previous social network studies, this study relied on social network theory (González Canché & Rios-Aguilar, 2015; Martinez, 2020; Small, 2017), which accounts for the importance of both institutional and structural inequities. This means that the study itself was centered around understanding the race/ethnicity and gender major and outcome discrepancies, as well as the shared ties within those groups to certain majors/outcomes, rather than around the relationships with a small set of friends and family and their influence on the major process.

Overall, this study provides new insights into the college major process and a methodological framework that could be used to further contextualize major outcomes at the institutional level.

Conclusion

Closing the racial/ethnic and gender gaps in major outcomes continues to be an issue for all universities around the United States. To address these inequities, institutions need to understand how these inequities are perpetuated and reproduced in their particular context. Most importantly, they need to examine the entire college major process (i.e., entering choice of major, change of major, and major outcomes) and identify the key issues and barriers that prevent students from graduating or make them decide to switch from a STEM field to a non-STEM major. The results of this case study demonstrate that students' choice of major and educational trajectory at the university are a racialized and gendered process that is contextual to the institution. This research provides a promising avenue for comparative case studies, as the micro-level analysis allows for an understanding of the organizational differences within and between universities, while also accounting for differences in context (e.g., racial/ethnic composition, institutional differences, educational outcomes, etc.).

This study also expands the traditional way of examining social networks (Gonzáles Canché & Rios-Aguilar, 2015; Small, 2017)—that is, the traditional model of understanding how a small group of friends or family influences choice of major. It focuses on the shared relationships of belonging to a major at the subgroup level and how that changes over time. I argue that more methods are needed that use this theoretical framework so we can expand our concept of "the network" to capture and understand network outcomes holistically (Small, 2017), and to show

how context and structures affect underrepresented students' access, persistence, and success in higher education (Gonzáles Canché & Rios-Aguilar, 2015).

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Table 8: Descriptive Statistics for the 2012-2013 Cohort (N=1,414)

	Freq.	Percentage
Race/Ethnicity and Gender		
Latinx Men	299	21.2%
Latinx Women	346	24.5%
Black Men	31	2.2%
Black Women	57	4.0%
Asian Men	215	15.2%
Asian Women	150	10.6%
White Men	117	8.3%
White Women	67	4.7%
Multiracial Men	37	2.6%
Multiracial Women	25	1.8%
Missing	70	5.0%
Total	1,414	100.0%
First Generation		
No	487	34.4%
Yes	927	65.6%
Total	1,414	100.0%
Pell Grant Eligibility 1st Year		
No	527	37.3%
Yes	887	62.7%
Total	1,414	100.0%
High School GPA		
Mean	3.47	
Std. Dev.	0.32	

Table 9: Percentage Entering Field for the 2012-2013 Cohort by Race/Ethnicity and Gender (N=1,414)

Race/Ethnicity and Gender	Social Science, Humanities, and Arts	STEM	Undeclared	Total
Latinx Men (n=299)	17.4	66.6	16.1	100.0
Latinx Women (n=346)	37.0	40.5	22.5	100.0
Black Men (n=31)	22.6	54.8	22.6	100.0
Black Women (n=57)	26.3	52.6	21.1	100.0
Asian Men (n=215)	12.1	72.1	15.8	100.0
Asian Women (n=150)	20.7	68.0	11.3	100.0
White Men (n=117)	19.7	64.1	16.2	100.0
White Women (n=67)	31.3	52.2	16.4	100.0
Multiracial/other Men (n=37)	18.9	56.8	24.3	100.0
Multiracial/other Women (n=25)	20.0	60.0	20.0	100.0
Missing (n=70)	21.4	52.9	25.7	100.0
Total (N=1,414)	23.3	58.4	18.3	100.0

Table 10: Percentage Entering STEM Major for the 2012-2013 Cohort by Race/Ethnicity and Gender (N=724)

Race/Ethnicity and Gender	Bio. Sci.	Chem. Sci.	Earth Syst. Sci.	Applied Math. Sci.	Physics	Bioengr.	Comp. Sci. & Eng.	Env. Eng.	Mat. Sci. and Eng.	Mech. Eng.	Total
Latinx Men (n=176)	30.1	6.8	0.0	4.6	2.3	6.3	20.5	5.7	0.6	23.3	100.0
Latinx Women (n=136)	73.5	11.8	0.0	0.0	0.7	4.4	2.2	0.7	1.5	5.2	100.0
Black Men (n=16)	37.5	6.3	6.3	6.3	0.0	12.5	6.3	0.0	0.0	25.0	100.0
Black Women (n=30)	80.0	13.3	0.0	0.0	0.0	0.0	3.3	3.3	0.0	0.0	100.0
Asian Men (n=146)	39.7	6.9	0.0	2.1	0.0	7.5	26.7	4.1	0.0	13.0	100.0
Asian Women (n=92)	71.7	9.8	0.0	2.2	0.0	5.4	4.4	4.4	1.1	1.1	100.0
White Men (n=67)	26.9	9.0	0.0	3.0	6.0	6.0	19.4	6.0	3.0	20.9	100.0
White Women (n=32)	65.6	6.3	0.0	3.1	3.1	9.4	3.1	6.3	0.0	3.1	100.0
Multiracial/other Men (n=18)	50.0	0.0	0.0	0.0	0.0	11.1	27.8	5.6	0.0	5.6	100.0
Multiracial/other Women (n=11)	72.7	18.2	0.0	0.0	0.0	9.1	0.0	0.0	0.0	0.0	100.0
Total (N=724)	50.1	8.6	0.1	2.4	1.4	6.2	14.2	4.0	0.8	12.2	100.0

Note: The table above does not include undeclared-natural sciences or undeclared-engineering students.

Table 11: Students in the STEM Field, Changes Over Time (N=774)

Race/Ethnicity and Gender	No Change	Change Within	Change to Social Science, Hum, & Arts	Total
Latinx Men (n=176)	68.8	16.5	14.8	100.0
Latinx Women (n=136)	52.2	15.4	32.4	100.0
Black Men (n=16)	50.0	31.3	18.8	100.0
Black Women (n=30)	56.7	10.0	33.3	100.0
Asian Men (n=146)	69.9	20.6	9.6	100.0
Asian Women (n=92)	60.9	21.7	17.4	100.0
White Men (n=67)	70.2	14.9	14.9	100.0
White Women (n=32)	71.9	9.4	18.8	100.0
Multiracial/other Men (n=18)	66.7	33.3	0.0	100.0
Multiracial/other Women (n=11)	63.6	9.1	27.3	100.0
Total (N=724)	64.1	17.7	18.2	100.0

Table 12: Students in the Social Science, Humanities, and Arts Field, Changes Over Time (N=297)

Race/Ethnicity and Gender	No Change	Change Within	Change to STEM	Total
Latinx Men (n=51)	64.7	25.5	9.8	100.0
Latinx Women (n=121)	76.9	14.1	9.1	100.0
Black Men (n=6)	83.3	16.7	0.0	100.0
Black Women (n=14)	71.4	28.6	0.0	100.0
Asian Men (n=24)	79.2	16.7	4.2	100.0
Asian Women (n=27)	59.3	29.6	11.1	100.0
White Men (n=22)	68.2	9.1	22.7	100.0
White Women (n=21)	57.1	33.3	9.5	100.0
Multiracial/other Men (n=7)	100.0	0.0	0.0	100.0
Multiracial/other Women (n=4)	75.0	25.0	0.0	100.0
Total (N=297)	71.7	19.2	9.1	100.0

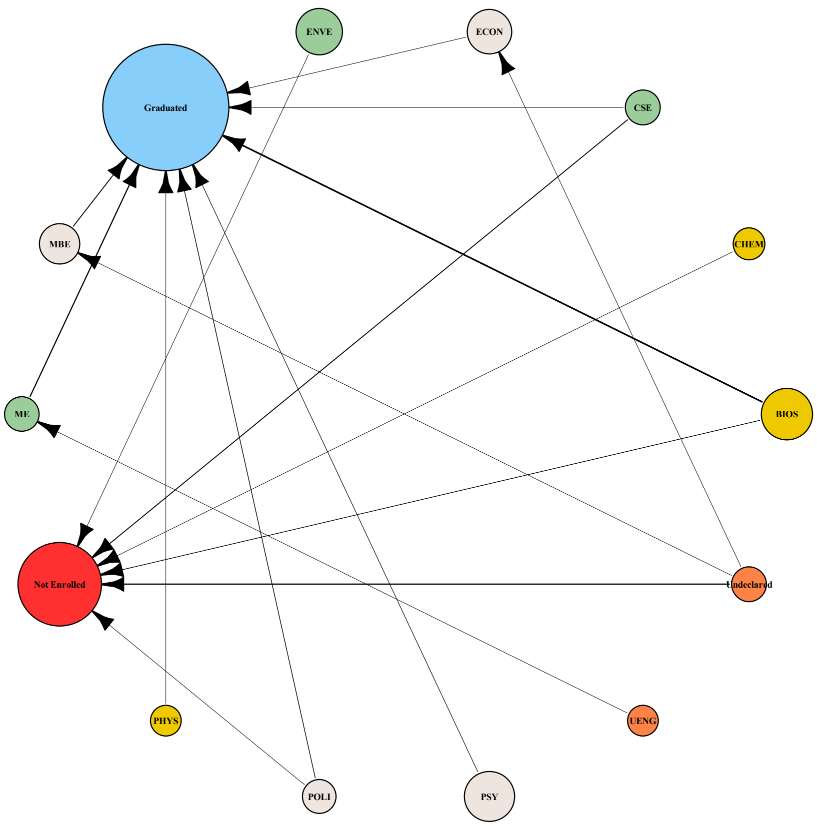
Table 13: Percentage Entering 4th-Year Field for the 2012-2013 Academic Cohort, by Race/Ethnicity and Gender (N=1,414)

Race/Ethnicity and Gender	STEM	Social Science, Humanities, and Arts	Undeclared	Not Enrolled	Total
Latinx Men (n=299)	36.5	21.1	0.3	42.1	100.0
Latinx Women (n=346)	19.7	42.5	0.6	37.3	100.0
Black Men (n=31)	25.8	22.6	0.0	51.6	100.0
Black Women (n=57)	31.6	45.6	0.0	22.8	100.0
Asian Men (n=215)	46.1	19.5	0.5	34.0	100.0
Asian Women (n=150)	42.0	26.0	0.7	31.3	100.0
White Men (n=117)	41.9	22.2	0.9	35.0	100.0
White Women (n=67)	34.3	34.3	0.0	31.3	100.0
Multiracial/other Men (n=37)	40.5	16.2	0.0	43.2	100.0
Multiracial/other Women (n=25)	36.0	40.0	0.0	24.0	100.0
Missing (n=70)	25.7	42.9	1.4	30.0	100.0
Total (N=1,414)	33.9	29.6	0.5	36.0	100.0

Table 14: Graduation Rates Over Five Years, by Race/Ethnicity and Gender (N=1,414)

Race/Ethnicity and Gender	No	Yes	Total
Latinx Men (n=299)	50.8	49.2	100.0
Latinx Women (n=346)	35.6	64.5	100.0
Black Men (n=31)	54.8	45.2	100.0
Black Women (n=57)	28.1	71.9	100.0
Asian Men (n=215)	40.0	60.0	100.0
Asian Women (n=150)	35.3	64.7	100.0
White Men (n=117)	41.0	59.0	100.0
White Women (n=67)	28.4	71.6	100.0
Multiracial/other Men (n=37)	54.1	46.0	100.0
Multiracial/other Women (n=25)	32.0	68.0	100.0
Missing (n=70)	37.1	62.9	100.0
Total (N=1,414)	40.2	59.8	100.0

Figure 2: White Men (n=117)



-Social Science, Humanities, and Arts
-Natural Science
-Engineering
-Undeclared
-Not Enrolled
-Graduated

Major abbreviations: ANTH: Anthropology, COGS: Cognitive Science, CRES: Critical Race and Ethnic Studies, ECON: Economics, ENG: English, GASP: Global Arts Studies Program, HIST: History, MBE: Management and Business Economics, POLI: Political Science, PSY: Psychology, PH: Public Health, SOC: Sociology, SPAN: Spanish, MATH: Applied Mathematical Sciences, BIOS: Biological Sciences, CHEM: Chemical Sciences, ESS: Earth Systems Science, PHYS: Physics, BENG: Bioengineering, CSE: Computer Science and Engineering, ENVE: Environmental Engineering, MSE: Materials Sciences and Engineering, and ME: Mechanical Engineering

Figure 3: White Women (n=67)

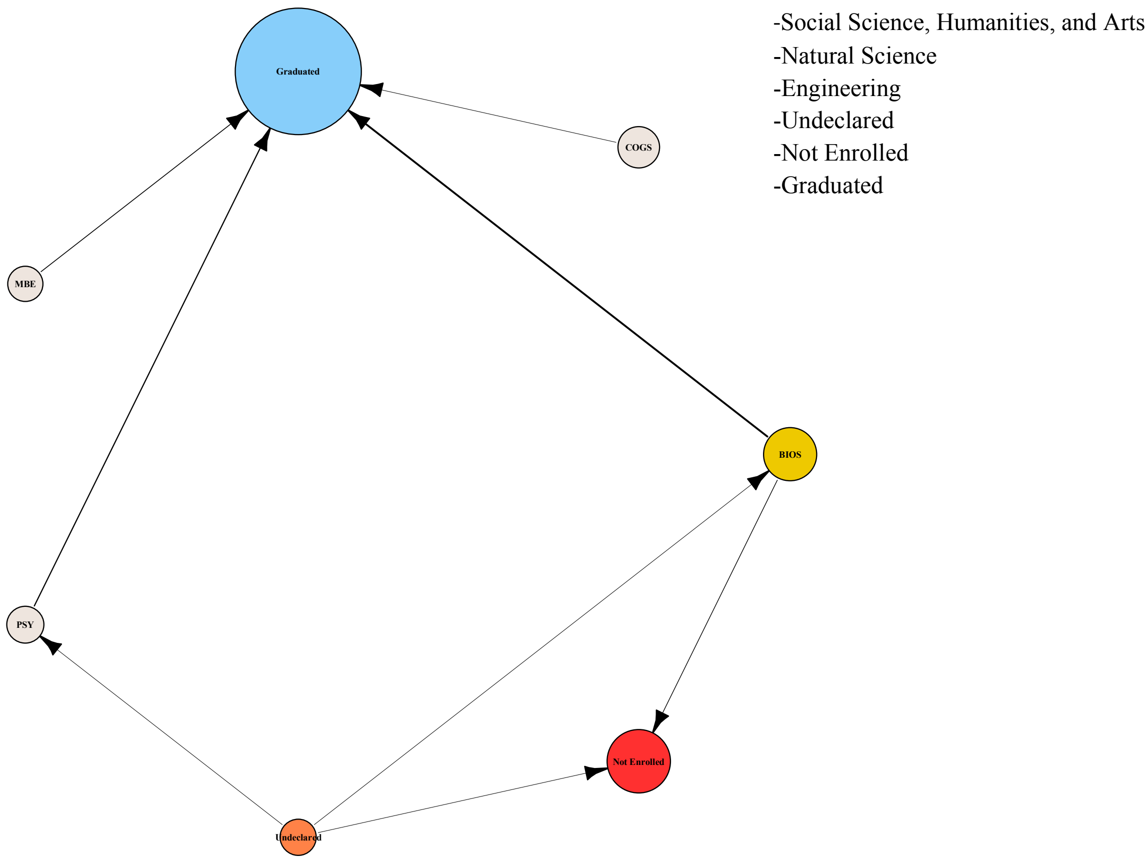


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Figure 4: Asian Men (n=215)

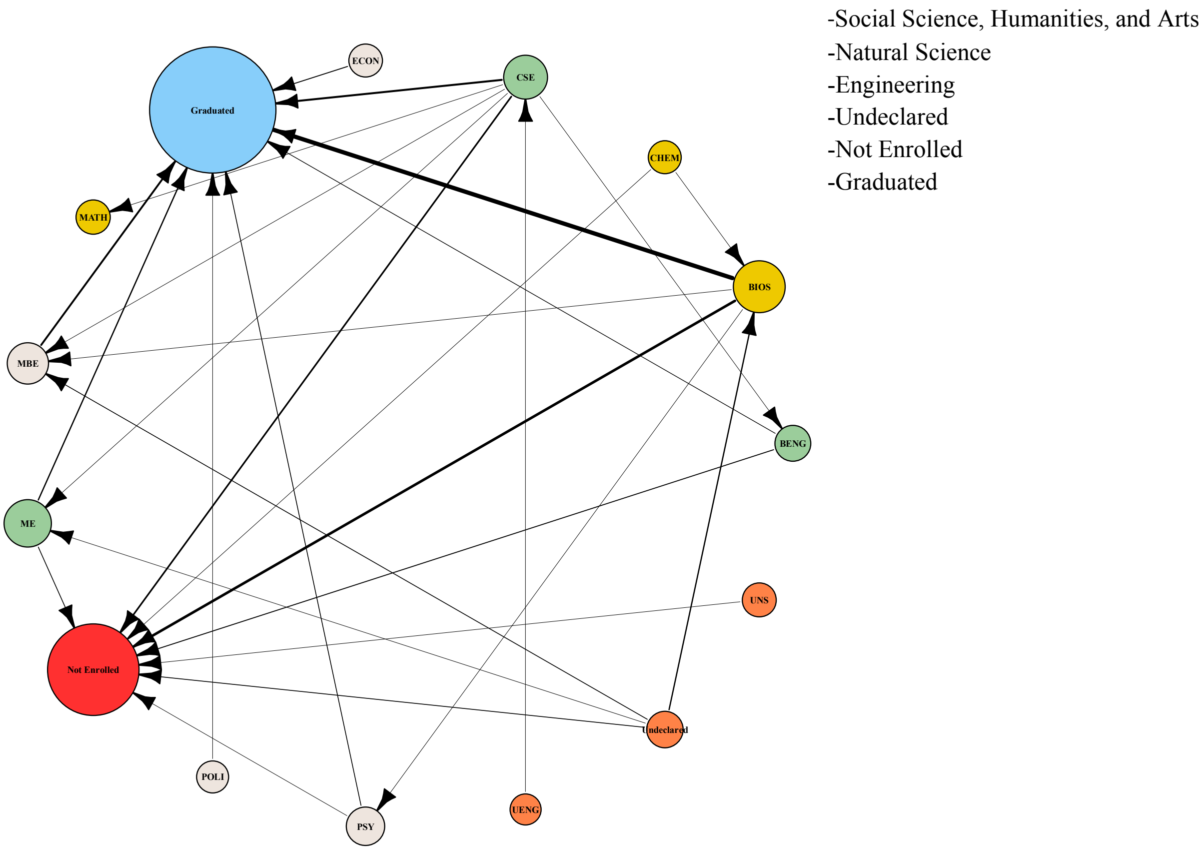

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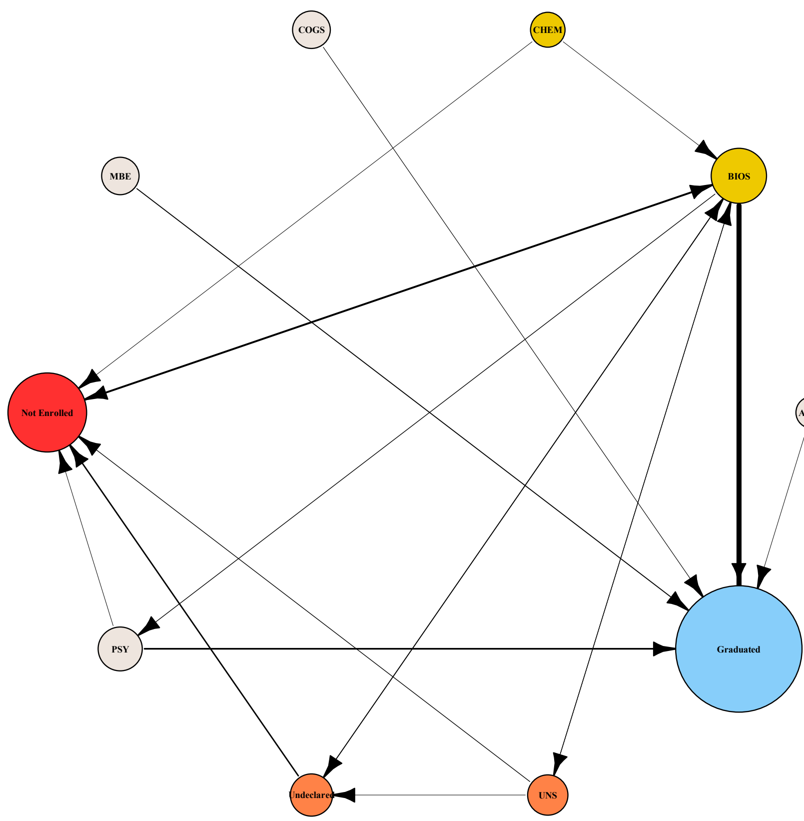
Figure 5: Asian Women (n=150)



-Social Science, Humanities, and Arts
-Natural Science
-Engineering
-Undeclared
-Not Enrolled
-Graduated

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Figure 6: Latinx Men (n=299)

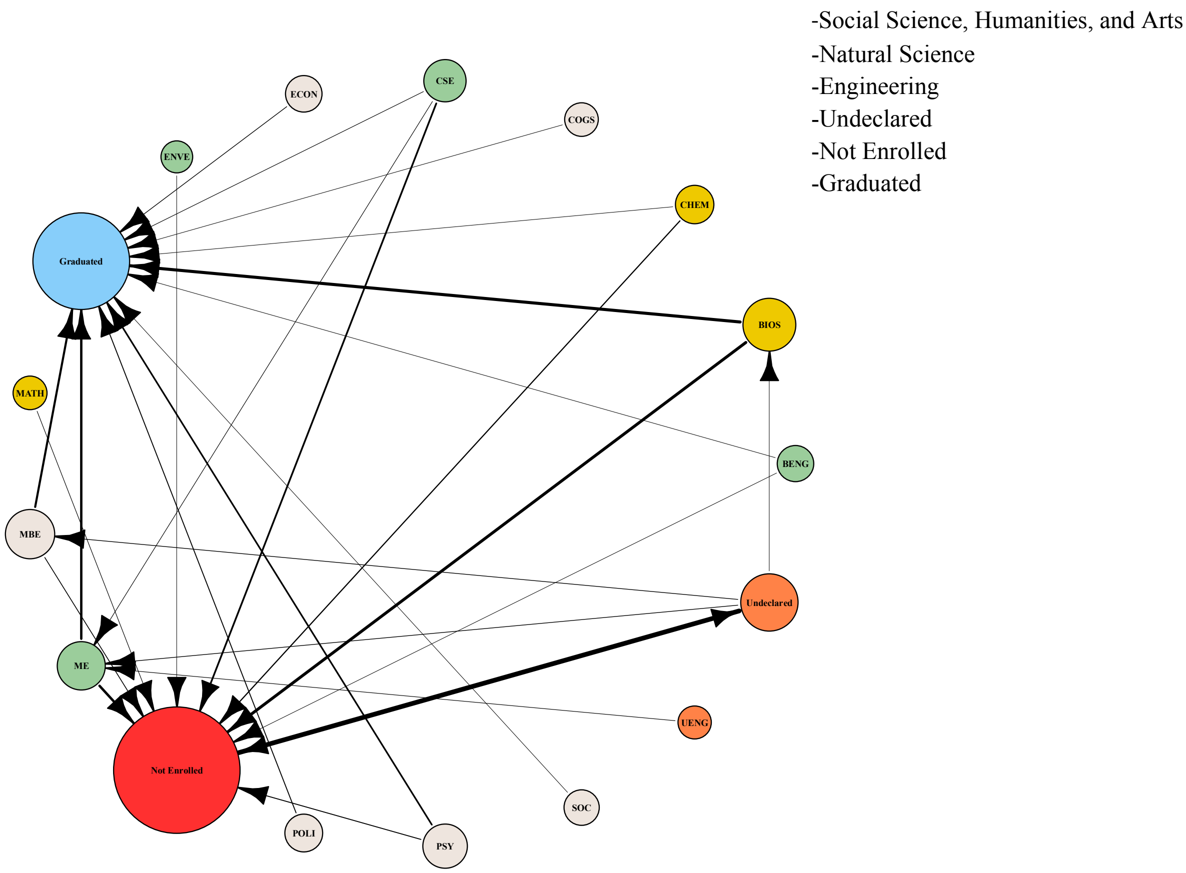

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Figure 7: Latinx Women (n=346)

-Social Science, Humanities, and Arts
-Natural Science
-Engineering
-Undeclared
-Not Enrolled
-Graduated

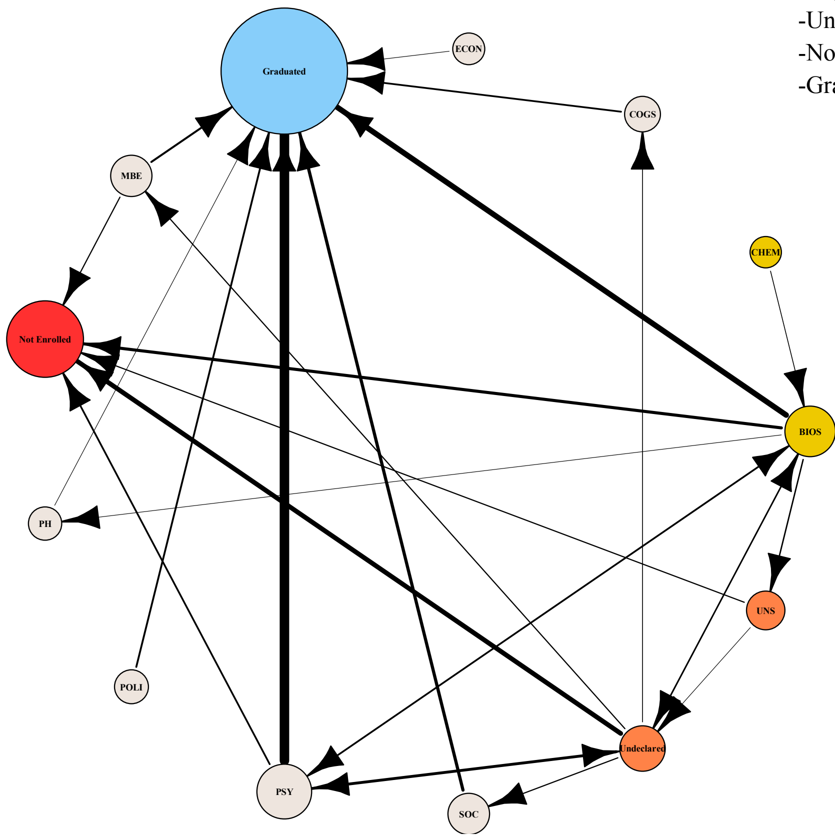

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Figure 8: Black Men (n=31)

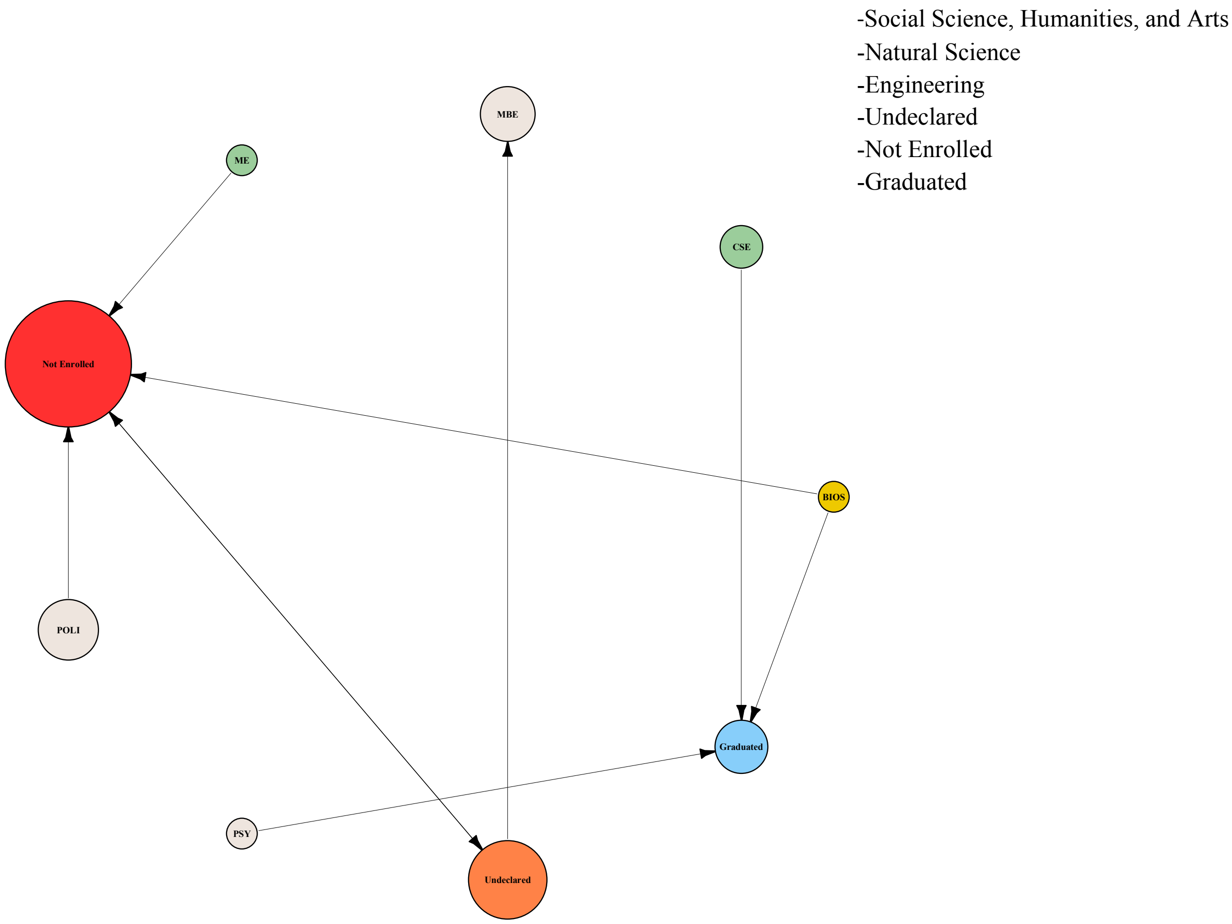

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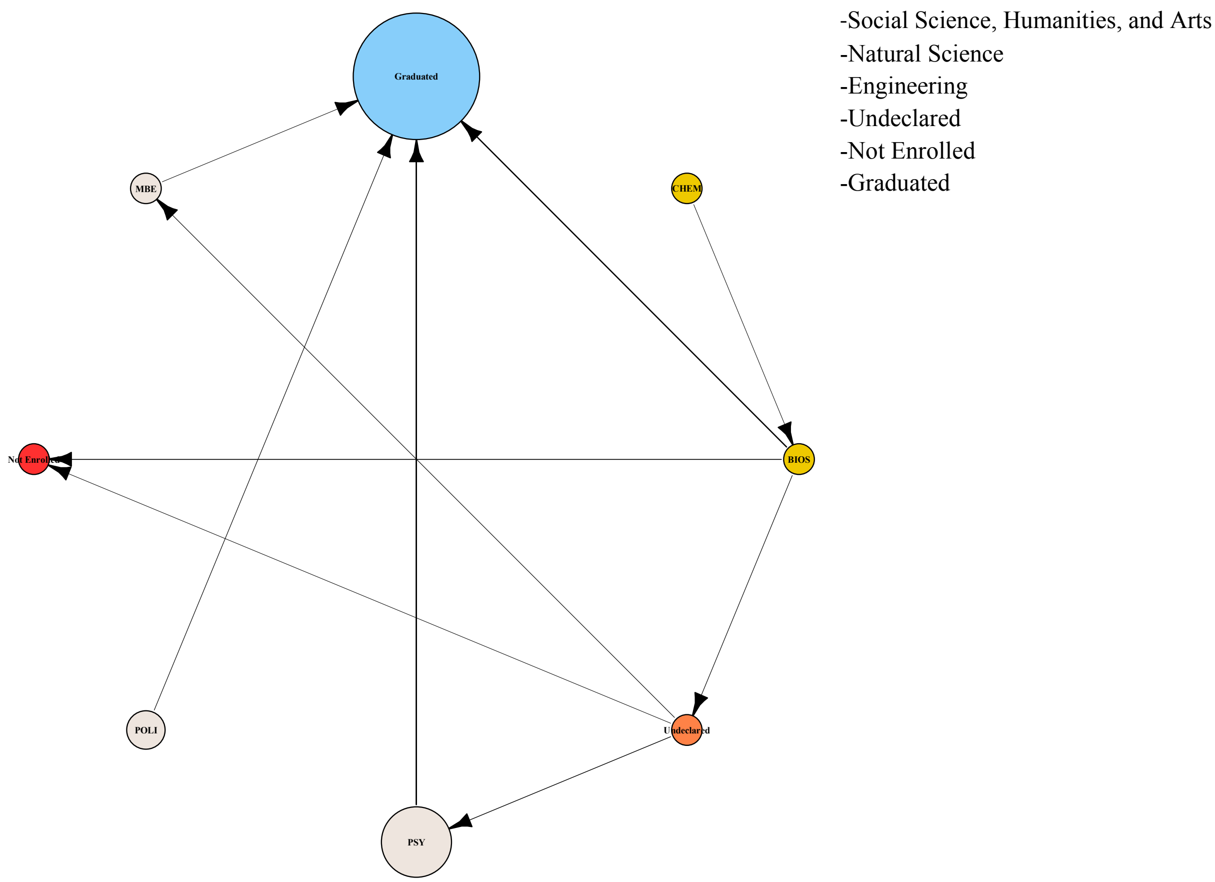
Figure 9: Black Women (n=57)



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Criminalization vs. Support: How the Type of Staff Matters in Days of Lost Instruction Time Due to Out-of-School Suspensions in U.S. Public Schools.

Abstract

This study used the 2015-16 Civil Rights Data Collection survey and other secondary data sources to explore the school-level factors that may contribute to days of lost instruction time due to out-of-school suspensions in U.S public schools. More specifically, using negative binomial regression, this study explored the relationship between staff-to-student ratios (among other school-level indicators) and days of lost instruction time due to out-of-school suspensions at the national level. The study found that an increase in the security staff-to-student ratio was related to an increase in the rate of lost instruction; the inverse-relationship was found between the support staff-to-student ratio and the rate of lost instruction. These findings suggest either that the policing staff in schools gets directly involved in routine school discipline disparities, or that their presence indirectly contributes to a harsher, more exclusionary climate; in contrast, school support staff may help alleviate these disparities.

Introduction

In the wake of the murder of George Floyd on May 25, 2020, and the massive protests against police brutality that followed, there is currently a heightened awareness of those protesting the racist and excessive use of force directed toward Black people. As a result, many school districts across the country are leading initiatives to sever or limit their relationship with local police departments (e.g., Denver, Milwaukee, Minneapolis, Oakland, and Portland, Oregon) (Chavez, 2020; Goldstein, 2020). While it remains to be seen if these shifts in policy will be effective, it is important to contextualize the many school districts that have relied heavily on police and security to maintain discipline since passage of the Safe Schools Act of 1994, and on the analogous state-level laws (Lyons & Drew, 2006; Simon, 2007). The over-reliance on policing staff to discipline students in many schools begs the question of the extent to which this reliance reduces the negative influence of disruptive students or even helps to maintain a healthy learning environment.

To address this question, we must first discuss what tactics are used to “discipline” students, including the frequent use of suspensions. Many researchers who have studied suspensions find that they are associated with lower academic achievement and educational attainment, perpetuating the school-to-prison pipeline, and generating tremendous economic costs (Mittleman, 2018; Pearman et al., 2019; Ramey, 2015; Rumberger & Losen, 2016, 2017).

Moreover, studies have revealed that disciplinary treatment varies within racial/ethnic groups. For instance, students of color are often punished more harshly than White students for the same offenses (Anyon et al., 2014; Arcia, 2007; Hannon et al., 2013; Krezmien et al., 2006; Skiba et al., 2011, 2015). Students attending schools with a high proportion of Black and Latinx students are also more likely than predominantly White schools to experience school exclusion, even after accounting for student-level demographics and behaviors (Anyon et al., 2014).

Scholars have found that studying only whether a student was suspended or not cannot fully capture the discipline disparities experienced in school by the most vulnerable populations. Some have focused on understanding the number of days of instruction time lost due to discipline. For instance, Losen and Whitaker (2018) found that students in the U.S. lost more than 11 million days of instruction as a result of out-of-school suspensions in 2015-16. They also found that the time lost was not distributed evenly between groups; that is, Blacks lost nearly five times the amount of instruction as Whites (Losen & Whitaker, 2018). Losen and Martinez (2020b) further disaggregated these data by grade-span categories at the secondary level (composed of both middle and high schools) and found that 103 days of instruction were lost for every 100 Black students, which compares to 21 days for White students. Given that students of color experience not only higher rates of suspension but also longer suspensions, these disparities are particularly alarming. However, little is known about the factors that contribute to such differences in days of lost instruction. For example, to what extent does the type of staff (policing vs. support) contribute to an increase or decrease in number of days lost due to suspension?

Using the 2015-16 Civil Rights Data Collection (CRDC) survey and other secondary data sources, this study explored how the type of staff may contribute to days of lost instruction time due to out-of-school suspensions. Additional factors were also considered to account for existing relationships in suspension scholarship; for example, scholars have shown that the number of suspensions and who gets suspended are primarily determined by the school context (Skiba, 2015). Therefore, this study controlled for the school-level characteristics (e.g., security and support staff, and teacher quality) and demographics (e.g., racial/ethnic composition, school locality, and region). Overall, the results found in this study mirror patterns observed by other studies on suspensions, but they also provide new insights into the factors that may contribute to days lost of instruction time due to suspension.

Background

Race, Criminalization, and School Discipline

The heightened criminalization of schools occurred during the late 20th century, largely as a result of the War on Crime declared in 1965 by President Lyndon Johnson (Hinton, 2016; Lyons & Drew, 2006; Simon, 2007). An important aspect of understanding the criminalization of schools is understanding that the War on Crime, and later the War on Drugs, predominantly targeted poor communities of color. This political agenda resulted in the disproportionate incarceration of Black and Latinx people, who together constituted 59 percent of the nation's prison population by 2013 despite representing only 25 percent of the entire U.S. (Hinton, 2016). These policies simultaneously fueled the nation's media, whose racist depictions of students of color (e.g., super predators) in inner-city schools resulted in fear mongering and laws that pushed heavily for more social control and harsher discipline (Moriearty, 2009; Lyons & Drew, 2006; Simon, 2007).

Since the Safe Schools Act of 1994 and analogous state-level laws were passed, schools have relied heavily on police and security tactics to maintain discipline (Lyons & Drew, 2006; Simon, 2007), including random sweeps, student searches and drug tests, and interrogations, and sworn police officers increasingly patrol the hallways of U.S. schools (Hirschfield, 2008a; Kupchik, 2010). This criminalization of schools has created an environment similar to that of high-crime neighborhoods or prisons (Noguera, 2003). In addition to the disciplinary tactics of suspension and expulsion, referrals to law enforcement and arrests are now common discipline strategies, even for such behavior as disrespecting authority or a minor dispute with another student (Hirschfield, 2010; Theriot, 2009). For instance, on a survey of school resource officers (SROs) in Delaware, 77 percent reported making an arrest to calm down a student, 68 percent to show a student that actions have consequences, and 55 percent because a teacher wanted the arrest to occur, even for a minor offense (Wolf, 2013). Gottfredson and colleagues (2020) similarly examined a small sample of public schools that increased their SRO staffing with funding from the Department of Justice's Community Oriented Policing Services Hiring Program. They found that SROs did not improve school safety and that school discipline incidents increased significantly after they had joined the staff.

The shift in public schools toward harsher discipline and criminalization is alarming in terms of how schools determine their staffing budgets. A recent report by the ACLU, "Cops and No Counselors: How the Lack of School Mental Health Staff Is Harming Students," found that millions of students attend schools that have law enforcement officers but no support staff. This means that, in 2015-16, 14 million students attended U.S. schools that had police on staff but no counselor, nurse, psychologist, or social worker. The decision to prioritize security staff over support staff may have severe consequences in terms of discipline disparities. For instance, Finn and Servoss (2015) found that greater Black-White suspension disparities occurred in schools with a higher degree of security.[6] Other scholars have also shown that investing in police and security hardware did not make teachers or students feel safer, and incidents of disruptive behavior did not decline (Osher et al., 2015).

Furthermore, the criminalization of schools and the security tactics developed in the process have helped perpetuate the school-to-prison pipeline. They have been especially harmful to students of color, as male Black and Latinx youth are often hyper-criminalized (Rios, 2007, 2011). The persistent effects of racism suggest that the higher rates of suspension and law enforcement referrals among Black and Latinx students are not solely the result of higher rates of

[6] Finn and Servoss (2015) defined a school with a high degree of security as having (1) metal detectors at the school entrance, (2) random metal detector checks on students, (3) drug testing, (4) random sweeps for contraband, (5) security cameras, (6) police or security guards on site during school hours, and (7) random "dog sniffs" to check for drugs.

misbehavior (Anyon et al., 2014). On the contrary, extensive research has shown that students of color are often punished more harshly than White students for the same offenses (Anyon et al., 2014; Arcia, 2007; Hannon et al., 2013; Krezmien et al., 2006; Skiba et al., 2011, 2015) and that misbehavior is not the driving factor of this disparity (Roque, 2010). Furthermore, students attending schools with higher proportions of Black and Latinx students are more likely to experience school exclusion and higher degrees of security (e.g., school guards) (Anyon et al., 2014; Osher, 2015). These patterns reflect differential selection of Black and Latinx students for office referrals and differential consequences for the same offenses committed by other students (Gregory et al., 2010; Hannon et al., 2013).

Days of Lost Instruction and School Discipline

Understanding the impact of suspensions on students' learning and future opportunities is central to understanding discipline inequities. Excluding a student from the classroom for even a few days can be disruptive to their education, and removing them from a structured environment may escalate their misbehavior. For instance, Ginsburg and colleagues (2014) found that missing three or more days of instruction was associated with lower achievement scores. Scholars have also found that neither suspended students nor their peers improve their behavior in a harsh disciplinary environment (Fabelo et al., 2011; Mendez, 2003).

While the student suspension rate is the most common metric used across studies, this is a conservative measure, as it does not reflect either the frequency of suspensions or the impact on instruction time. For example, a student receiving one long 20-day suspension will register the same impact (number of days lost) as four different students each receiving a 5-day suspension. By focusing on the days lost rather than on the common student suspension rate (based on the number of students suspended at least once), the rate of days of lost instruction prioritizes the educational impact of out-of-school suspensions. For the first time, in the 2015-16 school year, the CRDC dataset collected and reported the total of days of lost instruction for the majority of school districts across the nation. The magnitude of the total days lost in U.S. public schools was enormous; it added up to more than 11 million days of lost instruction due to out-of-school suspensions (Losen & Whitaker, 2018).

Few studies have examined or used days of lost instruction due to out-of-school suspension as a metric for understanding discipline disparities. This is explained in part by the fact that these are new data and that suspension rates are a well-established metric. Despite the lack of research examining days lost of instruction due to suspension, some descriptive reports found that Black students lost 66 days of instruction per 100 enrolled, as compared to just 14 days for White students (Losen & Whitaker, 2018). They found further that 14 percent of all Black students at the secondary level (composed of middle and high schools) attended districts with at least one year of lost instruction per 100 enrolled, as compared to just 0.2 percent of all White students at the secondary level (Losen & Martinez, 2020b). It is important to note that these rates are not explained just by the fact Black students get suspended more often but also that they receive longer suspensions.

Using regression analysis and the 2015-16 CRDC data, Losen and Martinez (2020a) examined the relationship between days of lost instruction and staffing in California high schools. They found that an increase in the security staff-to-student ratio was related to an increase in the rate of lost instruction. They also conducted a sub-analysis across high schools with at least 100 Black students and found a positive association between an increase in the security staff-to-student ratio and an increase in the rate of lost instruction for Black students.

Across this subset of high schools, they also found that an increase in the support staff-to-student ratio was associated with a decrease in the rate of lost instruction for Black students. While this research is based on a subset of high schools in California and therefore is not generalizable to all school in the U.S., it does highlight the importance of using days of lost instruction as a metric and provides new insights into how security staff (school guards) may contribute to larger discipline disparities. It also found an inverse relationship between support staff (counselors, social workers, psychologists, and nurses) and days of lost instruction.

Building on Losen and Martinez (2020a), this study further examines the relationship between staff-to-student ratios (among other school-level indicators) and days of lost instruction due to out-of-school suspensions at the national level, and for all grade levels. In particular, it hypothesizes that, if having higher security staff-to-student ratios increases the attention given to misconduct and the harshness of the response, these higher ratios are expected to be related to higher rates of lost instruction due to out-of-school suspension. If student support staff help prevent problem behavior and are involved in finding less punitive responses to misconduct, it is also expected that having incrementally higher support staff-to-student ratios would be related to lower rates of lost instruction.

Data and Methods

This study used data from two secondary sources: the restricted-use 2015-16 U.S. Department of Education CRDC, and the publicly available 2015-16 National Center for Education Statistics (NCES) Common Core of Data Elementary/Secondary School Universe Survey. The CRDC is a federally mandated biennial data collection that includes a wide range of school-level indicators for U.S. public schools. This study uses CRDC information on student enrollment, demographics, discipline, and staffing information. It is important to note that, while the CRDC has data that go as far back as the 1970s, the primary variable of interest—days of instruction lost due to out-of-school suspensions—was first collected in 2015-16. That year's CRDC included data from every public school district and public school in the nation (approximately 17,300 school districts, 96,300 schools, and 50.6 million students). The response rate for the 2015-16 collection was 99.8 percent. The NCES Common Core of Data Elementary/Secondary School Universe Survey was merged with the CRDC dataset to include two important factors: the total number of students who are eligible for free- and reduced-price lunch, and school locality. The CRDC does not currently collect any data on socioeconomic status or the type of school locality.

The CRDC unit of analysis is schools, not districts or individual students. The population examined excluded students in juvenile justice centers, and those attending virtual schools, schools with errors, and schools with missing data on outcome and predictor variables. In addition, a 200-student-per-school minimum was applied to ensure that the population was representative of traditional schools in the U.S. After dropping schools that did not meet the criteria, unmerged schools between datasets, and the small proportion of schools with missing data, the final analysis included a population of 72,209 schools. School grade configuration is an important factor when examining discipline disparities (Kupchik & Ward, 2014; Losen & Martinez, 2020b). Students attending secondary-level schools (5-8, 6-8, 7-9, 6-12, 9-12, 10-12, and 9th-grade academies) experience much higher rates of disciplinary action than students attending elementary-level schools (any school with any combination of K-5 and without a 7th or 8th grade). Therefore, this study included a sub-analysis at the elementary (n=39,545 schools) and secondary levels (n=26,707 schools).

Omitted Cases

Juvenile justice centers: Students in 650 juvenile justice facilities were excluded from this study. Although their information is valuable, these educational settings are different enough from regular schools that the data on them deserves separate treatment (Losen & Martinez, 2020b). Most of these schools reported no out-of-school suspensions, but that may mean that, in some cases, the students did not actually attend school while in the facility or that the responding correctional center did not regard disciplinary removal from a classroom as an out-of-school suspension. Furthermore, the out-of-school suspension of students attending a correctional facility has different implications, as those students remain under adult supervision eve when suspended. Moreover, all the students in these settings are there for disciplinary reasons, although not necessarily for misbehaving at school.

Virtual schools: The majority of virtual schools (n=240) that offered only remote instruction were removed. When most students are attending school from their own home, the term "out-of-school" suspension has an entirely different meaning. For this reason, we exclude any virtual schools that had an out-of-school suspension risk less than or equal to 1 percent, or a total count of out-of-school suspensions less than or equal to one. We include virtual schools that had more than one suspension, given the chance that they use virtual in their name but are not necessarily an actual "virtual" school.[7]

[7] While alternative schools are distinct from traditional public schools, it is important to include them because students in grades K-12 who attend alternative schools lost almost twice the number of days of instruction as secondary students (in non-alternative schools) overall. Losen and Martinez (2020) argue that, if alternative schools were better at meeting the needs of the students than traditional schools, the fact that they disproportionately enroll Black students and those with disabilities would not be troubling. However, students in these schools are losing a far greater amount of instruction than all students on average; for example, Black students attending traditional schools lost 103 days per 100 enrolled at the secondary level but nearly twice that amount (203 days per 100) when they

Erroneous schools: Some schools in the CRDC dataset reported suspension rates that were not possible and therefore were errors: 61 schools were removed because they reported suspension rates greater than 100 percent for all students or for any racial/ethnic group; 72 alternative schools were removed because they reported suspension rates above 150 percent for all students or for any racial/ethnic group. The alternative school suspension rate threshold was slightly higher, given that alternative schools tend to have fluctuating enrollment; therefore, it is possible for suspension rates at these schools to be slightly above 100 percent.

200-student minimum: According to 2015-16 NCES data, the average public school enrollment is 528 students; it ranges from an average of 358 students in rural areas to 591 students in cities (Snyder et al., 2018). A 200-student minimum was chosen as a conservative measure to capture all schools with a student body that reflects the average U.S. public school; 16,327 schools enrolled fewer than 200 students.

Outcome Variable

The total days of lost instruction time due to out-of-school suspensions is the total number of all days lost by all students due to an out-of-school suspension; this includes those with one or multiple suspensions and all types of suspensions. The dependent variable used in this study was total days of instruction lost due to out-of-school suspension per 100 students; that is, the total number of days lost due to suspensions, divided by total enrollment, and then

attended alternative schools. While not present here, all analysis was conducted without alternative schools and the results mirrored what is presented in this paper.

multiplied by 100. This measure allowed us to adjust for school enrollment, regardless of enrollment differences among schools (Losen & Martinez, 2020b).

Predictor Variables

To capture the negative effects of policing in school discipline data, a proxy variable was constructed by dividing the number of security guards at each school by the total enrollment of each school. The security staff-to-student ratio variable did not include sworn law enforcement officers because of an error in the 2015-16 CRDC data collection.[8] The measure of support staff-to-student ratio variable was created, which includes the sum of the number of counselors, psychologists, social workers, and nurses at each school, divided by total student enrollment. This study included this variable in part because a high level of security in schools has been associated with an increase in disciplinary actions (Anyon et al., 2014; Osher, 2015); it is possible that high levels of support staff may counter these effects and reduce the number of disciplinary actions.

Across the U.S., students continue to experience institutional inequities on the basis of race/ethnicity and socioeconomic class. For instance, predominantly poor students and students of color often attend schools without qualified or fully prepared teachers (Darling-Hammond, 2004; Kozol, 2005; Shields et al., 2001). Schools with a higher proportion of unprepared teachers may experience some of the highest levels of disciplinary action, due to their lack of training in handling student misbehavior. To capture this effect, a novice teacher-to-student ratio variable

[8] The initial construct included the combined total number of security guards and sworn law enforcement officers. However, the sworn law enforcement officer's indicator question was mistakenly carried over from the 2013-14 data collection to 2015-16. CRDC categorized this as an error for many schools. The data element was skipped for more than 69,000 schools, which was approximately 72 percent of the entire national dataset. Therefore, this study did not include the sworn law enforcement officer variable and used security staff as a proxy for examining policing in schools.

was constructed as a proxy, which includes the number of first- or second-year teachers, divided by total student enrollment. Scholars also have suggested that teacher absences can affect student achievement by creating discontinuity in instruction, difficulty forming meaningful relationships with multiple or mobile substitutes, and disruption of regular classroom routines and procedures (Cantrell, 2003; Clotfelter et al., 2009; Lewis, 1981; Miller et al., 2008; Rundall, 1986; Tingle et al., 2012). If misbehavior increases due to a lack of structure in the classroom, a high rate of teacher absenteeism may also contribute to the discipline disparity gap. A teacher absenteeism-to-student ratio variable was constructed by adding the number of times teachers were absent more than 10 days during the school year and diving that by the total student enrollment.

The percentage of students enrolled in each school by subgroup (e.g., race/ethnicity, gender, English language learners, and students with disabilities) was also controlled for because of the existing group disparities documented in school discipline scholarship (Anyon et al., 2014; Bertrand & Pan, 2011; Kim et al., 2010; Losen & Orfield, 2002). The school locality variables control for differences in school discipline across rural, suburban, and urban contexts (Welch & Payne, 2010). The school locality variable was constructed by combining the following categories: Urban ("City, Large": a territory within an urbanized area and inside a principal city with a population of 250,000 or more; "City, Midsize": a city with a population greater than or equal to 100,000 and less than 250,000; "City, Small": a city with a population less than 100,000); Suburban ("Suburban, Large": a territory outside a principal city and inside an urbanized area with population of 250,000 or more; "Suburban, Midsize": a city with a population greater than or equal to 100,000 and less than 250,000; "Suburban, Small": a city with a population less than 100,000; Town ("Town, Fringe": a territory inside an urban cluster that is less than or equal to 10 miles from an urbanized area; "Town, Distant": a town more than

10 miles and less than or equal to 35 miles from an urbanized area; “Town, Remote”: a town more than 35 miles from an urbanized area); and Rural (“Rural, Fringe”: a census-defined rural territory that is less than or equal to 5 miles from an urbanized area, and rural territory that is less than or equal to 2.5 miles from an urban cluster; “Rural, Distant”: a territory more than 5 miles but less than or equal to 25 miles from an urbanized area, and more than 2.5 miles but less than or equal to 10 miles from an urban cluster; “Rural, Remote”: a territory more than 25 miles from an urbanized area and more than 10 miles from an urban cluster). Lastly, the U.S. Census Region categories (West, Midwest, South, and Northeast) were constructed by combining the schools’ states that corresponded to each region assigned by the U.S. Census Bureau.[9]

Analysis Strategy

Negative binomial regression was used in the models to test the relationship between school-level factors and lost instruction due to out-of-school suspensions. Negative binomial regression is the preferred method because the variable of days of lost instruction per 100 students followed a negative binomial distribution, also known as a variable with over-dispersed count data, where the conditional variance exceeds the conditional mean (Cameron & Trivedi, 1998). Further, to contextualize the ratios in the regression models, all ratios were divided by 0.001. This allowed for the interpretation of the regression coefficients of the ratios to be understood in increments of one-thousandth. Increasing a ratio by 1, as is standard in any regression, would overestimate an actual increment within a school. For example, the security staff-to-student ratio had a mean of 0.0004. The ratio indicated an average of one security guard for a school with 2,500 students enrolled. Applying the one-thousandth increment represents a

[9] See U.S. Department of Commerce Economics and Statistics Administration U.S. Census Bureau, https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf.

rough estimate of adding one security guard. This increment is more realistic than looking at what the model predicted if we added ten security guards to one school.

Findings

The descriptive statistics presented in Table 15 show all variables used in the analysis that examined total days of lost instruction due to out-of-school suspensions per 100 students. These descriptive statistics are broken down by grade configuration (e.g., K-12, elementary, and secondary) for U.S. public schools. Stark discipline and staffing disparities were found for each grade configuration. Among K-12 schools, an average of 20 days of lost instruction due to out-of-school suspension was found among every 100 students. A total of 7 days were lost per 100 students at the elementary level, and 38 days were lost per 100 students at the secondary level. The security staff-to-student ratio (0.4 estimation*0.001 adjustment=0.0004 actual ratio) for all schools, for example, indicated an average of one security guard for a school with 2,500 students enrolled. At the elementary level, the ratio on average revealed no security guard for a school with 2,500 students enrolled, while it indicated an average of two security guards at the secondary level.

Further, the support staff-to-student ratio was similar across grade-level configurations. For example, an average of 12 support staff (a combination of the number of counselors, psychologist, social workers, or nurses) was found for a school with 2,500 students enrolled. This ratio was similar at the elementary level (11 support staff) and the secondary level (13 support staff) for schools with the same enrollment. The novice teachers-to-student ratio descriptive statistics also revealed a similar number of first- or second-year teachers across grade configurations; that is, an average of 20 first- or second-year teachers for every 2,500 public K-

12 students. When looking at the teacher absenteeism-to-student ratio, the data revealed that, on average, for a school with an enrollment of 2,500 students, teachers were absent more than 10 days during the school year 46 times.

Across grade-level configurations, the average student demographic characteristics between schools was relatively the same. Between 21 percent and 25 percent of students were Latinx, 15-16 percent were Black, 51-56 percent were White, 4 percent were Asian, 1 percent were Native American, and 0.3-0.4 percent were Hawaiian/Pacific Islander; in addition, 12 percent of students had disabilities, and 50 percent to 55 percent were low income. A slightly larger percentage of students with limited English proficiency were found at the elementary level (13 percent) that at the secondary level (6 percent). The school locality data point revealed that the majority of schools were located in suburban areas. At the elementary level, 39 percent were located in suburban areas, as were 34 percent at the secondary level. At 28 percent, the second highest percentage at the elementary level was schools located in urban areas. However, this was not the case at the secondary level, where the second highest percentage, 26 percent, was located in rural areas, compared to 24 percent in urban areas. The school locality among towns was relatively low; 13 percent of schools were located at the elementary level, 17 percent at the secondary level. Lastly, the descriptive statistics revealed that the majority of schools—that is, around 40 percent of schools across grade-level configurations—were located in the South. At the elementary level, 24 percent of schools were located in the West and the same percentage in the Midwest. At the secondary level, 20 percent of schools were located in the West, 26 percent in the Midwest, and around 14 percent in the Northeast.

Table 16 presents coefficients and standard errors from negative binomial regression models examining the relationship between school-level factors and days of lost instruction time due to out-of-school suspensions. The results revealed wide disparities and differences among grade-level configurations. A positive relationship was found at K-12 and secondary-level schools between increasing the security staff-to-student ratio and the rate of lost instruction, after controlling for the support staff-to-student ratio, novice teacher-to-student ratio, teacher absenteeism-to-student ratio, as well as the percentage of low-income students, students with disabilities, limited English proficiency students, and racial/ethnic and gender groups. Specifically, as shown in Table 16, with a one-thousandth-unit increase in the security staff-to-student ratio, the difference in the logs of expected counts would increase by 0.012 days of lost instruction per 100 students in the all-schools model and an increase of 0.025 days at the secondary level, while holding constant other school-level factors.

On the other hand, accounting for the same factors, an inverse relationship was found between increasing the support staff-to-student ratio and the rate of lost instruction among all models. With a one-thousandth-unit increase in the support staff-to-student ratio, the difference in the logs of expected counts would decrease between 0.002 and 0.001 days of lost instruction per 100 students. Across grade-level configurations, the coefficients for the novice teacher and teacher absenteeism-to-student ratios were all positively associated in terms of increasing the ratios and an increase in the rate of lost instruction. For example, with a one-thousandth-unit increase in the teacher absenteeism-to-student ratio at the secondary level, the difference in the logs of expected counts would increase by 0.007 days of lost instruction per 100 students.

Moreover, the regression coefficients for demographic characteristics revealed wide disparities between racial/ethnic groups. When looking at the racial composition, the multi-racial, Black, and Native American student percentages were positively correlated with increasing rates of lost instruction across all grade levels. For example, with a population percentage increase in Black students for the all-schools model, the difference in the logs of expected counts would increase by two days of lost instruction in comparison to White students. Similarly, in comparison to White students, an increase in the Hawaiian and Pacific Islanders population percentage was also associated with an increase in the rate of lost instruction at the secondary and the all-schools models. Other school-level demographic characteristics revealed that students with disabilities, male students, and low-income students were positively correlated with increasing rates of lost instruction across all grade levels. When examining school locality, the regression coefficients estimated that schools located in suburban, town, or rural areas had fewer days of lost instruction than schools located in urban areas. Lastly, the U.S. Census region analysis revealed that the West was correlated with an increase in rates of lost instruction in comparison to the South, Midwest, and the Northeast.

Limitations

Most importantly, the purpose of this study is to understand if an association exists between school-level factors and days lost of instruction—not to establish such a causal relationship. While this in itself is not a limitation per se, this study sought to further understand and contextualize days of lost instruction by examining school-level factors, which were informed by the extensive scholarship on suspensions. The present analysis only takes school-level factors into account, and it is based on cross-sectional data. Having longitudinal data would be ideal, as it would allow one to follow schools over time. Finally, by restricting the enrollment to schools with at least 200 students, findings cannot be generalized to all public schools in the U.S.

The analysis at the school level did not allow for an examination of the effects of individual-level factors, such as implicit bias or overt discrimination on the basis of race/ethnicity, gender, and/or disability status. Future research should consider the ways these factors impact days of instruction lost due to suspension. Moreover, although each was reported to the Office for Civil Rights separately, all counselors, psychologists, nurses, and social workers were grouped together under the term "support staff." It is possible that different results may have been found if each type of support staff had been analyzed separately. Also, because the data on days of lost instruction are tied only to out-of-school suspensions in the CRDC, it is possible that the study didn't capture the full degree to which security staff-to-student ratios correlate with higher rates of days of lost instruction due to all forms of discipline. While this study intended to analyze and include referrals to law enforcement and school-based arrests as factors in the regression models, the data on school-based arrests for 2015-16 were either zero or were missing for the majority of the largest districts in the nation, including Los Angeles and New York City. This means that schools are seriously under-representing the degree of referrals and arrests for school-based behaviors; therefore, these two factors were not included in the analysis.[10]

Discussion

Since the War on Crime, policy shifts resulted in public schools implementing harsher discipline and institutionalizing the criminalization of students of color (Hinton, 2016; Lyons & Drew, 2006; Simon, 2007). In fact, many of today's public schools now have environments that

[10] Losen and Martinez (2020b) report that the researchers analyzed the likelihood that the zeros were not accurate in the referrals to law enforcement and school-based arrests at middle and high schools. As reported by CRDC in 2015-16, they found that, of 1,630 districts in the United States that enrolled at least 3,000 secondary students, (1) approximately 60 percent of all the large districts reported zero school-based arrests; (2) just over 32 percent reported zero referrals to law enforcement and zero school-based arrests; and (3) slightly more than 16 percent reported the identical number of referrals to law enforcement as school-based arrests. Additional analysis was conducted, and the researchers concluded that these data are not accurate.

resemble those of high-crime neighborhoods or prisons (Noguera, 2003). For instance, many schools rely heavily on police and security officers to maintain discipline (Lyons & Drew, 2006; Simon, 2007). The staffing disparities in schools are so wide that a recent report found that 14 million students in the United States attend schools that have police on the premises, but no counselor, nurse, psychologist, or social worker (Whitaker et al., 2019).

Moreover, this study took on the task of examining the extent to which these staffing disparities contribute to discipline disparities. Using national-level data from nearly every school in the United States, this study is the first to explore how the type of staff may contribute to days of lost instruction time due to out-of-school suspensions. While this study looked at several indicators to account for existing relationships found in discipline studies, two important findings emerged from the analysis conducted. First, among K-12 and secondary schools, a positive relationship was found between increasing the security staff-to-student ratio and the rate of lost instruction, after controlling for other school-level factors. On the other hand, a negative relationship was found between increasing the support staff-to-student ratio and the rate of lost instruction at all grade-level configurations.

Even though these correlational findings are not sufficient to establish a causal relationship, they do alert policymakers to the possibility of the unintended negative consequences from adding school policing staff and the trade-offs such personnel expenditures entail. These findings suggest either that policing staff in schools may get directly involved in routine school discipline or that their presence contributes indirectly to a harsher, more exclusionary climate. The association found with the support staff ratio suggests that increasing the number of school counselors, psychologists, social workers, and/or nurses may help alleviate discipline disparities in schools.

While the results found in this study mirror some overall patterns observed by other suspensions studies, they also provide new insights into discipline disparities. In particular, unlike Losen and Martinez (2020a), this study found that the support staff-to-student ratio was statistically significant across all grade configurations, including secondary schools. This difference may be explained by the fact that Losen and Martinez (2020a) only examined high schools in California, while this study took into account nearly every school in the nation. Similarly, Finn and Servoss (2015) examined high schools in the U.S. and found a statistically significant relationship between greater Black-White disparities and higher degrees of security. However, Finn and Servoss found that the relationship between security and out-of-school suspensions was not statically significant. While this study doesn't use the same security metric as Finn and Servoss, a positive association was found between the security staff-to-student ratio and days of lost instruction due to out-of-school suspension.

Discipline disparities in schools are not as simple as different students "misbehaving" and each receiving the punishment deemed "appropriate." The process behind discipline disparities is more complex and it relies on unequal treatment, ineffective practices that yield no positive results, and the criminalization of schools; it also varies according to each school's demographic and institutional characteristics (Anyon et al., 2014; Hirschfield, 2008b; Mendez, 2003). Suspension, one of many discipline strategies, has led to large discipline disparities between groups, further embedded the school-to-prison pipeline, and helped to perpetuate the educational gaps between student groups (Kim et al., 2010; Mittleman, 2018; Pearman et al., 2019). The analysis conducted in this study helped to further contextualize discipline disparities and showed the importance of the type of staff in schools, including the ways they may or may not exacerbate the discipline disparities existing in schools today.

Conclusion

There currently is heightened awareness of the abusive policing directed at Black people in the United States, and an increase in the number of protests against systemic racism and the White supremist movement. As a result, many school districts across the country have started to sever or limit their relationship with local police departments. Many large districts are taking steps to eliminate school-based law enforcement altogether, including Minneapolis, Denver, Milwaukee, Oakland, and Portland, Oregon (Chavez, 2020; Goldstein, 2020).

There are many perspectives on having a police presence in the public schools. On the one hand, it's not surprising that wanting to protect students from dangerous outsiders would lead many to want to hire school resource officers and/or security guards. The thinking is that, besides preventing school shootings, having more policing staff might discourage gang involvement and drug activity; however, there is no research demonstrating a need for a regular police presence in our schools (Devlin et al., 2018). Despite the common rhetoric about the increasing dangers inside U.S. public schools, school crime has been declining over the past two decades (Musu et al., 2019). In 1992, the rate of crime (violent and nonviolent combined) against students at school was 144 incidents per 1,000 students. The rate had dropped to 57 per 1,000 students by 2005, and it has continued to drop since then.

While some may argue that law enforcement and security officers help control "chaotic" schools and instill order, these people are not trained teachers or behavior specialists. Moreover, schools cannot depend on police and security guards to enforce disciplinary measures and thus only educate the "best behaved" children; they need to address the fundamental inequities around race, socioeconomic isolation, resource inequity, and inadequate school environments.

Ultimately, all teachers need more support and tools (e.g., better training and financial support), which will render calling a law enforcement officer or sending students to the office a measure of last resort.

Eliminating unnecessary suspensions will mean hundreds of millions in reduced costs to taxpayers. More importantly, discipline reform, if done well, will contribute to a more economically efficient public education system. Therefore, the goal for all schools and all students is to reduce suspension rates till suspension truly becomes a measure of last resort. This goal is the position recommended by the NEA, the AFT, the Academy of American Pediatrics, the National Association of School Psychologists, the Council of State Governments, the American Association of School Administrators, and numerous others. The idea that some subgroups of students should be suspended at high and disparate rates simply because they are perceived to have broken minor school rules more often, is contrary to this goal.

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Table 15: Descriptive Statistics of Regression Models Examining Total Days of Lost Instruction Due to Out-of-School Suspensions per 100 Students in U.S. Schools

	All Schools		Elementary Schools		Secondary Schools	
Variable	*Mean*	*St. Dv.*	*Mean*	*St. Dv.*	*Mean*	*St. Dv.*
Total Days Lost per 100	20	47	7	20	38	67
Security Staff-to-Student Ratio	0.4	2.0	0.2	1.3	0.8	2.6
Support Staff-to-Student Ratio	4.7	9.3	4.3	6.7	5.3	12.2
Novice Teachers-to-Student Ratio	8.0	8.8	7.8	8.5	7.9	8.5
Teacher Absenteeism-to-Student Ratio	18.7	14.4	19.2	14.2	18.6	14.1
Racial Composition						
Latinx	23.3%	0.3	24.8%	0.3	20.8%	0.3
Native American	1.2%	0.1	1.0%	0.1	1.2%	0.1
Asian	4.0%	0.1	4.4%	0.1	3.7%	0.1
Hawaiian/Pacific Islander	0.4%	0.0	0.4%	0.0	0.3%	0.0
Black	15.6%	0.2	14.6%	0.2	15.2%	0.2
Multiracial	3.6%	0.0	4.1%	0.0	2.9%	0.0
White	52.0%	0.3	50.7%	0.3	55.9%	0.3
Other Demographic Composition						
Students with Disabilities	12.6%	0.1	12.5%	0.1	12.4%	0.1
Male	51.4%	0.0	51.6%	0.0	51.2%	0.0
Limited English Proficiency	10.1%	0.2	13.1%	0.2	5.7%	0.1
Low-Income	53.4%	0.3	55.0%	0.3	49.6%	0.3
School Locality Percentage						
Suburban	35.6%	0.5	38.9%	0.5	33.5%	0.5
Town	14.2%	0.3	13.5%	0.3	16.9%	0.4
Rural	22.9%	0.4	19.6%	0.4	26.1%	0.4
U.S. Census Region Percentage						
Midwest	24.9%	0.4	23.9%	0.4	26.1%	0.4
South	38.6%	0.5	39.3%	0.5	39.5%	0.5
Northeast	13.7%	0.3	13.0%	0.3	14.2%	0.3
n (schools)	72,209		39,545		26,707	

Table 16 : Negative Binomial Regression on Total Days of Lost Instruction Due to Out-of-School Suspensions per 100 Students in U.S. Schools

	All Schools		Elementary Schools		Secondary Schools	
Variable	*b*	*SE*	*b*	*SE*	*b*	*SE*
Security Staff-to-Student Ratio	0.012***	0.003	-0.002	0.005	0.025***	0.004
Support Staff-to-Student Ratio	-0.001**	0.000	-0.002***	0.001	-0.001**	0.001
Novice Teachers-to-Student Ratio	0.011***	0.001	0.011***	0.001	0.004***	0.001
Teacher Absenteeism-to-Student Ratio	0.003***	0.000	0.002***	0.000	0.007***	0.000
Racial Composition (Reference: White)						
Multiracial	3.597***	0.146	4.251***	0.193	4.680***	0.263
Black	1.991***	0.027	2.117***	0.039	1.547***	0.041
Hawaiian/Pacific Islander	1.946***	0.207	-0.325	0.282	3.582***	0.356
Native American	1.223***	0.078	1.114***	0.115	1.075***	0.118
Latinx	-0.278***	0.031	-0.270***	0.047	-0.565***	0.044
Asian	-1.888***	0.067	-1.587***	0.096	-2.400***	0.100
Other Demographic Composition						
Students with Disabilities	1.831***	0.084	1.607***	0.134	2.282***	0.150
Males	1.892***	0.131	0.934***	0.228	2.162***	0.163
Limited English Proficiency	-0.463***	0.048	-0.669***	0.066	0.887***	0.102
Low-Income	1.843***	0.023	2.174***	0.03	1.494***	0.037
School Locality (Reference: Urban)						
Suburban	-0.147***	0.012	-0.157***	0.016	-0.023	0.018
Town	-0.128***	0.016	-0.064***	0.023	-0.079***	0.023
Rural	-0.035**	0.015	-0.046**	0.022	-0.073***	0.022
U.S. Census Region (Reference: West)						
Midwest	-0.109***	0.015	-0.048**	0.021	-0.060***	0.022
South	-0.289***	0.014	-0.327***	0.019	-0.031	0.021
Northeast	-0.179***	0.018	-0.332***	0.025	-0.084***	0.026
Schooling Level						
Secondary	1.766***	0.010				
Intercept	-0.694***	0.069	-0.505***	0.120	0.881***	0.088
n (schools)	72,209		39,545		26,707	

*** p<0.01, **p<0.05, * p<0.1.
Data are from the restricted 2015-16 CRDC, and the 2015-16 NCES Common Core of Data Elementary/Secondary School Universe Survey.

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CONCLUSION

Overall, the first two articles presented in this dissertation are able to provide additional context as to why racial/ethnic and gender disparities persist in post-secondary college process.

In the first article, I implemented the framework of emergent structures (Friedkin and Thomas 1997; Heck et al. 2004) at the university level for the first time to examine the student groupings that emerge from course-taking with peers, and to illustrate that the differences between these groupings may contribute to the disparities that persist in the college experience (i.e., major choice, graduation rates). The student groupings that emerged in this study from course-taking patterns at the university level were differentiated by major choice, race/ethnicity, gender, financial aid availability, and academic achievement. The community-detection method used revealed four distinct curricular pathways among students' course-taking patterns over five years. Overall, the wide variation in student characteristics between the emerging student groups indicate that some type of stratification occurred. While the university doesn't have a tracking system per se, this stratification likely occurred due to a combination of decision processes at the university and individual levels. In this study, I showed how student's racial/ethnic background and gender (among other factors) increased their likelihood of having particular course-taking patterns.

Moreover, the second article found that new insights emerged after mapping five years of the college major process—major selection, change of major, and major at graduation. For instance, Ma and Liu (2017) found that women, Latinx, and Black students are more underrepresented in the physical STEM fields (i.e., computer, math, physical science, and engineering) than in life STEM fields (i.e., agriculture, biology, and life-science related), whereas this study found that

Latinx and Black women are less likely than any other group to study in a STEM-related field. While women from all racial groups initially enter the university with a life STEM major, women of color tend to eventually change to an social science major. In this case study, neither Latinx nor Black men were underrepresented in STEM. In fact, they had a higher percentage of representation in STEM-related majors by the start of their fourth year than in social science majors. This finding may be due to the fact that this university is a Hispanic-Serving Institution; note that Thomas (1991) found that Black students who attended predominantly White colleges were less likely to choose natural and technical science majors than those who attended predominately Black colleges. This institution being a Hispanic-Serving Institution may similarly influence the STEM representation of both Latinx and Black men. However, the STEM underrepresentation of men of color by the end of 5th year is not due to major choice or major changes, but due to the fact that by this time the majority of men color have already dropped out.

To further contextualize suspensions in the last article, using national-level data from nearly every school in the United States, this study is the first to explore how the type of staff may contribute to days of lost instruction time due to out-of-school suspensions. The findings in this study suggest that when students are policed in our schools, policing staff either get directly involved in routine school discipline or their presence indirectly contributes to a harsher, more exclusionary climate. Overall, the results found in this study mirror patterns observed by other studies on suspensions, but they also provided new insights into the specific factors contributing to days lost of instruction time due to suspension. In particular, unlike Losen and Martinez (2020), this study found that the support staff-to-student ratio was statistically significant across all grade configurations, including secondary schools. This difference may be explained by the fact that Losen and Martinez (2020) only examined high schools in California, while this study took into account nearly every school in the nation. Similarly, Finn and Servoss (2015) examined high schools in the U.S. and found a statistically significant relationship between greater Black-White disparities and higher degrees of security. However, Finn and Servoss found that the relationship between security and out-of-school suspensions was not statically significant. While this study doesn't use the same security metric as Finn and Servoss, a positive association was found between the security staff-to-student ratio and days of lost instruction due to out-of-school suspension.

In conclusion, the dissertation as whole demonstrated the lingering effects of race, gender, and class in the educational pipeline. These background characteristics keep defining the differences in our society whether we focus on graduation rates in college or who gets suspended in high school. More importantly, these disparities are due to the systemic and structural features in our society today. At the structural level, for instance, Bonilla-Silva's (1997, 2001) theoretical framework alludes to the importance of the long history of U.S. educational institutions being part of a racialized social system, which means that students experience a form of hierarchy that produces definite social relations and puts them in a specific position based on their social identities and background characteristics. I argue that this dissertation showed some of the factors at the individual, institutional, and structural levels that further perpetuate and reproduce educational inequities.

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