Title: The Effect of iMentor's College Ready Program on High School Students' College Aspirations and Non-Cognitive Skills

Authors and Affiliations: Lisa Merrill, Nina Siman, David Kang, Jasmine Soltani, and Suzanne Wulach,

Research Alliance for New York City Schools, New York University

Background / Context:
A growing body of research shows that school-based mentoring programs can be a flexible and cost-effective way to improve student outcomes (Angrist et al., 2009). Effective mentoring programs create close bonds between students and caring adults, providing students with an important source of emotional support (Deutsch & Spencer, 2009; Spencer & Rhodes, 2005). Research shows that mentoring programs typically have greater effects on non-academic areas like self-esteem and attitudinal changes than on academic outcomes like test scores (Wood & Mayo-Wilson, 2012; Herrera et al., 2007). However, mentors can provide important motivation for students by highlighting the importance of succeeding in school and showing how academic skills can be used in the real world (Bayer et al., 2013).

Of course, mentoring programs come in many shapes and sizes. Researchers have identified three important characteristics that can make some mentoring programs more successful than others. First, programs that carefully match mentees and mentors based on similar interests are more successful (Ensher & Murphy, 1997; Madia & Lutz, 2004). Second, mentors who are well trained offer better support (MENTOR, 2009). Finally, programs that monitor and nurture mentor-mentee relationships over multiple years through programmatic supports are particularly successful (DuBois et al., 2002; Herrera et al., 2000; Rhodes et al., 2005).

This study tests the effects of a new model—whole school-based mentoring that aims to prepare students to be college-ready. The whole-school model enables iMentor to enhance the effects of the mentoring relationships with a structured, college-readiness curricular component. In this study, we follow 16 cohorts of 9th grade students participating in iMentor over five years beginning in 2012-13 school year. This paper provides results from the 9th grade year.

Purpose / Objective / Research Question / Focus of Study:
The focus of this study is to identify the effects of the iMentor program after being exposed to one year of treatment.

Research Questions:

1. Do the iMentor evaluation schools implement iMentor's College Ready Program with fidelity to the program model?

2. What are the effects of iMentor on students' non-academic outcomes, such as building and maintaining strong adult relationships, college aspirations, and non-cognitive skills?

3. Do the overall effects of iMentor on students' outcomes depend on the relative intensity and quality of various components of the iMentor program?

Setting:
iMentor is being implemented in eight public, non-charter high schools in New York City, the largest school district in the country. With over 1,600 schools, 1.1 million students, and 75,000 teachers, the district is characterized by a wide range of school and student characteristics. iMentor recruited these eight schools because they serve low-income students. These schools have varying performance levels, student demographics, and have been in operation for a varying amount of time. (See table 1)

Population / Participants / Subjects:
The population consists of 300 9^{th} grade students in 3 schools over the 2012-13 school year, and 800 9^{th} grade students in 8 schools in the 2013-14 school year. The characteristics of the evaluation schools in comparison to the rest of NYC's public high schools are in Table 1.

Intervention / Program / Practice:
The iMentor College Ready Program
iMentor's College Ready Program is a four-year intervention that seeks to promote college enrollment and persistence. The program attempts to recruit every member of a given 9^{th} grade cohort and match each student with his or her own college-educated, adult mentor, with whom they are supposed to communicate online at least weekly and meet in person monthly.

In addition to fostering a mentoring relationship, iMentor staff teach the iMentor college ready curriculum weekly and organizing monthly curricular events. During class, students email their mentors about the day's lesson. Student meet with their mentors during iMentor events that are designed to align with the iMentor curriculum.

iMentor supports the pairs and works to integrate its program into partner schools' by providing a full-time iMentor employee for each cohort of students. This employee leads the weekly iMentor class (with a school staff member in the room to help facilitate), plans and manages events, and supports pairs.

Research Design:
Implementation
To study the implementation fidelity we measure core program elements (student emailing, class attendance, event attendance, and mentor-mentee match consistency) and determine if the iMentor College Ready Program occurred in the school sites. We use continuous measures of each program component as well as relationship strength to study the variation in program intensity. We depend on program data as well as student surveys to create implementation measures.
Non-Academic Outcomes
Our analysis of non-academic outcomes relies on student survey data collected specifically for the iMentor evaluation. We will focus on nine measures, which are aligned with the core non-academic outcomes that iMentor aims to achieve for all students enrolled in the College Ready Program. The nine measures are (1) Growth Mindset, (2) Perseverance, (3) Optimism, (4) Critical Thinking, (5) Self Advocacy, (6) Help Seeking, and (7) Social Capital, (8) Strong Relationships, and (9) College Aspirations.

This study uses a lagged cohort design with two treatment cohorts —essentially a double lagged design. To that end, all of the comparison students and students iMentor intends to treat attend these eight schools. The first cohort is a comparison cohort who entered one of the eight iMentor evaluation schools prior to implementing iMentor. The next cohort was treated with iMentor, and then there is a second lagged cohort in the same school designed to increase the power of the study. These lagged cohorts are staggered that phases in programmatic scale-up. Three schools began treating students with iMentor in 2012-13, and five schools began treating students in 2013-14. In total, there are about 800 comparison students and 1,100 treatment students. The strength of this design rests on the assumption that cohorts are well-matched—that 9^{th} graders entering a school in one year are similar to 9th graders the following year, or that differences can be controlled for using available data. One weakness of this design is that we cannot differentiate between the effects of iMentor and time or unobservable differences between cohorts.

Data Collection and Analysis:

Programmatic Data:

iMentor collects data from mentees and mentors via iMi, their interactive online platform. This platform requires a username and password and is accessible to mentees and mentors, as well as iMentor staff and administration. For mentees and mentors, iMi is largely a place to send and receive emails, fill out surveys, and receive and respond to iMentor event invitations. iMentor staff use iMi to access data including information about student participation in iMentor class, logs of sent and received emails, and event attendance.

Administrative Data:

The Research Alliance for New York City Schools has created a rich administrative database about New York City students, schools, and educators. The individual-level data provide covariate controls to ensure statistical parity between the comparison and treatment cohorts. Variables include student demographic characteristics, 8th grade achievement scores, and 8th grade attendance.

Survey Data

Students in iMentor schools take a baseline survey in the fall of 9th grade (before mentors and mentees are matched), and complete another survey each spring. The student survey contains over 100 items, including measures of non-academic outcomes, their experience with mentors, as well as details about their background that cannot be obtained with administrative data (e.g., parent education level).

Analysis

Cronbach's alpha and factor analysis show that the theoretical constructions are valid and reliable. They have high internal correlation and are correlated with other desirable outcomes such as passing the end of year exam (New York State Algebra Regents).

For each of the 9 outcomes, we will build a multi-level model with year fixed effects that accounts for non-independence of error of students in the same school. We will correct for multiple-hypothesis testing using the Benjamini-Hochberg correction as recommended by the What Works Clearinghouse's Procedures and Standards Handbook, 3.0.

Model:

Social Emotional Effects:

$Y_{ij} = INT + \beta_1 IMN_j + \beta_2 STUCOV_{ij} + \beta_3 COHCOV_j + \beta_4 SCH_j + \epsilon_j + \epsilon_{ij}$

Y_{ij} = non-academic outcome for student I in cohort j

IMN_j= 1 if cohort is participating in iMentor, 0 if comparison cohort

$STUCOV_{ij}$= series of student background covariates such as baseline non-academic characteristics, prior test scores, SES, parental background, and student demographics. Depending on the variables, these may be group mean centered if the cohort average is used at a covariate at the cohort level of analysis.

$COHCOV_j$= series of cohort background covariates such as average baseline characteristics and average prior student test scores, and demographic characteristics for the cohort.
SCH_j= indicates that we will be using a school fixed-effects model—all estimates will be within school estimate
ϵ_j = error associated with the cohort
ϵ_{ij} = unexplained error

Findings / Results:
The analysis is currently underway and will be completed by January 2015, in time for a published report in March.

Conclusions:
Description of conclusions, recommendations, and limitations based on findings.

It is important to note some limitations to our design. First, our study of non-academic outcomes does not allow us to differentiate between the effects of iMentor and time. For example, if later cohorts are doing better than the prior cohorts, we cannot be certain that these differences are due to iMentor exclusively. Second, we cannot control for other initiatives that aim to improve college readiness and are introduced at the same time as iMentor. Thus, we must be cautious about drawing causal inferences from these analyses.

Despite these limitations, we are confident that our analyses will provide valuable insights and lessons—for mentoring programs, schools and districts—about the potential for using iMentor's model to impact important nonacademic outcomes.

Appendices

Appendix A. References

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Appendix B. Tables and Figures

Table 1: Demographic Profile of iMentor College Ready Program Evaluation Schools and All Other NYC High Schools, 2011-2012

	Other NYC High Schools[a]	Evaluation Schools
Gender (%)		
Female	51.3	54.0
Male	48.7	46.0
Race (%)		
Latino	43.3	55.0
Black	38.4	38.4
White	7.5	2.4
Asian	9.5	2.7
Receiving special education services (%)	15.0	12.8
English language learners (%)	12.7	19.7
Poverty[b] (%)	72.0	81.1
Students per school	553.7	326.5[c]
Total number of schools	460	8
Total number of students	254,706	2,612

Source: Research Alliance calculations using data provided by the NYC DOE.

Notes: [a] High schools are defined as any school serving students grades 9-12; table does not include District 79, District 75, or specialized high schools. Total number of other NYC high schools varies between Tables 2, 4, and 5 due to data availability for different student characteristics..[b] Includes students who turned in their free or reduced price lunch form and those who did not turn in their form but attend a school that receives universal free lunch. Many students who are eligible for free or reduced lunch do not turn in their forms, therefore including universal programs is a more accurate measure of poverty. [c] The slight discrepancy between the calculated number of students based on the listed average school size and the total number of schools due to rounding.