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Combating Summer Melt: The Impact of Near-Peer Mentor Matriculation Program in New York City

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Abstract
College education plays a crucial role in upward social mobility. However, despite applying to and being accepted by colleges, students often fail to matriculate—a phenomenon known as "summer melt". The summer after high school graduation is a vulnerable period for these students due to limited counseling support from both high schools and accepted colleges. While summer counseling has been studied as an intervention to address summer melt, little research exists on programs using "near-peer" counselors, despite evidence from smaller-scale interventions suggesting their positive impact and cost-effectiveness. This study utilizes administrative data for 54,000 New York City high school seniors who graduated in June 2020 at the peak of the COVID-19 Pandemic. It aims to examine the impact of a remote near-peer college matriculation support program on students' enrollment in Fall 2020 using propensity score matching. The results indicate that the program increased matriculation by seven percentage points. Notably, it proved particularly effective for Black and Hispanic students, as well as students residing in low-income neighborhoods—groups that are typically underserved in higher education. These findings, drawn from the largest public school system in the nation, offer evidence supporting the efficacy of near-peer mentoring programs in promoting college matriculation.

Keywords Propensity score matching · Matriculation · Mentoring · Racial minority students · Low-income students

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Introduction

A college degree has increasingly replaced the high school diploma as the minimum requirement for entry-level jobs (Rampell, 2012). College-educated individuals reap life long benefits in terms of earnings and health, while also contributing positively to society by reducing dependence on welfare programs and alleviating the burden on the criminal justice system (e.g., Barrow & Rouse, 2005; Card, 1999; Gunderson & Oreopolous, 2020; Lochner & Moretti, 2004). Certain student populations, including those from low-income backgrounds, racial/ethnic minorities, first-generation college students, and immigrants, face challenges enrolling in college even after gaining acceptance to a college (Castleman & Page, 2014; Rall, 2016). This phenomenon, known as summer melt, affects up to 40% of college-intending seniors every year (Castleman & Page, 2014). Youth from the lowest socioeconomic status (SES) quartile are 20% more likely to experience summer melt than their peers (Castleman & Page, 2014), further exacerbating existing inequalities that equitable access to higher education could minimize.

Recognizing this pressing need, various programs have emerged to support graduating seniors during the vulnerable summer period between high school graduation and the start of college, a time when school-based counseling services are typically unavailable. While there is widespread agreement among researchers, policymakers, and practitioners about the importance of mitigating summer melt to enhance access to higher education for low-income students, consensus on the most efficient and cost-effective intervention is lacking. In contrast to automated approaches like text bots, research suggests that individualized and personalized matriculation support has a more significant impact on enrollment, particularly among students with limited access to college information (Bettinger et al., 2012; Castleman et al., 2014). However, research on near-peer matriculation support remains limited in both volume and generalizability. More evidence is needed to understand how current college students can enhance high school students' enrollment outcomes through individualized matriculation support.

College matriculation support programs are especially vital in light of the decline in college enrollment nationwide during the COVID-19 pandemic. Community college enrollment was severely affected by a 9.5% decrease from Fall 2019 to Fall 2020 (Schanzenbach & Turner, 2022). This decline disproportionately affected low SES and racial/ethnic minority students—the very groups susceptible to summer melt (NSC, 2021). Research attributes this trend to a combination of high unemployment and escalating costs of college (Schanzenbach & Turner, 2022). Yet the decline was somewhat unexpected, given historical trends of increased college enrollment during economic downturns (Schanzenbach & Turner, 2022). Consequently, high school and college administrators across the nation are actively seeking evidence-based programs to promote college matriculation. This study explores the impact of a substantial near-peer college matriculation support program during the summer of 2020, amidst the height of the COVID-19 pandemic.

College and Career Bridge for All

College & Career Bridge for All (CCB4A) represents a significant partnership between the City University of New York (CUNY) and the New York City Public Schools (NYCPS). Running from June through September, it's the largest near-peer matriculation support program in the nation. CCB4A hires and trains current college students to support graduating seniors with a range of postsecondary planning and matriculation-related tasks. These tasks encompass applications, enrollment, financial aid processes, course registration, and providing essential socio-emotional guidance.

CCB4A leverages the close collaboration between NYCPS and CUNY in three primary ways: First, mentors receive training and supervision from professional counselors working in NYCPS high schools during the school year, using a "train the trainer" model to ensure mentors have access to institutional expertise throughout the summer. Second, approximately 80% of CCB4A mentors enroll in CUNY after graduating from an NYCPS high school. This shared background and small age gap enable CCB4A mentors to work with students from their alma mater, offering personalized support and insights based on their common and recent experiences, a vital aspect of providing graduates with near-peer mentorship. Finally, CCB4A facilitates near real-time data sharing from CUNY and NYCPS sources, allowing mentors to maintain timely and personalized outreach. This data includes updates on CUNY college applications and admissions status, as well as a student's progress in completing necessary matriculation steps, such as transcript and commitment deposit submission. Armed with this information, mentors can offer tailored support and timely reminders to students based on their individual matriculation journeys.

Launched in 2017, CCB4A initially served 6,300 graduates across 46 NYCPS high schools, with mentors stationed on school premises. Subsequent years of 2018 and 2019 saw rapid expansions, with services extending to 15,000 high school graduates. In response to the COVID-19 pandemic, additional emergency funding enabled citywide expansion in Spring 2020, ensuring that all members of the NYCPS graduating class of 2020 had access to fully remote matriculation support from a near-peer mentor. Consequently, CCB4A experienced remarkable growth, increasing by 350% from Summer 2019 to Summer 2020 to offering services to over 54,000 students across 400 NYCPS high schools.

Present Study

Using propensity score matching (PSM) methods, this study aims to address the following research questions:

(1) What are the characteristics of students most likely to connect with a peer mentor?
(2) What are the impacts of connecting with a CCB4A peer mentor on college application, admission, and matriculation rates of high school graduates?
(3) Do these rates differ by demographic characteristics including race/ethnicity and SES?

This study uniquely contributes to the body of evidence on matriculation support programs in two significant ways. First, it examines the effectiveness of training college students as near-peer mentors, a rarity compared to programs utilizing professional adults. This analysis offers valuable insights for practitioners and policymakers considering these approaches.

Second, although this research is centered in New York City, it holds broader implications. NYCPS is the largest urban public school system in the nation, renowned for its diversity. A significant proportion of its students come from low-income backgrounds, with a notable representation of Hispanic and Black communities. This demographic diversity provides us with a large sample and statistical power, enabling a focused examination of the impacts on historically underrepresented groups in higher education. The lessons drawn from this case study can serve as a valuable blueprint for other urban school districts and regions looking to break down the socioeconomic barriers perpetuating disparities in college access and academic achievement.

Behavioral Framework

Behavioral Framework to Explain Summer Melt

The commitment to postsecondary college enrollment can shift during students' senior year (Castleman & Page, 2015).[1] The concept of "time-inconsistent preference" is often associated with the limitations of self-control and the inclination to prioritize short-term benefits over long-term gains when evaluating college costs. As students approach college enrollment, their focus shifts towards immediate costs, overshadowing the greater long-term benefits of a college education (Castleman & Page, 2015). The summer after high school graduation is a particularly vulnerable period for students intending to matriculate. While the majority of students have completed the college application process, admitted students still need to undertake crucial enrollment steps—such as submitting financial aid applications and verification, making enrollment deposits, registering for classes, purchasing course materials, and/or enrolling in opportunity programs—to secure a place as a freshman in the fall. Students who did not apply or gain acceptance to a college during the academic year face additional stress due to late applications. Missing deadlines for any one of these activities can have significant academic and financial repercussions. For example, incomplete financial aid paperwork could prevent enrollment due to high out-of-pocket costs. Students often struggle to navigate these tasks without access to the high school or college counselors' expertise (Avery & Kane, 2004; Dynarski & Scott-Clayton, 2006) while juggling work and family responsibilities (Castleman & Page, 2014).

Moreover, some matriculation tasks are challenging for students to manage independently. For example, the financial aid application literature indicates that navigating the complexity of financial aid applications stop many from attending college or enrolling in an institution that aligns with their academic needs (Bettinger et al., 2012; Dynarski & Scott-Clayton, 2006; Hoxby & Turner, 2013). Additionally, research indicates that more affluent families increasingly invest substantial time in their children's college application process (Lareau, 2018; Ramey & Ramey, 2009), exacerbating SES disparities in college access and attainment. Particularly during the summer months, students must rely on support from their guardians to navigate these processes, disadvantaging first-generation and low SES students.

Behavioral Framework for CCB4A

The CCB4A intervention is designed to tackle challenges associated with time-inconsistent preferences, informational complexity, and disparities in college information accessibility. Drawing insights from behavioral economics and the summer melt literature, it aligns with programs that successfully simplify and assist students in these processes, boosting college enrollment and receipt of financial aid (Bettinger et al., 2012; Castleman & Page, 2014; Hoxby & Turner, 2013).

[1] For more discussion on this framework, please see Castleman and Page (2015).

Compared to other matriculation programs reviewed in the literature, CCB4A proves moderately intense by combining the use of automated nudges with personalized one-on-one interactions. Consistent electronic communication via email, texts, and social media delivers manageable "bursts" of information to students. Research has shown that such messages effectively encourage students to act on enrollment tasks, thereby reducing summer melt (Castleman & Page, 2015). For example, students who have not completed their financial aid applications may be uncertain about the necessary steps or who to contact for assistance. However, a simple text may guide on late financial aid application options, inviting them to schedule an online mentor discussion via a link, significantly reducing the time and cognitive costs associated with late applications. Consequently, these nudges serve as helpful engagement strategy for mentors to initiate contact with their mentees.

Additionally, CCB4A enhances the effect of regular digital nudges by integrating them with peer mentorship. This personalized one-on-one assistance not only nudges students on their enrollment steps but also reshapes students' norms by showcasing how a similar individual surmounted obstacles (Castleman & Page, 2015). Mentors offer a tangible psychosocial support, and exemplify postsecondary success, enabling active envisioning and realization of students' personal paths forward (Castleman & Page, 2015).

The innovative CCB4A near-peer mentor model is comprised of college students sharing certain common characteristics or experiences with mentees, which may include living in the same geographical area, speaking the same language, or having attended the same high school. The fundamental principle behind this approach is to establish a strong rapport, trust, and mutual understanding between mentors and mentees. This, in turn, fosters a sense of belonging and identity among program participant, providing valuable guidance and feedback based on relatable experiences (Redding, 2019; Stephens et al., 2014; Walton & Cohen, 2011).

This absence of this innovative approach in automated models or matriculation programs highlights the unique value of near-peer mentors. Automated models often lack the personal touch, cultural relevance, and shared experience that near-peer mentors bring, making the CCB4A model distinct in its ability to provide tailored, context-specific support to students, thus enhancing its effectiveness. Extensive research underscores the substantial positive impact of near-peer mentorship on students' academic performance, motivation, and self-efficacy (Castleman & Page, 2015; Gurantz et al., 2019; Redding, 2019). These comprehensive findings collectively suggest that near-peer mentors play pivotal roles as role models, sources of essential social support, and facilitators of the learning process for their mentees.

The strategic combination of electronic communication and peer mentorship is expected to alleviate near-term cognitive and psychosocial costs of college-going, yielding positive impacts on students' academic outcomes, particularly immediate college matriculation. Such support is vital for historically underserved student groups in higher education, implying that CCB4A's impact may be most significant largest among these student groups.

Related Literature

Existing research on near-peer mentorship programs for college enrollment is limited. Therefore, we begin by examining the broader body of research on summer counseling programs. Next, our focus shifts to large-scale programs with moderate intensity, akin to the CCB4A program. We then delve into interventions that also utilize peer mentors. Finally, we present evidence from the impact evaluation of the pilot year of the CCB4A program.

Summer counseling interventions provide vital resources when traditional school guidance counselors are unavailable. Castleman and colleagues tested the efficacy of several summer counseling interventions for graduating seniors concerning college enrollment (Castleman & Page, 2015; Castleman et al., 2012, 2014, 2015a, 2015b). These interventions targeted underserved students in higher education, low-income groups, or were conducted in large urban school districts. Notably, they varied in contact methods, timing, intensity, and staffing. Nonetheless, summer counseling is recognized by the U.S. Department of Education's What Works Clearinghouse as effective, particularly for college persistence over matriculation.

When examining interventions promoting college enrollment, we consider their intervention scope and advising intensity (Avery et al., 2021). Research on low intensity interventions, such as automated communications via email or text messages, often referred to as "behavioral nudges" is extensive but has demonstrated limited positive impacts on enrollment or financial aid receipt for students in higher education (Bird et al., 2021; Castleman & Page, 2014; Gurantz et al., 2019; Hyman, 2019; Nurshatayeva et al., 2020; Oreopoulos, 2020).

In contrast, evidence suggests that more intensive, in-person programs tend to have larger enrollment effects, although they often operate on a smaller scale due to higher costs (Carrell & Sacerdote, 2017). Limited studies have explored large state or national-scale programs with varying levels of virtual/multi-modal or moderate in-person intensity. Limited to high-achieving low-income students, Guarantz et al. (2019) and Sullivan et al. (2021) examined two large-scale multi-modal interventions, which utilized a combination of text-messaging, mail, e-mail, and low-intensity remote advising. They both found small increases in college selectivity, but no effect on enrollment. Another randomized control study (Bettinger et al., 2012) evaluated a large-scale intervention, helping more than 10,000 participants complete the Free Application for Federal Student Aid at 156 tax preparation sites across two states. This study found that informational outreach coupled with one-on-one counseling resulted in an eight-percentage point increase in the likelihood of college enrollment compared to a control group, with no effects for the group receiving information only.

The study of near-peer mentoring's impact is even more limited. Berman et al. (2008) conducted a randomized control trial of the Student Outreach for College Enrollment program, utilizing University of California, Los Angeles and University of Southern California students as mentors for Los Angeles high school students. These services were remotely provided from May of the students' junior year through May of their senior year. To be eligible for the program, high school students needed a minimum GPA of 2.5, had to be on track for graduation, and had to meet California State University (CSU) standards. The study did not find an impact on college matriculation overall, but did indicate an increase in students opting for four-year universities over community colleges. In a follow-up study, students were randomly assigned to receive in-person mentoring, online mentoring with email and text messages, or no mentoring. While online mentoring increased application rates, it had no effect on enrollment. However, women who received in-person mentoring were 15 percentage points more likely to enroll in college than their male counterparts (Chin et al., 2015).

The most relevant peer-reviewed study on the impact of a large-scale near-peer mentoring program is Castleman et al. (2015a). The study randomized students at urban sites across Texas, Massachusetts, and Pennsylvania into peer mentorship, text message, or control groups. The 20 peer mentors worked with approximately 40 high school students each. The peer mentors were responsible for outreach, and referring students' requests for assistance with college-going tasks to trained counselors. Peer mentorship was associated with a 4.5 percentage point increase in the likelihood of a student attending a four-year college, while text message intervention had null effects, aligning with previous studies.

While some research suggests that higher-intensity summer counseling is a more promising intervention for matriculation support than automated support, and peer mentors can be a cost-effective programming model (Castleman & Page, 2015), further research is necessary to determine the effectiveness of a large scale near-peer program. CCB4A stands out from any previously studied intervention in several dimensions. It is nearly universal across NYCPS, making it the largest program in the nation. Each of the 195 mentors in Summer 2020 had an average caseload of 280, allowing them to offer services to a total of 54,517 students, representing approximately 85% of NYC public high school seniors.[2] Additionally, CCB4A mentors are matched with students based on borough of residence, high school, and language spoken. This personalized approach, grounded in shared high school experiences and geographic proximity, enhances program effectiveness. Moreover, various communication strategies are employed, extending beyond texting. Mentors also utilize social media to engage students and offer one-on-one assistance for specific tasks via virtual meetings, going beyond the information-centric approach of previous studies.

To date, only one quantitative impact assessment has been conducted on CCB4A, focusing on the 2017 pilot program. Using PSM methods, this evaluation revealed that the program increased college matriculation by 3 percentage points, with a more pronounced impact among Hispanic students, females, English-Language Learners, and those from impoverished households (Polon et al., 2019). Since this pilot evaluation, CCB4A has expanded ten-fold, integrating real-time admissions and enrollment data along with data on mentor-student connections. This study aims to build upon existing literature and advance our knowledge of the impact of a moderate-intensity, large-scale near-peer mentoring matriculation programs, specifically CCB4A, particularly in the context of the pandemic.

Data and Sample

The NYCPS stands as the largest public school system in the United States, serving over a million students and graduating more than 60,000 annually from over 400 high schools across the city's five boroughs. Among those matriculating to college in the Fall following their graduation, 60% enroll at the City University of New York system (Domanico, 2021; NYCPS & CUNY, 2014). Hence, NYCPS graduates comprise 73% and 59% of first-time freshmen in baccalaureate and associate degree programs at CUNY, respectively (Domanico, 2021).

Our data are compiled from five sources tracking the transition of NYCPS students from the 2020 graduating cohort. First, NYCPS administrative data provides student demographic characteristics, high school transcript records, and attendance information. Second, CUNY's administrative data contains details on students' college application, admission, and enrollment at the university. Third, National Student Clearinghouse (NSC) provides record of college enrollment at non-CUNY institutions, encompassing private higher education institutions as well as the State University of New York (SUNY) and out-of-state

[2] The other 15% of the high school seniors are being served by other affiliated matriculation programs in the city.

public colleges.[3] The fourth source, Grouptrail's Enroll NYC program database, catalogs all connections made between peer mentors and students within CCB4A. Using Grouptrail's platform, mentors record each connection with a student, providing insight into the frequency and timing of these communications.

Finally, aligning with the equity focus of our study, we merge census tract level socioeconomic status data from the American Community Survey (ACS) (2019 5-year estimates). We geocode students' residential addresses (including building number, street name, and zip code) to the census tract level and subsequently merge this information with the ACS data. These data serve as both matching variables and covariates in our analysis, encompassing average household income, average food stamp (SNAP) benefits, average unemployment rate, percentage of households with health insurance, and percentage of households below the federal poverty line.

Together, this unique dataset offers a comprehensive link between students' high school information, dating back to 9th grade, and their college matriculation post-graduation. One notable limitation of the data is its exclusion of college application and admission information for non-CUNY institutions. Therefore, students exclusively applying to non-CUNY institutions (such as in-state and out-of-state public or private colleges) have missing application records in our dataset, and are categorized as not having applied to college. Nonetheless, it is important to note that students generally apply to multiple colleges, encompassing both two-year and four-year institutions. Therefore, the college choices made within the CUNY system can provide insights into their broader college application portfolio. According to NYCPS and CUNY administrative data, 85% of NYCPS students who eventually enroll at four-year colleges also apply to at least one of CUNY's four-year colleges. Existing research on students' college application decisions indicates that those applying to private or out-of-state colleges often include in-state public colleges of similar selectivity in their overall choices (Fu, 2014). Furthermore, as our primary focus lies in evaluating the impact of the program conducted during the summer, our analysis primarily considers application rates after May. Most students enrolling in non-CUNY colleges typically apply before May, mitigating this concern for our analysis. Additional detail on application patterns and timing can be found in Appendix Table 6.

Our analytical sample contains 47,290 12th grade students who graduated from one of the 400 high schools participating in the CCB4A program during Summer 2020.[4] Close to a third of the students (28%) made at least one connection with a CCB4A mentor via any communication method; hereafter, these students are referred to as "active participants".[5] Table 1 presents a descriptive summary of the entire sample (Column 1) and a breakdown

[3] The NSC contains records of 98% of college-going individuals (Dynarski et al. 2015).

[4] These are all NYC publics schools, excluding charter schools and schools exclusively serving students with disabilities. With multiple sources of administrative data, the degree of missing data is minimal. Among key matching and control variables, only 0.5% of our sample lack gender information, three percent lacks regent test scores, and two% misses any data on high school GPA and credit info. Less than five percent of our sample is missing data on the day of absence. Given the low percentage of missing, our imputation strategy assigns missing values the average value at the high school level.

[5] Among students initially contacted by mentors through various means such as email, phone, text, or social media, approximately 28% of them responded (as shown in Appendix Fig. 2A). Roughly half of the connected students engaged with the mentors for one week, while a quarter engaged for two weeks. They can interact multiple times within a given week. Appendix Fig. 2B displays the overall engagement levels by week, highlighting the peak engagement during the second half of July and the first half of August, just before the school year commences. Even when students do not respond, mentors consistently send weekly reminders with relevant deadlines for the students. Appendix Figs. 2C, D respectively depict the level of outreach sent by mentors and the responses from students, revealing a consistent pattern.

by whether a student had ever connected with a mentor or never connected[6] (Columns 2 and 3, respectively). Those students who fall into the categories of female, Hispanic, English Language Learners, impoverished, attending a high school in Queens, or residing within a census tract with a low average household income have a higher probability of making at least one connection compared to those who did not connect with a coach. Finally, students with at least one connection are more likely to identify college as their postsecondary plan (81% versus 73%).

Measures

The study investigates three primary student-level academic outcomes: application to, admission to, and enrollment at an institution of higher education. For application outcomes, we consider three binary indicators: whether a student applied to any CUNY college, to a two-year CUNY college, or to a four-year CUNY college during the CCB4A program (between May 2020 and September 2020). Similarly, for admission outcomes, we examine if a student received admission for Fall 2020 enrollment at any CUNY college, specifically at a two-year CUNY college, or at a four-year CUNY college within the same time frame (between May 2020 and September 2020). While the application and admissions data are confined to the CUNY system, enrollment outcomes are assessed universally through NSC postsecondary enrollment records for Fall 2020, the term immediately following students' graduation.

Table 1 offers a brief overview of these outcomes. Overall, 79% of all students in our sample applied to a CUNY college, with 75% and 51% applying to four-year and two-year colleges respectively. Over 90% of the students who applied to CUNY did so before May 2020, when CCB4A mentors began their work with students. Consequently, our estimation centers on outcomes occurring from May onward. Regarding admission, 57% gained admission to a four-year college, and 45% to a two-year college. Consistent with application trends, most students received their admissions' decisions before May 2020, coinciding with the commencement of CCB4A mentoring. It is noteworthy that students were more likely to connect with a mentor if they had applied to and been admitted to CUNY. This suggests that CCB4A primarily functions as a support program for college matriculation, rather than for college application.

Concerning college enrollment, 71% of the sample enrolled in college in Fall 2020, immediately following their high school graduation. Notably, the matriculation rate is 8 percentage points higher for those who connected with a CCB4A mentor (77%) than for those who did not (69%). Furthermore, participants were more inclined to attend a two-year college, a public institution, and/or a CUNY college compared to their peers without a CCB4A connection.

Analytic Strategy

Connecting with a CCB4A mentor involves a decision influenced by a mix of internal factors—such as students' preferences, postsecondary aspirations, and academic drive—and external influences like guidance from high school counselors, educators, and peers. To

[6] Students who did not connect with a mentor did receive electronic communications (or nudges) with information from CCB4A mentors but did not connect with the mentor one-on-one.

address the inherent selection bias in program participation, we utilize a radius propensity score matching method with replacement to assess students' college choices and enrollment outcomes.[7] Our two-stage PSM then compares results among individuals matched based on their propensity to engage with a mentor.

In the first stage, we compute the propensity of a student to connect with a mentor. This likelihood is determined by various observable pre-treatment characteristics, including demographic and socioeconomic data, academic achievement, proxies of academic motivation, and post-high school plans. These factors are assessed before the program's commencement, guided by insights from existing literature on participation in college matriculation programs like CCB4A. Additionally, CCB4A operates on an "opt-out" model, requiring students who no longer wish to receive the service to actively opt out of the program. Anecdotal evidence suggests that academically motivated students or those already committed to their college enrollment plans (particularly in four-year or non-CUNY colleges) are more inclined to opt out of the program.[8] Hence, it is crucial to consider pre-treatment application status and post-high school plan as significant determinants that need to be controlled for. The first stage is as follow:

$$\mathrm{logit}\left(\mathrm{Connect_i}\right) = \beta_0 + \beta_1 \mathrm{X_i} + \beta_2 \mathrm{S_i} + \beta_3 \mathrm{SES_c} \tag{1}$$

where $\mathrm{Connect_i}$ equals one if a student has previously established a connection with a mentor; $\mathrm{X_i}$ represents a vector of student-level demographics and SES variables measured prior to May 2020 (such as gender, race/ethnicity, ELL status, poverty status, borough of the high school), indicators of academic preparedness (highest mathematics and English Language Arts [ELA] Regents scores prior to 12th grade, total credits attempted in 11th grade, mathematics grade point average [GPA] in 11th grade), a proxy for academic motivation (total number of days absent in 11th grade), and post-college plans (survey results regarding post-high school plan, application status to any colleges and two-year colleges before May). Census-tract-level SES characteristics of student's residing neighborhoods is represented by $\mathrm{SES_c}$ and include average household income, average Food Stamp benefits, average unemployment rate, percentage of household with health insurance, and percentage of the household below poverty level. Finally, $\mathrm{S_i}$ represents the school fixed effect[9] as research

[7] The radius method is similar to caliper matching. But instead of matching a treated unit with its closest control within a caliper, all the units that fall within the caliper or radius are selected. Our PSM approach also allows for replacement so that a control observation can be paired with more than one treated observation.

We use a caliper width of 0.1 standard deviations in the propensity score. Austin (2011) showed that a caliper of 0.2 standard deviations eliminates at least 98% of the bias, using a tighter caliper in our study allows us to find a closer match when there is sufficient overlap between the treated and control groups. In the next section, we will examine the quality of our PSM techniques by assessing post-match balance and overlap across the treatment and control groups.

[8] It is beyond the scope of the paper to delve into the behavior of students who choose to opt out or connect, even if they appear to be typical candidates who would benefit from mentorship. However, insights from the end-of-program focus group with mentors reveal that some students were hesitant to engage with the program when they perceived the messages as generated by bots. When the mentors were able to demonstrate that they were real people, rather than automated systems, many students start to show a genuine interest in the program.

[9] Analyses did not control for mentor, as it is highly collinear with school.

shows that this is the best way to reduce school-level omitted variable bias (Arpino & Mealli, 2011; Li et al., 2013).[10]

In the second stage of the analysis, we compare the outcomes of the two groups within matched pairs using ordinary least squares regression as follows:

$$Y_i = \alpha_0 + \alpha_1 Connect_i + \alpha_2 X_i + \alpha_3 S_i + \alpha_4 SES_c + \varnothing_i \quad (2)$$

where Y_i represents the probability of application, admission, and enrollment outcomes listed in the outcome measure section, $Connect_i$ indicates if a student has ever connected with a CCB4A mentor, X_i, SES_c and S_i are the vector of student characteristics, census-tract-level SES characteristics, and school fixed effect as Eq. (1). The coefficient of interest is α_1, which estimates the average effect of the treatment on the treated (ATT). In comparison to average treatment effect, ATT is the ideal estimand to answer the policy questions that motivate this study, such as: should other states and education systems implement programs similar to CCB4A to improve enrollment of those who most needed it? As such, it is important to estimate the impact of CCB4A on students, who are likely to take advantage of the program, based on their individual, school, and community- level characteristics.

Given that students groups with certain characteristics, such as low-income status, and being Black or Hispanic, are underrepresented in higher education, we will perform subgroup analyses to better understand the impact on different populations. These analyses aim to provide deeper insights into the varied impacts across different populations.

Model Assumptions

For PSM to estimate a causal impact, three key assumptions must be satisfied. First, the Conditional Independence Assumption (CIA) dictates that the selection process relies solely on observable characteristics and that all variables that can affect the treatment assignment and potential outcomes simultaneously are observed by researchers (Caliendo & Kopeinig, 2008). The literature review and summary of student characteristics stratified by connection reveal numerous deterministic factors influencing students' connection with a mentor, as well as their application and enrollment decisions. These include students' demographic characteristics and socioeconomic background, high school performance, academic motivation, postsecondary plans, school environment, and neighborhood characteristics. Our model attempts to control for these factors directly and with proxies, as detailed in the preceding section.

While direct testing of CIA is technically infeasible, the Oster test (Oster, 2019) is widely employed to assess the likelihood of its violation. Findings in Appendix Table 7 indicate a low probability of our model violating this assumption. This underscores the model's effectiveness in managing the selection process mentor connection.

The second key assumption for PSM is common support, requiring adequate overlap across treatment and comparison groups for a representative range of propensity scores. Figure 1A displays the sample distribution of estimated propensities for our treated and control groups before and after PSM. Post-matching, both groups share a large region of common support on covariates, indicating that we successfully find

[10] Following Stuart's (2010) liberal inclusion approach, we take advantage of the low cost of including non-relevant predictors to overcome the high penalty of excluding important predictors by introducing about 31 pre-treatment variables capturing a wide range of characteristics, including demographic characteristics and academic performance in high school.

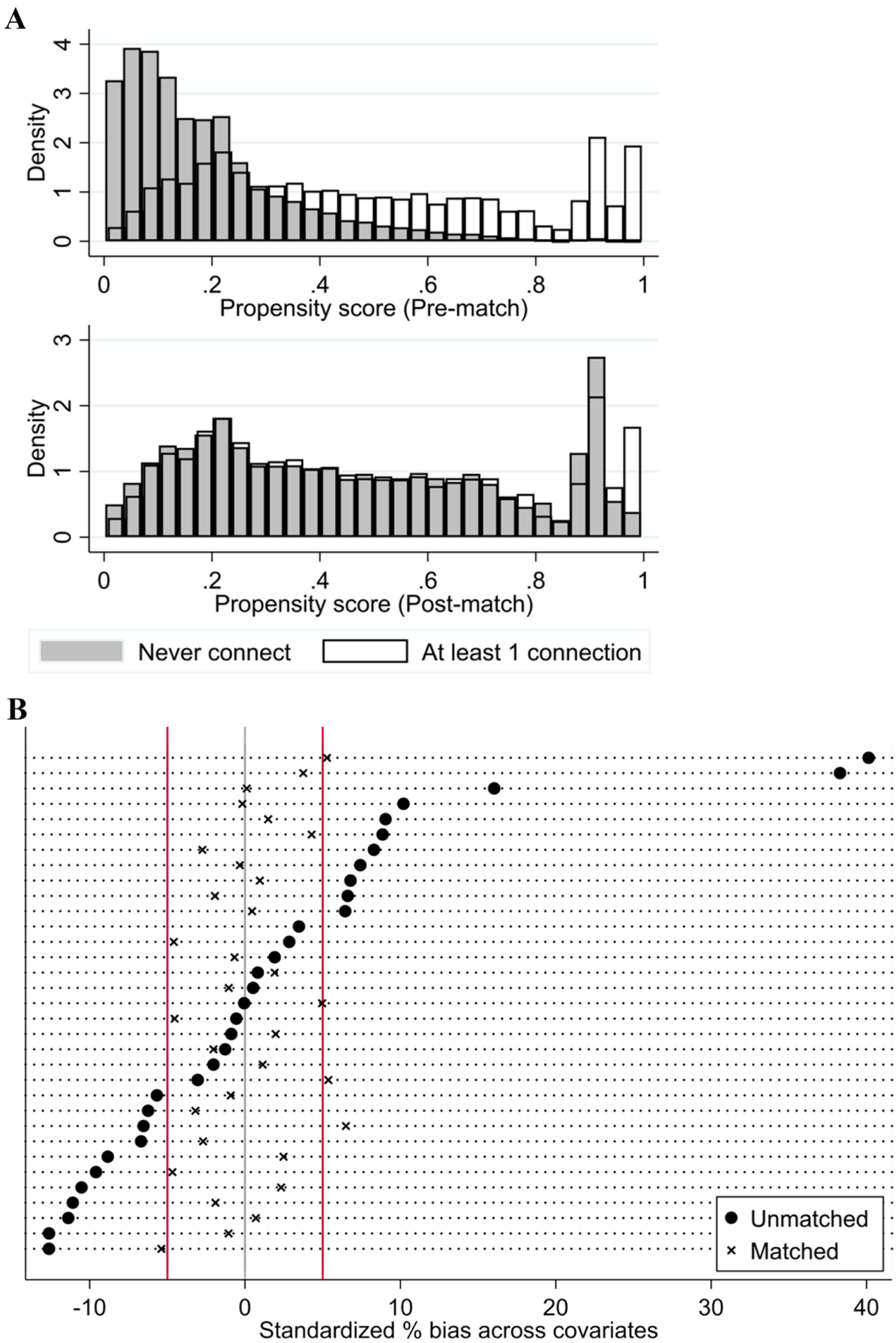

Fig. 1 (**A**) Distribution of propensity score pre- and post-match. **B** Balance check of covariates pre- and post-match

Table 1 Summary statistics

	(1) All students	(2) Never connect	(3) > = 1 connection
Demographic characteristics			
Female	51%	50%	55%
White	17%	19%	14%
Black	23%	23%	23%
Hispanic	35%	34%	38%
Asian	22%	22%	21%
Other races	3%	3%	3%
English language learner	15%	14%	18%
Student with disability	14%	14%	14%
In poverty	83%	82%	88%
Brooklyn	29%	30%	29%
Bronx	14%	13%	16%
Manhattan	18%	20%	15%
Queens	31%	29%	37%
State Island	7%	8%	2%
High school performance			
Total days absent	10	11	10
Total days present	97	96	98
Total HS credits attempted	13	13	13
Total HS credits earned	12	12	12
Average HS GPA	82	82	82
Average HS English GPA	83	83	83
Average HS Math GPA	79	79	79
Math regents score	77	77	76
ELA regents score	81	82	81
Missing math scores	3%	2%	4%
Missing ELA scores	1%	1%	1%
Post-HS plan			
College	75%	73%	81%
Training	2%	3%	2%
Employment or military	5%	5%	4%
Unknown	18%	20%	13%
School characteristics			
Total high school enrollment	1900	1998	1651
Graduating cohort size	464	487	404
% graduating among on-time grade cohort	86%	86%	84%
Student attendance rate	90%	90%	89%
% students chronically absent[a]	29%	28%	31%
Average ELA regents scores	78	78	76
Average Algebra Scores	70	70	69
Census-tract-level characteristics			
Unemployment rate	6%	6%	7%
Total household income & benefits (2019$)	61,589	62,621	58,999

Table 1 (continued)

	(1) All students	(2) Never connect	(3) > = 1 connection
Total Food Stamp/SNAP benefits in the past 12 months (2019$)	547	538	571
%with health insurance	92%	92%	92%
Application and Admission outcomes			
Ever applied to a college	79%	74%	90%
Applied to a four-year college	75%	70%	85%
Applied to a four-year college after/in May 2020	2%	2%	2%
Applied to a two-year college	51%	46%	65%
Applied to a two-year college after/in May 2020	2%	2%	2%
Admitted to a four-year college after/in May 2020	1%	1%	1%
Admitted to a two-year college after/in May 2020	2%	1%	2%
College enrollment outcomes			
Any college enrollment	71%	69%	77%
Four-year college	53%	54%	52%
Two-year college	18%	15%	25%
Public college	56%	52%	67%
Private college	15%	16%	11%
CUNY college	43%	37%	57%
SUNY college	10%	11%	8%
Out-of-state college	8%	9%	4%
Private in-state college	10%	11%	8%
Observations	47,290	33,816	13,474

The sample includes all 12th graders in NYCPS, who are in schools that participate in CCB4A in 2020

[a]The definition for chronically absent is when attendance rates drop below 90%

both students who have connected and those who have not within each propensity score stratum.

The final PSM assumption requires similarity in observable characteristics across the treated and control groups post-matching to ensure high match quality. Figure 1B visually assesses match quality using black dots and cross markers, representing the standardized measure of bias on main variables across treatment and comparison groups before and after matching respectively. Each row represents one variable we match on. Post matching, most variables fall within the 5 standardized percentage bias range, indicating a high-quality (balanced) match, as outlined in the PSM literature (Caliendo & Kopeinig, 2008). A more detailed balance check of average values and percentage bias for each variable is presented in Appendix Table 8.

Table 2 Individual predictors of connecting with a coach, logistic regression

Variables	Ever connected with a mentor	
	B	[S.E.]
Female	0.155***	[0.038]
White	– 0.208	[0.151]
Black	– 0.140	[0.121]
Hispanic	– 0.115	[0.111]
Asian	– 0.114	[0.184]
Student with Disability	– 0.021	[0.058]
In Poverty	0.177***	[0.062]
Log Math Regent test scores	1.877	[2.503]
Log ELA Regent test scores	0.266	[0.266]
ELA test scores quantile		
25th	0.002	[0.099]
50th	0.084	[0.080]
75th	0.110*	[0.066]
Post-secondary plan: training	– 0.209	[0.179]
Post-secondary plan: employment or military	– 0.133	[0.089]
Total high school credits attempted	– 0.001	[0.021]
Average high school Math GPA	0.005	[0.005]
Total days absent	– 0.003*	[0.002]
Applied to a two-year college by May	0.308***	[0.077]
Applied to any colleges by May	0.705***	[0.083]
High school Borough: Brooklyn	– 0.139	[0.279]
High school Borough: Bronx	0.020	[0.265]
High school Borough: Manhattan	– 0.311	[0.283]
Unemployment Rate	1.365*	[0.815]
Total median household income (2019$)	– 0.000	[0.000]
Total Food Stamp/SNAP benefits in the past 12 months (2019$)	0.000**	[0.000]
% with health insurance	– 1.564	[0.000]
% of families below poverty level past 12 months	– 0.553	[1.069]
Observations	47,290	

This regression also controls for high school fixed effect, highest Math and ELA Regents test score and missing either test scores. Robust standard errors in brackets

***$p<0.01$, **$p<0.05$, *$p<0.1$

Results

Characteristics of Connected Students

Our first research question delves into the characteristics of students likely to connect with a peer mentor. Table 2 displays the first-stage results. Column (1) indicates that females, students in poverty, those with the highest quartile of ELA regents test scores, and students with fewer absences exhibit a higher likelihood of connecting with a mentor, suggesting that students with greater financial needs and stronger academic motivation are more responsive to mentorship.

Consistent with the descriptive indicators in Table 1, students who have applied to any CUNY college or more specifically to CUNY two-year colleges are more likely to connect with a mentor. Additionally, students residing in census tracts with higher unemployment rates also demonstrate a higher likelihood of mentor connection, consistent with the trend of students with greater financial need being more responsive to mentorship.

Main Results

To examine the impact of connecting with a CCB4A mentor, Table 3 presents the PSM estimates on application, admission, and enrollment outcomes for those who connect with a mentor. Although CCB4A primarily focuses on assisting students with matriculation tasks, Columns 1 through 3 of the top panel demonstrate unintended yet positive impacts on students' application and admission to CUNY schools. Active participants are 1.7 percentage points (pp) more likely to apply to any public colleges in the city (CUNY) post-May compared to those who did not connect with a mentor. This effect is more pronounced for two-year (1.6 pp) than four-year college applications (1.2 pp), consistent with the broader summer application trends. The higher application rate translates to increased acceptance rates at any CUNY college (1.7 pp), two-year colleges (1.4 pp), and four-year colleges (0.6 pp) for active participants. Given CUNY's "open access" mission, ensuring a seat at a CUNY college for all New York City applicants, these gains suggest that CCB4A offers students who might have missed the initial application window a second chance.

Nonetheless, the most significant impact of the program lies in matriculation outcomes. Active participants exhibit a 6.7 percentage points increase in college enrollment by fall 2020. This increase is more pronounced for two-year colleges (4.9 pp) compared to four-year colleges (1.9 pp).

Next, we examine the types of higher education institutions students attend, in terms of both location and sector. In addition to the two-year versus four-year college breakdown, we categorize colleges as public versus private (in and out-of-state) and by location (in-state options such as CUNY, SUNY, and private in-state) versus out-of-state private and public colleges. We found that active participants show a 9.5 pp increase in enrollment in public compared to private colleges. Given their preference for two-year colleges, this aligns with the prevalence of the public sector among such institutions. Active program participants are also most likely to matriculate to CUNY colleges (12.6 pp) compared to other college types. The notable higher net gains in CUNY enrollment, twice the sum of reductions in SUNY, private in-state and out-of-state enrollment, suggest that the CUNY application information leveraged by mentors to personalize outreach is a major driver of program participation. The program does not have access to comparable administrative data for colleges outside of the CUNY system.

Heterogeneous Impact of Connecting with a Mentor

Thus far, our results indicate that participating in the CCB4A program (defined as connecting with a mentor) has an overall positive impact on students' application, admission, and matriculation outcomes. Addressing the historically lower college access and enrollment rates among racial minorities and low-income students has been a persistent concern for policymakers and scholars due to their underrepresentation in higher education. As such,

Table 3 Effect of connecting with a mentor on application, admission, and enrollment outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Application Outcomes			Admission Outcomes			Enrollment Outcomes		
	Any colleges	Two-year	Four-year	Any colleges	Two-year	Four-year	Any colleges	Two-year	Four-year
Ever connected with a mentor	0.017***	0.016***	0.012***	0.017***	0.014***	0.006***	0.067***	0.049**	0.019***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.001]	[0.006]	[0.008]	[0.008]
Observations	43,227	43,227	43,227	43,227	43,227	43,227	43,227	43,227	43,227
R-squared	0.167	0.155	0.122	0.167	0.130	0.057	0.316	0.427	0.193
	Enrollment by college type								
	Public colleges	Private colleges	CUNY colleges	SUNY colleges	Private in-state	Out-of-state			
Ever connected with a mentor	0.095***	− 0.028***	0.126***	− 0.018*	− 0.018**	− 0.021***			
	[0.010]	[0.009]	[0.019]	[0.011]	[0.008]	[0.003]			
Observations	43,227	43,227	43,227	43,227	43,227	43,227			
R-squared	0.197	0.135	0.194	0.071	0.076	0.106			

All regressions contain HS fixed effect, control for students' gender, race/ethnicity, ELL status, SWD, poverty status, ELA and Math test scores, their postsecondary plan, total HS credits attempted in 11th grade, average 11th grade HS GPA, total day absent, whether completed an application to any college before May, and whether applied to a community college before May

Robust standard errors are clustered at the high school level and are in brackets

***$p<0.01$, **$p<0.05$, *$p<0.1$

our analysis also looks at the impact of connecting with a mentor by racial subgroups and residential census-tract household incomes. We examine the overall impact on application, admission, and enrollment, rather than the impact on specific types of colleges.

We conducted the PSM analysis separately for students within each racial subgroup, presenting the results in Table 4. Despite the overall positive impact and similar pattern found in Table 3 on most outcomes, there is a notable discrepancy in the effects of connecting with a mentor among racial groups. Specifically, Black and Hispanic students experience a significantly larger impact compared to white students for application and admission outcomes. For example, the increase in applying to any colleges after May is nearly double for Black (2.0 pp) and Hispanic students (2.1 pp) compared to that for white students (1.1 pp), with both difference being statistically significant at the 90% and 95% confidence intervals, respectively.

The enrollment gains by racial subgroup exhibit a similar pattern, though it is less pronounced. The effect sizes for enrolling in any college are 8.2 pp for Black students, 9.1 pp for Hispanic students, and 6.3 percentage points for white students. The Hispanic over White gain is statistically significant at the 90% confidence interval. Moreover, the relative gains between minority and white students are notably larger, positive, and statistically significant for outcomes related to two-year colleges compared to for four-year colleges.

Our final analysis examines the impact of connecting with a mentor by whether a student resides in a census-tract with average household incomes above or below the sample median, shown in Table 5.[11] Panels A and B display the PSM results for students living in census tracts with the lowest and highest 50 percentile household incomes, respectively. While the effects are largely positive and consistent with those in Table 3, connecting with a mentor appears to have a slightly greater impact on application and admission outcomes for students in less affluent neighborhoods. For instance, having at least one connection with a mentor increases the likelihood of applying to both two-year and four-year colleges by 1.8 pp and 1.4 pp respectively for those living in less affluent neighborhoods. The corresponding figures for those in the top 50 percentile household income tracts are 1.4 pp and 1.1 pp respectively.

Regarding enrollment outcomes, the impacts on any colleges and two-year colleges are generally more favorable for students in less affluent neighborhoods. However, connecting with a mentor seems to have a positive impact specifically on matriculating to a four-year college for students residing in more affluent neighborhoods. This result underscores the need for additional matriculation resources and support for students from less affluent backgrounds.[12]

Robustness checks

To assess robustness, we conducted analyses utilizing inverse probability weighting (Appendix Table 10) and alternative matching methods such as near-neighbor matching, matching without replacement, using probit instead of logit in the first stage, and employing the Abadie and Imbens (2011) standard errors which consider the separate step in the estimation of propensity scores. The results remained consistent across these approaches.

[11] We have also examined the impact of connecting with a mentor by the economic need of the high school. The results are consistent with the estimation by census-tract household income here.

[12] As suggested by the reviewers, we have also looked the heterogeneous effect across students with varying academic performances in Appendix Table 9. The results indicate that students with GPAs below 2.5 who connected with a mentor exhibited a higher likelihood of enrolling in community colleges. On the other hand, connecting with a mentor was associated with a higher overall college enrollment rate, particularly in four-year institutions, for students with GPAs above 2.5.

Table 4 Heterogeneous effect of connecting with a mentor on application, admission, and enrollment outcomes by racial subgroup

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Applied in/after May			Admission outcomes			Enrollment Outcomes		
	Any colleges	Two-year	Four-year	Any colleges	Two-year	Four-year	Any colleges	Two-year	Four-year
Panel A. White students only									
Ever connected with a coach	0.011***	0.011***	0.011***	0.011***	0.009***	0.005**	0.063***	0.011	0.051***
	[0.004]	[0.003]	[0.003]	[0.004]	[0.003]	[0.002]	[0.011]	[0.012]	[0.014]
Observations	7,486	7,486	7,486	7,486	7,486	7,486	7,486	7,486	7,486
R-squared	0.150	0.145	0.119	0.150	0.136	0.048	0.305	0.279	0.39
Panel B. Black students only									
Ever connected with a coach	0.020***	0.020***	0.014***	0.020***	0.019***	0.007***	0.082***	0.058***	0.025*
	[0.005]	[0.005]	[0.004]	[0.005]	[0.004]	[0.002]	[0.013]	[0.012]	[0.014]
Observations	9399	9399	9399	9399	9399	9399	9399	9399	9399
R-squared	0.203	0.193	0.160	0.203	0.167	0.090	0.321	0.158	0.352
Panel C. Hispanic students only									
Ever connected with a coach	0.021***	0.019***	0.014***	0.021***	0.018***	0.007***	0.091***	0.091***	0.002
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.002]	[0.014]	[0.011]	[0.014]
Observations	14,533	14,533	14,533	14,533	14,533	14,533	14,533	14,533	14,533
R-squared	0.209	0.192	0.148	0.209	0.173	0.077	0.327	0.182	0.411

Regressions are estimated separately for each outcome (column) and panel (row). Each panel presents the regression adjusted treatment effects of students matched within the specific racial subgroup only. All regressions contain HS fixed effect, control for students' gender, ELL status, SWD, poverty status, ELA and Math test scores, their postsecondary plan, total HS credits attempted in 11th grade, average 11th grade HS GPA, total day absent, whether completed an application to any college before May, and whether applied to a community college before May

Robust standard errors are clustered at the high school level and are in brackets

***p < 0.01, **p < 0.05, *p < 0.1

Table 5 Heterogeneous effect of connecting with a mentor on application, admission, and enrollment outcomes by census-tract household income

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Applied in/after May			Admission outcomes			Enrollment Outcomes		
	Any colleges	Two-year	Four-year	Any colleges	Two-year	Four-year	Any colleges	Two-year	Four-year
Panel A. Students reside in census-tract with below median household income									
Ever connected with a coach	0.019***	0.018***	0.014***	0.019***	0.015***	0.006***	0.071***	0.060***	0.011
	[0.003]	[0.002]	[0.002]	[0.003]	[0.002]	[0.001]	[0.009]	[0.012]	[0.010]
Observations	20,471	20,471	20,471	20,471	20,471	20,471	20,471	20,471	20,471
R-squared	0.196	0.184	0.149	0.196	0.157	0.068	0.324	0.176	0.419
Panel B. Students reside in census-tract with above or at median household income									
Ever connected with a coach	0.015***	0.014***	0.011***	0.015***	0.012***	0.006***	0.062***	0.039***	0.025***
	[0.003]	[0.003]	[0.002]	[0.003]	[0.002]	[0.002]	[0.007]	[0.008]	[0.008]
Observations	22,480	22,480	22,480	22,480	22,480	22,480	22,480	22,480	22,480
R-squared	0.162	0.149	0.122	0.162	0.124	0.066	0.314	0.230	0.436

Regressions are estimated separately for each outcome (column) and panel (row). Each panel presents the regression adjusted treatment effect of students matched within the specific subgroup only. All regressions contain HS fixed effect, control for students' gender, race/ethnicity, ELL status, SWD, poverty status, ELA and Math test scores, their postsecondary plan, total HS credits attempted in 11th grade, average 11th grade HS GPA, total day absent, whether completed an application to any college before May, and whether applied to a community college before May

Robust standard errors are clustered at the high school level and are in brackets

***$p<0.01$, **$p<0.05$, *$p<0.1$

We also explored an alternative specification by removing the school fixed effect and replacing it with school-level characteristics. This analysis further underscores the robustness of our findings (Appendix Table 11). Lastly, we addressed concerns about the CIA violation through the Oster test. The results indicate a very low likelihood of excluding variables that might impact both the treatment and outcomes.

Conclusion and Discussion

Identifying effective programs and policies to support college enrollment for low-income youth is critical, considering the financial benefits of a college degree for both individuals and society. However, summer remains a time filled with important matriculation tasks but with limited support.

Discussion of key findings: By matching students' high school academic records with college application, admission, and enrollment outcomes, our results indicate that connecting with a CCB4A peer mentor has a significant and positive impact on both late applications and college matriculation. These gains are higher for two-year colleges compared to four-year colleges. Stratified models show a larger impact on students who are Black, Hispanic, and/or reside in census tracts with average household incomes below the sample median. While the program aims to assist all students with matriculation needs, our analysis suggests that historically underserved student groups in higher education demonstrate the highest need for matriculation assistance and benefit the most from a near-peer mentor program like CCB4A.

Our findings are consistent with prior literature indicating the effectiveness of higher intensity (Bettinger et al., 2012) or peer-mentor enrollment support programs (Berman et al., 2008; Castleman et al., 2015a; Chin et al., 2015). Similar to Chin et al. (2015), we found heterogeneous effects largest amongst students historically underrepresented in higher education, who have less access to crucial information on college application, admissions, and enrollment.

Our research found significant effects for applications and admissions to two-year colleges but not four-year colleges, contrary to prior research suggesting that enrollment support programs positively impact the selectivity of college choice (Berman et al., 2008; Castleman & Page, 2015; Gurantz et al., 2019; Sullivan et al., 2021). This divergence could be the result of CCB4A's timing during the summer months; most prior research assesses programs implemented earlier in the academic year when applications for fall enrollment are still opened. Consequently, students in the summer CCB4A program have greater success applying and gaining admissions to two-year colleges.

Policy Implications: Our study highlights the importance of moderate-intensity matriculation support, especially for students traditionally underrepresented in higher education. Matriculation programs on the scale of CCB4A, reaching over 54,000 students to bridge the transition from public high schools to public colleges, are relatively uncommon. To the best of our knowledge, this study is the first evaluation of a large-scale, universal intervention using remote near-peer mentors, contributing to evidence that moderate-intensity and personalized support yield higher enrollment rates compared to nudge-based initiatives.

Given the significance of the "summer melt" phenomenon and the absence of matriculation support between high school graduation and college enrollment, it is imperative for policymakers to ensure the availability of matriculation support for all students, particularly those historically underrepresented in higher education.

Secondly, CCB4A provides an effective and cost-efficient model for large-scale matriculation support programs. While the program's scale is unique to New York City, the

CCB4A model can serve as a template for successful partnership programs in other urban school districts. Several elements make the program particularly effective. The CCB4A near-peer model places great emphasis on the matching of mentors and students, ensuring that mentors share similar characteristics with the high school students they support. This approach fosters strong connections between mentors and students. Additionally, these mentors are uniquely positioned to understand and address students' concerns, especially those related to attending college during a pandemic.

Doing so also maximizes the use of existing funding to employ current college students, instead of incurring additional expenses associated with hiring professional counselors.[13] This approach keeps costs low while offering employment opportunities and valuable learning experiences to college students. Finally, the program's opt-out feature guarantees universal support without costs to high school students, raising awareness of available assistance.

Limitations and future research: Despite the significance of our findings, this paper has several limitations that provide directions for future research. In terms of internal validity, the PSM approach only produces causal estimation if the matching process satisfies the CIA assumption, which we cannot prove empirically. However, our models include controls for over 30 variables that may affect the treatment status, including demographic characteristics, socioeconomic background, high school achievement, academic motivation, postsecondary plan, school environment, neighborhood characteristics, and high school fixed effects. The Oster test, along with alternative specification and methods in our robustness checks section, support the internal validity of the PSM analysis.

Regarding external validity, the unique context of New York City is different from the rest of the nation, but more importantly, the CUNY—NYCPS relationship is unique: close to 66% of all CUNY first-time college freshmen attend with all tuition and fees covered by financial aid, and the cost of living is higher. Nonetheless, this study is significant given that this is the only program to our knowledge that serves an entire city, that is also the largest school system in the nation, serving a high percentage of historically underrepresented students.

Finally, this study only examines application and admission data to CUNY schools and is unable to provide the impact of CCB4A on non-CUNY application and admissions behavior. This problem is attenuated by the existence of the NSC data that tracks all college enrollment, which is the key outcome and goal of the program. Furthermore, 80% of all high school seniors apply to CUNY, providing a high coverage of application data for all students.

Future research should examine the mechanism by which CCB4A works and identify effective program components. For example, does the near-peer model make high school students feel more connected to mentors who went to schools like theirs? Or does the nature of CCB4A as an opt-out program ensure all students are contacted and eliminate the barriers from the students' side to seek out resources or assistance, as they do not have to apply or opt-in to anything? Additionally, it would be important to do a follow-up analysis using longer-term college outcomes. While access to college is important, success in college cannot be overlooked. Furthermore, qualitative data would be helpful in identifying specific components of the matriculation process that might be particularly challenging (e.g. financial aid application, registration for class, emotional support), and the timing of assistance (e.g. when students seek help and for what purpose). Finally, it would be helpful

[13] In 2020, mentors received an hourly rate of $17, while professional counselors earned $53 per hour. The program employed a total of 14 professional counselors, each overseeing an average of 18 mentors. For the rough estimate of the total cost in 2020, the back-of-the-envelope calculation amounted to $1.9 million for reaching 51,000 students, resulting in an average cost of $37 per student served.

to conduct a cost–benefit analysis to see how cost-effective a program like this is and assess the scalability to other cities and states.

This study demonstrates the effectiveness of a large-scale peer-mentor matriculation program in boosting matriculation rates among high school students. Although this paper does not delve into an examination of the CCB4A program in 2021 and 2022, it's worth considering that the impact of CCB4A may change as we move further away from 2020. The estimates derived from this study may represent an upper bound, considering the heightened demand for matriculation services and support resulting from the added stress caused by the pandemic and the transition of nearly everything to the virtual world.

One thing that has remained constant is the reliable funding of CCB4A. During the height of the pandemic, the program expanded to include the majority of NYCPS high schools with support from external funders. Recognizing the ongoing importance of CCB4A, NYCPS has successfully secured funding through summer of 2023, ensuring the program's continuity.

Furthermore, lessons learned in 2020 has shaped and improved its methods for engaging participants in future years. With the pandemic limiting in-person access to school counselors, college admissions, and other face-to-face support, CCB4A program staff and mentors have had to rely more on virtual communication tools like Zoom, email, and text messaging. This reliance and user-preference on virtual interaction has continued even after the pandemic subsides.

Appendix

See Fig. 2 and Tables 6, 7, 8, 9,10 and 11.

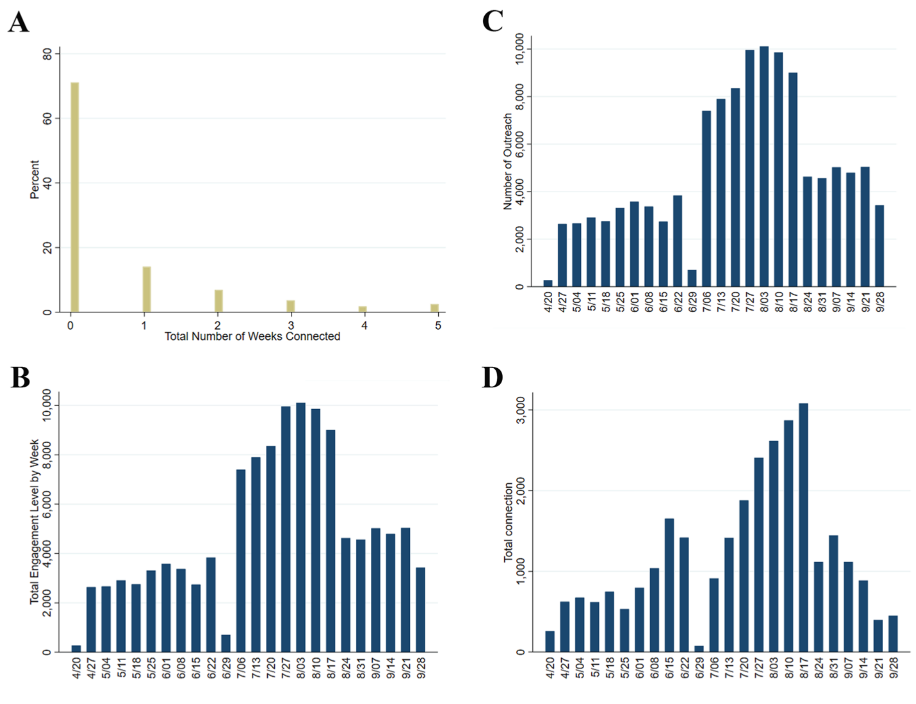

Fig. 2 Engagement detail by week. **A** Distribution of total of weeks connected. **B** Total engagement level by week. **C** Total number of outreach by mentor by week. **D** Total connection by student by week

Table 6 Application rate by college type and timing

	Overall	Enrolled in any Colleges	Enrolled in CUNY Colleges	Enrolled in non-CUNY Colleges
Applied to any colleges anytime	79%	89%	100%	72%
Applied to any colleges by May	76%	86%	96%	71%
Applied to a 4 year by May	73%	84%	92%	71%
Applied to a 2 year by May	48%	50%	66%	27%
Applied to any colleges after May	2%	2%	3%	0%
Applied to a 4 year after May	2%	1%	2%	0%
Applied to a 2 year after May	2%	2%	2%	0%
Observations	47,215	33,550	20,284	13,266

Table 7 Oster test of sensitivity to unobservable selection

Outcome	Delta
Applied to any college after/in May 2020	– 9.84
Applied to a two-year college after/in May 2020	– 9.5
Applied to a four-year college after/in May 2020	– 65.07
Admitted to any college after/in May 2020	– 9.85
Admitted to a two-year college after/in May 2020	– 8.98
Admitted to a four-year college after/in May 2020	3.27
Any college enrollment	2.52
Enrolled in a Four-year college	0.97
Enrolled in a Two-year college	– 5.56

This table shows the results of the Oster test. Each row presents the results for each outcome used. A delta between -1 and 1 reveals the possibility of a high chance of violating the CIA assumption

Table 8 Sample mean and standard difference pre- and post-match

		Mean		% Bias	% Bias reduced	T-test of the difference	
		Treated	Control			T	p > t
Female	Unmatched	0.55	0.50	9.9		9.69	0
	Matched	0.54	0.54	0	99.8	0.01	0.989
White	Unmatched	0.14	0.19	− 12		− 11.51	0
	Matched	0.14	0.14	0.1	98.8	0.12	0.905
Black	Unmatched	0.23	0.23	0.8		0.77	0.44
	Matched	0.23	0.23	− 0.7	5.5	− 0.59	0.557
Hispanic	Unmatched	0.38	0.34	9.8		9.65	0
	Matched	0.38	0.37	1.3	86.5	1.04	0.3
Asian	Unmatched	0.21	0.22	− 1.7		− 1.71	0.088
	Matched	0.22	0.23	− 2	− 15.6	− 1.58	0.115
Other races	Unmatched	0.03	0.03	0.8		0.75	0.453
	Matched	0.03	0.02	2.8	− 262.4	2.29	0.022
Student with disability	Unmatched	0.14	0.14	0.4		0.36	0.716
	Matched	0.14	0.16	− 4.9	− 1224.2	− 3.8	0
In poverty	Unmatched	0.88	0.82	16.7		15.83	0
	Matched	0.88	0.87	0.3	98.1	0.28	0.782
Log math regent test scores	Unmatched	4.32	4.33	− 10.8		− 10.42	0
	Matched	4.32	4.32	2	81.8	1.6	0.11
Log ELA Regent test scores	Unmatched	4.37	4.38	− 5.7		− 5.5	0
	Matched	4.38	4.37	4.4	21.6	3.72	0
ELA test scores quantile: 25th	Unmatched	0.29	0.27	4.2		4.16	0
	Matched	0.29	0.31	− 4.3	− 2.7	− 3.38	0.001
ELA test scores quantile: 50th	Unmatched	0.27	0.23	8.4		8.29	0
	Matched	0.27	0.28	− 2.4	70.9	− 1.87	0.061

Table 8 (continued)

		Mean		% Bias	% Bias reduced	T-test of the difference	
		Treated	Control			T	p>t
ELA test scores quantile: 75th	Unmatched	0.25	0.24	3		2.96	0.003
	Matched	0.25	0.24	2.9	2.8	2.31	0.021
Math Regents Score	Unmatched	76	77	− 12.4		− 11.96	0
	Matched	76	76	1.8	85.6	1.46	0.144
ELA Regents Score	Unmatched	81	82	− 8.9		− 8.63	0
	Matched	81	80	5.5	37.8	4.54	0
Missing Math Scores	Unmatched	0.04	0.02	8.3		8.6	0
	Matched	0.03	0.03	− 2	75.7	− 1.56	0.118
Missing ELA scores	Unmatched	0.01	0.01	− 3.9		− 3.63	0
	Matched	0.01	0.01	− 4	− 4.3	− 3.24	0.001
Training	Unmatched	0.02	0.03	− 5.8		− 5.47	0
	Matched	0.02	0.02	− 1.2	78.8	− 1.08	0.279
Employment or Military	Unmatched	0.04	0.05	− 6.6		− 6.27	0
	Matched	0.04	0.04	− 3.3	49.6	− 2.73	0.006
Total HS credits attempted	Unmatched	13.30	13.32	− 0.7		− 0.71	0.476
	Matched	13.34	13.29	2.1	− 180.4	1.64	0.1
Average HS Math GPA	Unmatched	78.61	78.86	− 2		− 1.91	0.056
	Matched	78.70	78.07	4.8	− 144.1	3.92	0
Total days absent	Unmatched	9.55	10.51	− 7.3		− 6.93	0
	Matched	9.31	9.96	− 4.9	32.8	− 4.08	0
Applied to a 2 year	Unmatched	0.62	0.43	37.5		36.64	0
	Matched	0.62	0.59	4.2	88.7	3.38	0.001
Applied to any college	Unmatched	0.87	0.72	38.7		35.85	0
	Matched	0.88	0.86	5.8	85	5.38	0

Table 8 (continued)

		Mean		% Bias	% Bias reduced	T-test of the difference	
		Treated	Control			T	p > t
High school Borough: Brooklyn	Unmatched	0.29	0.30	− 2.3		− 2.24	0.025
	Matched	0.28	0.27	1.2	46.4	0.99	0.324
High school Borough: Bronx	Unmatched	0.16	0.13	8.6		8.65	0
	Matched	0.15	0.13	5	41.9	4.06	0
High school Borough: Manhattan	Unmatched	0.15	0.20	− 11.2		− 10.78	0
	Matched	0.15	0.16	− 2.1	81.5	− 1.71	0.088
Unemployment rate	Unmatched	0.07	0.06	7.8		7.7	0
	Matched	0.06	0.06	− 0.2	97.6	− 0.15	0.883
Total median household	Unmatched	58,999	62,621	− 13.1		− 12.51	0
	Matched	59,627	60,012	− 1.4	89.4	− 1.16	0.246
Total median household income (2019$)	Unmatched	126.32	123.27	2.5		2.43	0.015
	Matched	123.84	124.72	− 0.7	71	− 0.6	0.545
Total Food Stamp/SNAP benefits in the past 12 months (2019$)	Unmatched	571.38	537.86	6.9		6.81	0
	Matched	559.13	556.35	0.6	91.7	0.46	0.647
% with health insurance	Unmatched	0.92	0.92	− 12.6		− 12.4	0
	Matched	0.92	0.92	− 5.5	56.1	− 4.51	0
% of families below poverty level past 12 months	Unmatched	0.16	0.15	7.1		6.95	0
	Matched	0.15	0.15	1.3	81	1.09	0.277

Table 9 Heterogeneous effect of connecting with a mentor on application, admission, and enrollment outcomes by GPA

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Applied in/after May			Admission outcomes			Enrollment Outcomes		
	Any colleges	Two-year	Four-year	Any colleges	Two-year	Four-year	Any colleges	Two-year	Four-year
Panel A. Students with HS GPA < 2.5									
Ever connected with a coach	0.029***	0.028***	0.020***	0.029***	0.024***	0.009***	0.092***	0.081***	0.012
	[0.004]	[0.004]	[0.003]	[0.004]	[0.003]	[0.002]	[0.009]	[0.012]	[0.011]
Observations	20,532	20,532	20,532	20,532	20,532	20,532	20,532	20,532	20,532
R-squared	0.215	0.202	0.152	0.215	0.17	0.073	0.302	0.151	0.282
Panel B. Students with HS GPA ≥ 2.5									
Ever connected with a coach	0.008***	0.006***	0.006***	0.008***	0.005***	0.003***	0.042***	0.023***	0.021**
	[0.002]	[0.001]	[0.001]	[0.002]	[0.001]	[0.001]	[0.009]	[0.007]	[0.010]
Observations	22,556	22,556	22,556	22,556	22,556	22,556	22,556	22,556	22,556
R-squared	0.11	0.1	0.097	0.11	0.087	0.07	0.183	0.22	0.295

Regressions are estimated separately for each outcome (column) and panel (row). Each panel presents the regression adjusted treatment effect of students matched within the specific subgroup only. All regressions contain HS fixed effect, control for students' gender, race/ethnicity, ELL status, SWD, poverty status, ELA and Math test scores, their postsecondary plan, total HS credits attempted in 11th grade, average 11th grade HS GPA, total day absent, whether completed an application to any college before May, and whether applied to a community college before May

Robust standard errors are clustered at the high school level and are in brackets

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 10 Effect of connecting with a mentor using inverse probability treatment weighting

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Application outcomes			Admission outcomes			Enrollment outcomes		
	Any colleges	Two-year	Four-year	Any colleges	Two-year	Four-year	Any colleges	Two-year	Four-year
Ever connected with a mentor	0.017***	0.015***	0.012***	0.017***	0.013***	0.006***	0.079***	0.048***	0.033***
	[0.002]	[0.001]	[0.001]	[0.002]	[0.001]	[0.001]	[0.006]	[0.006]	[0.007]
Observations	43,222	43,222	43,222	43,222	43,222	43,222	43,222	43,222	43,222
R-squared	0.205	0.195	0.152	0.205	0.172	0.086	0.373	0.201	0.460
	Enrollment by college type								
	Public colleges	Private colleges	CUNY colleges	SUNY colleges	Out-of-state	Private in-state			
Ever connected with a mentor	0.104***	− 0.025***	0.132***	− 0.016***	− 0.018***	− 0.017***			
	[0.007]	[0.005]	[0.007]	[0.004]	[0.003]	[0.004]			
Observations	43,222	43,222	43,222	43,222	43,222	43,222			
R-squared	0.241	0.175	0.256	0.073	0.152	0.086			

Regressions are estimated separately for each outcome (column) and panel (row). Each panel presents the regression adjusted treatment effects of students matched within the specific racial subgroup only. All regressions contain HS fixed effect, control for students' gender, ELL status, SWD, poverty status, ELA and Math test scores, their postsecondary plan, total HS credits attempted in 11th grade, average 11th grade HS GPA, total day absent, whether completed an application to any college before May, and whether applied to a community college before May

Robust standard errors are clustered at the high school level and are in brackets

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 11 Effect of connecting with a mentor using school-level characteristics instead of school fixed effect

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Application outcomes			Admission outcomes			Enrollment outcomes		
	Any colleges	Two-year	Four-year	Any colleges	Two-year	Four-year	Any colleges	Two-year	Four-year
Ever connected with a mentor	0.017***	0.016***	0.012***	0.017***	0.013***	0.006***	0.065***	0.048***	0.018**
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.001]	[0.006]	[0.008]	[0.009]
Observations	42,281	42,281	42,281	42,281	42,281	42,281	42,281	42,281	42,281
R-squared	0.155	0.14	0.111	0.155	0.115	0.051	0.294	0.179	0.41
	Enrollment by college type								
	Public colleges	Private colleges	CUNY colleges	SUNY colleges	Private in-state	Out-of-state			
Ever connected with a mentor	0.093***	− 0.029***	0.124***	− 0.017	− 0.022***	− 0.032***			
	[0.010]	[0.009]	[0.019]	[0.011]	[0.005]	[0.004]			
Observations	42,281	42,281	42,281	42,281	43,222	43,222			
R-squared	0.174	0.118	0.171	0.059	0.086	0.152			

Regressions are estimated separately for each outcome (column) and panel (row). Each panel presents the regression adjusted treatment effects of students matched within the specific racial subgroup only. All regressions contain HS fixed effect, control for students' gender, ELL status, SWD, poverty status, ELA and Math test scores, their postsecondary plan, total HS credits attempted in 11th grade, average 11th grade HS GPA, total day absent, whether completed an application to any college before May, and whether applied to a community college before May

Robust standard errors are clustered at the high school level and are in brackets

***p < 0.01, **p < 0.05, *p < 0.1

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