Why Does Mentoring Matter?
The Effect of Non-Financial Support on College Enrollment and Persistence

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Abstract

There is a wealth of anecdotal support for the importance of mentors in supporting aspiring college students – particularly those who would be the first in their families to enroll – and a growing body of experimental and quasi-experimental work estimating the impact of college mentoring and college coaching. We leverage the recent history of Tennessee Promise, a last-dollar community college financial aid program, to understand more about the value of a large-scale, voluntary mentorship program at the post-secondary crossroads. In addition to providing financial aid, Tennessee Promise semi-randomly links thousands of volunteer mentors each year to the majority of public high school seniors in the state. This feature allows us to assess whether particular mentor characteristics matter more for college success, whether some mentors are more effective than others at helping students enroll and success in college, and whether mentor effectiveness with respect to college-going is also associated with greater credit accumulation in the first year of college.

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Introduction

It is estimated that each year, somewhere between 10-40 percent of high school students planning to continue their education in college do not follow through in enrolling (Castleman & Page, 2014a). There is a fast-growing literature that investigates a range of reasons for the "melt" that occurs between the time of preparation in high school to time of enrollment in college, including inadequate knowledge and guidance in the steps required to make the transition to college enrollment (Arnold et al., 2009; Castleman, Arnold, & Wartman, 2012; Castleman & Page, 2014); burdens experienced in the process of securing financial aid and completing other required paperwork for college entry (Bettinger et al., 2012; Bird & Castleman, 2016; Dynarski & Scott-Clayton, 2006); structural barriers that are more likely to affect low-income students (credit constraints, informational complexity, etc.) (Bailey & Dynarski, 2011; Stephan & Rosenbaum, 2013), and student deficits in self-regulation and persistence, combined with lack of familiarity, for managing the mechanics of the transition to college (Castleman & Page, 2014b). There is likewise a burgeoning literature on interventions that are being tested to mitigate these challenges and constraints, from personalized texts and related messaging strategies (Castleman & Page, 2015; Hoxby & Turner, 2013), to financial aid simplification efforts (Bettinger et al., 2012, Dynarski et al., 2013) and advising and mentoring interventions (Arnold et al., 2015; Barr & Castleman, 2017; Castleman, Page, & Schooley, 2014).

The State of Tennessee has recently made considerable strides in improving college access and enrollment through a suite of initiatives known as "Drive to 55" that aim to increase the percentage of Tennessee adults with a postsecondary credential to 55 percent by 2025. At the core of this effort is Tennessee Promise, a last-dollar financial aid program that covers the gap between community college tuition/fees and students' other sources of grant and scholarship aid (federal Pell grants, state HOPE scholarships, and any institutional awards). Additionally, Promise provides prospective college students with crucial non-financial support by pairing participants with volunteer mentors from the community. These mentors guide students through the basic logistical hurdles that they face as they prepare for college: federal financial aid applications (chiefly, the Free Application for Federal Student Aid, or FAFSA), college applications, FAFSA

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verification, and college enrollment and persistence in the first year. Mentors serve as role models, advisers, and advocates for students and their families.

We leverage the recent history of Tennessee Promise and its (nonprofit) partnering organization tnAchieves to better understand the role of structured, large-scale mentoring in supporting student transitions to college. Using data on nearly 6,700 unique mentors and 33,000 mentees from the graduating high school class of 2014-2015, we first assess whether particular mentor characteristics (such as age or industry of occupation) contribute to enrollment or persistence outcomes. We go on to develop estimates of mentor effectiveness in terms of the extent to which they elicit college enrollment in excess of the counterfactual. In doing so, we ask the question: Does this form of mentoring appear to be a skill or intervention with a distribution of effectiveness, or are mentors roughly equivalent in how well they influence student progression toward and success in college? Early indications suggest that some mentors are indeed more effective than others at contributing to higher rates of college enrollment. Finally, we assess whether mentors who appear to be more successful at guiding students into college are also associated with higher-than-expected rates of student persistence in college.

Key to our pursuit of these inquiries is the way in which tnAchieves mentors were assigned to students. The program had the intention of random mentor-mentee assignment within specific parameters (gender and school). Mentors are typically assigned a block of same-gender mentees within a given high school. Conditional on school and gender, matches were not explicitly based on any criteria that might correlate with future college outcomes. We assess the extent to which matches were as good as random, finding that in 2014-2015 (the first year that the program was brought to a statewide scale), mentees' race, ethnicity, and achievement are not systematically related to observable features of mentors, once we condition on school and gender. Also important is the quality of counterfactual college outcomes. We rely on the enrollment and persistence behavior of similar students from earlier cohorts to form counterfactual expectations, and in turn, to estimate the degree to which a given mentor's student outcomes differed from those expectations.

Preliminary results indicate that this form of light-touch counseling is a skill that accrues more strongly to some than others, although observable characteristics of mentors (age, occupation) have very limited associations with students' postsecondary participation and

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persistence. Mentors who are more effective at aiding students on the college enrollment margin are also linked to more earned credits among the college-goers.

Related literature

While the literature continues to grow in this area of mentoring and college outcomes, the existing rigorous studies have been conducted in diverse (mainly state and local) contexts and have investigated a variety of different advising models and structures, most of which differ from tnAchieves in terms of target populations, scale, and other program features. If, as a field, we are going to better understand what features of these programs and their implementation are critical to scaling up these types of interventions with success, we need to continue to build the evidence base in this area, including understanding the cost-effectiveness of these interventions. And as noted above, the Tennessee context is particularly important because the Promise program is one of a suite of state initiatives falling under the umbrella of the "Drive to 55" campaign to raise postsecondary attainment. Many other states are looking to Tennessee's efforts (and evaluations of them) for policy guidance, as they similarly seek to increase college completion and the skill levels and labor force participation of their state workforces.

One of the more exciting developments in the education policy and research landscape of the last several years has been the identification of new ways to narrow information gaps at the junction between high school and college, particularly among first-generation students. Midsummer outreach from counselors, peers, or even automated text messages has been shown to substantially mitigate the "summer melt" phenomenon among college-intending students (Castleman and Page, 2014a, 2014b). Carrell & Sacerdote (2017) find that a more intensive "boots on the ground" approach to college coaching raises college-going for some students, likely by filling in the information gap faced by those without college-educated parents. Perhaps most relevant to our study are experimental findings from Barr & Castleman (2017), who show that randomized offers of intensive college counseling using the Bottom Line (BL) college advising model (implemented in several cities in three states) raised college enrollment by 7 percentage points, and importantly, that these effects grew over time through higher rates of college persistence among program participants.

The BL college advising model studied by Barr & Castleman (2017) differs from the tnAchieves mentoring model in several important ways. First, BL counselors are full-time

employees and are required to have a college degree or higher postsecondary education credential. The counselors are assigned to work with caseloads of approximately 40-60 students and are expected to meet with their advisees for an hour every three-four weeks during their senior year at a local BL office. On the contrary, tnAchieves mentors are a fully volunteer force, with varying levels of education and life experiences. There is a mandatory face-to-face meeting between students and mentors in the spring semester of the students' senior year, but there are wide-ranging levels of contact reported between students and mentors in surveys conducted by tnAchieves, from no contact to extensive interactions continuing through the first year of college, including assistance with college transfers in some cases. In addition, the BL model is distinctive in that counselors encourage students to apply to and attend a target set of colleges identified by BL for their "optimal combination of quality and affordability" (Barr & Castleman, 2017). The support provided by BL counselors continues at the college level for those students (approximately 50 percent of caseloads) who attend these selected institutions.

Like other text-messaging/light-touch interventions, tnAchieves also utilizes text-messaging strategies that begin in August of students' senior year of high school, including weekly informational emails that are accompanied by a series of three informational meetings (one of these attended by mentors). For the regular messaging component, which continues after high school graduation with twice monthly text message reminders between May and December, tnAchieves relies on a private text-messaging operator. Castleman & Page's (2014a) pioneering research in this area shows that students who complete high school and are randomly assigned to receive text message reminders that encourage and support their follow-through on the tasks required for college enrollment are significantly more likely to enroll in college than their counterparts who did not receive the text messages. And in a recent randomized controlled trial of a text messaging intervention to support college enrollment that relies on "conversational" artificial intelligence, Page and Gelbach (2017) found that students who accepted admission at a specific university and received personalized, text message-based outreach and guidance were 3.3 percentage points more likely to enroll in that university on time.

We add to this growing body of research in three primary ways. First, we examine a college mentoring model that has been scaled to cover most of the state of Tennessee (85 of 95 counties), yet preserves quasi-random assignment of nearly 6,700 volunteer mentors to over

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33,000 prospective college students. Second, mentors working in this program have a level of involvement that varies considerably in intensity, but it is generally much less intensive and less costly than interventions such as BL (Barr & Castleman, 2017) and others such as that studied by Carrell & Sacerdote (2017). The tnAchieves mentoring program is slightly more heterogeneous and more personalized than automated text messages, which are also part of the tnAchieves student support model. Importantly, we do not assess the effect of mentorship *per se*, as nearly every Tennessee high school senior was touched by Tennessee Promise. Instead, we unpack the mentorship skillset in this scaled setting, assessing whether mentors vary in their effectiveness along observed and unobserved dimensions.

Background

The tnAchieves model of financial aid paired with mentoring pre-dated Tennessee Promise by several years. Beginning with the 2009-2010 senior class in Knox County, Tennessee, privately funded Knox Achieves committed to cover students' community college tuition and fees the following year if they (1) met regularly with an assigned mentor from the community, (2) filed a FAFSA on time (with assistance from mentors and staff), (3) completed an eight-hour community service project, and (4) enrolled seamlessly in a community college program after high school graduation. Departing from predecessors such as the Kalamazoo Promise, Knox Achieves was a last-dollar financial commitment, such that the program paid for any gap between tuition and entitled sources of aid. After three years, the program expanded under the new name tnAchieves to serve counties other than Knox, growing to cover more than 40 percent of high school seniors in the state by 2013-14. Based in part on qualitative success of tnAchieves and its low cost (under $1,000 per student-year), the broad outline of this model was adopted statewide as the publicly funded Tennessee Promise, with tnAchieves acting as one of three partnership organizations that implemented eligibility and mentorship aspects of the new program. At its initiation, tnAchieves administered Tennessee Promise in all but 12 of the state's 95 counties. The first cohort of Tennessee Promise students signed up for the program as high school seniors in 2014-15. The tnAchieves subset of this cohort is our primary analytical sample.

Research on mentoring programs identifies multiple mechanism through which mentoring is intended to help students navigate challenges and overcome barriers to progressing through the college application and enrollment process. Nora and Crisp (2007) reviewed the literature on

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mentoring programs and described four major domains of mentoring effectiveness: 1) psychological or emotional support, 2) goal setting and career paths, 3) knowledge support, and 4) role modeling. Mentors or coaches of InsideTrack, for example, a student coaching service studied by Bettinger & Baker (2013), contact students regularly to help them develop their goals and support them in building skills such as time management, self-advocacy, and study skills. Bettinger and Baker found that students who were randomly assigned to a coach were more likely to be attending college one year after the coaching ended. Larose et al. (2010) found that mentors who focused their interactions with students on activities (e.g., addressing academic needs) rather than on student behaviors had more significant and positive effects on mentees. These findings appear to be consistent with those of Walker & Taub (2001), who found that the frequency of contact was more strongly correlated with mentors' and mentees' satisfaction than factors such as demographic similarity and personality characteristics.

In the tnAchieves mentoring handbook, the mentor is described to students as a resource and an "encourager" who wants the student to succeed. Mentors are instructed to be in touch with their mentees at least every two weeks, reminding them of tasks and deadlines pertaining to the college enrollment process, encouraging them to follow through on the process, and offering assistance at important steps. Thus, the tnAchieves mentoring model is focused primarily on activities that students need to perform to ensure their successful transition to college, while at the same time providing positive messages and encouragement that is intended to continue into the first year of college. The handbook also suggests that mentors attempt multiple approaches to communication (e.g., email, texting) and identify the students' preferred means of communicating, and contact is also established with the students' parents to ensure that they are aware of the mentor role. Responses to surveys of both mentees and mentors (examples below) suggested that some communications and mentoring relationships were working as intended:

> *He always checked in on me and helped me create my schedule. He was always answering my questions about college and helped me better manage my time.*
>
> *I love staying in touch with my students over the summer to ease their anxiety and help them plan for their freshman year. They know they have someone they can call at home with any questions or issues that come up after they start college and just to let me know how it is going for them.*

While in other cases, the mentor and mentee failed to even establish contact:

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My mentor never showed up. Never contacted me, and was no help at all.

My student didn't attend the meeting and didn't respond to any of my follow-up attempts at contacting him.

In light of the variation in treatment (mentoring activities and relationships) in practice, the assignment of tnAchieves mentors to Tennessee high school students might be best characterized (in the analysis) in an "intent to treatment" framework that recognizes the wide range of mentoring experiences occurring in the program.

Data

Staff from tnAchieves provided data with matched mentor-mentee information from 2009-10 through 2014-15 cohorts to the state's longitudinal data system, whose administrators merged these records to de-identified student data on public high school and college progression. We focus on the 2014-15 cohort for much of the analyses below, as this was the first year of statewide implementation of Tennessee Promise. Earlier cohorts help to form counterfactual postsecondary outcomes, as described in the next section.

Our primary analytical sample describes 34,140 tnAchieves students who were matched to administrative longitudinal data including schools of record, end-of-course (EOC) achievement, basic demographics, and ACT records. This represents 57% of all 60,217 public high school seniors observed in 2014-15. [1] We match these seniors to all available postsecondary information, both within and beyond the state system of public higher education institutions. EOC scores are normalized to have mean equal to zero and standard deviation equal to one within test subjects and academic years. Postsecondary data are provided to the state longitudinal data system by the Tennessee Higher Education Commission and the National Student Clearinghouse. We observe college and sector of enrollment, cumulative credits attempted, cumulative credits earned, and

[1] The 2014-15 cohort of seniors were the first to participate in the Tennessee Promise. Roughly 58,000 students signed up for Promise that year. Our match rate is only 57% for several reasons. First, the 58,000 Promise participants include an unknown number of home-schooled students and private school students who we do not observe in administrative data. Second, tnAchieves was the largest of three partnering organizations working with Tennessee Promise, and we do not have mentor details from the other two. Third, about 25% of tnAchieves students could not be found in administrative data. Some would have been private or home-schooled students, but we expect that most had mismatched or insufficient identifying information in program versus administrative data. Last, the analyses to follow include students with matched data on end-of-course achievement and high school of record. We exclude 353 tnAchives students without this information.

grade point average by term. We limit postsecondary outcomes to those in the year immediately following the senior year of high school. Credit and GPA data are much better populated for in-state public institutions. Unless noted otherwise, we code cumulative credit as zero for students who did not go on to college and missing for students who enrolled in a private or out-of-state college. We code GPA as missing for all who did not go on to college in the year after high school.

Descriptive statistics in Table 1 illustrate that matched tnAchieves students were similar to their peers in terms of gender, race, and Hispanic ethnicity. Our sample of tnAchieves students exhibits slightly lower achievement in terms of normed EOC scores and ACT composite scores, though only the latter difference is statistically significant. Program participants were nonetheless almost four percentage points more likely than their peers to enroll in any college the year after high school, eight percentage points more likely to enroll in a two-year public Tennessee community college (where Tennessee Promise aid could be used toward tuition and fees), and four percentage points less likely to enroll in a four-year university.

Table 2 describes observable features of mentors. Mentors were 45 years old, typically, with a 41% plurality coming from education occupations. Just over one third worked in the private sector, 15% worked in the public or non-profit sectors, and 10% had unknown or unreported occupations.[2]

Methods and (Preliminary) Results

Our understanding from several conversations with tnAchieves staff is that mentors are semi-randomly assigned to student mentees. This is to protect against liability but also for convenience. Assigning several thousand mentors to tens of thousands of students affords very little time to accommodate mentor or mentee preferences. Preferences for a mentee of the same gender are honored, and in practice, female students are 64 percentage points more likely than males to have a female mentor. Mentors are almost always assigned a group of students at the same school and in their home county. Within school and gender, our understanding is that mentor-mentee matches are intended to be random. Nevertheless, on-the-ground realities of matching students to volunteer

[2] Education workers were almost divided evenly between K-12 and post-secondary educators. We grouped school board members with other educators and chamber of commerce members with public/non-profit occupations. Retired individuals were grouped by their prior occupation, if noted, and self-employed mentors were grouped with private sector occupations. We additionally observe mentors' zip code. In ongoing work we are matching these data to local socioeconomic characteristics. We do not observe mentors' race or educational attainment.

mentors may result in non-random, systematic sorting. Perhaps, for example, matches are made in a "first-come, first-served" manner, such that students who sign up earlier are matched to mentors who volunteer earlier.

To start, we empirically test the randomness of pairings by examining whether mentor characteristics are predictive of several pre-existing student characteristics: race, Hispanic ethnicity, number of EOC records (a signal of advanced coursework in core subjects), normalized EOC achievement, number of ACT sittings, and students' best ACT composite score.[3] Specifically, we regress each student characteristic in turn against mentor age and binary indicators for sector of employment (with private-sector employment serving as the omitted category), and school-by-gender fixed effects. These falsification exercises ask the following: "Conditional on a student's school and gender, are mentor characteristics systematically related to race, ethnicity, and achievement?" Point estimates and cluster-robust standard errors are reported in Table 3. Of the 36 coefficients estimated, we find that two (5.6%) are statistically significant at conventional levels of precision. We take this to be supportive evidence that tnAchieves realized their intent of random mentor assignment within schools and genders.

In ongoing work, these regression-based inferences are complemented with a series of placebo re-assignments of mentors to mentees, wherein we test whether observed assignments are as good as random. See Carrell et al. (2016), Kofoed (forthcoming), and Lim and Meer (forthcoming) for similar applications of this technique.

Confidence in the randomness of mentor-mentee pairings informs the methods we deploy to answer the following research questions:

1. Are observable mentor features predictive of students' college enrollment and first-year credit accumulation?

1(a). Similarly, are particular types of mentor-mentee pairing more effective than others?

2. Are some mentors systematically more effective in raising the likelihood of college enrollment or the volume of college credits?

2(a). If so, are these two skill distributions related? That is, are mentors who are more effective at guiding students into college also more effective at helping students persist in college?

The first set of questions have important programmatic implications. If we find, for example, that private-sector mentors are more effective at raising college-going and credit

[3] Results are similar if we exclude senior-year ACT and EOC scores from this analysis.

accumulation rates, or that private-sector mentors are particularly effective in schools with low *ex ante* college enrollment, then tnAchieves and programs like it may benefit from recruiting more volunteer mentors fitting this description. These questions are also adjacent to scholarly research on the effects of student exposure to teachers and other role models sharing the same gender or race (see, among others, Dee (2005); Gershenson et al. (2017); Kofoed (forthcoming); Lim and Meer (forthcoming)). Although gender is not a random factor in mentor-mentee pairings and mentors' race is not observed, our preliminary and ongoing work assess whether other aspects of mentor-mentee profiles have consequences for later student outcomes.

To address questions 1 and 1(a), we estimate linear regression models of the following form:

$$Y_{imsg} = \alpha_0 + X_m\beta + W_i + \rho_{sg} + \varepsilon_{imsg,} (1)$$

where Y_{imsg} is one of the college enrollment or persistence outcomes listed at the bottom of Table 1 for student i in school s, of gender g, and with mentor m, X_m is a vector of mentor characteristics (at this point in our research, this includes age and sector of occupation), W_i controls for observable student characteristics (race, ethnicity, EOC achievement and frequency, ACT achievement and frequency), ρ_{sg} is a fixed effect for school and gender, and ε_{imsg} is an error term. Equation (1) estimates of β indicate whether postsecondary participation or persistence are discernibly affected by mentor characteristics. Student and school controls are not necessary for β identification if (as we suspect) pairings are random within school-by-gender cells, but we include them for precision. We allow for cluster-robust standard errors to be correlated within school-by-gender cells.

Preliminary results are reported in Table 4. Younger mentors are significantly linked to higher rates of college going, higher rates of two-year college going, and lower rates of four-year enrollment, but each of these point estimates is well under one percent of the relevant mean. Relative to mentors working in the private sector, public/non-profit mentors are linked to a meaningful 32% drop in the likelihood of enrolling in a private or out-of-state university. But these four significant gradients may be the result of chance, as there are no other discernible patterns connecting mentor characteristics to student outcomes. No observable mentor profiles are associated with greater college persistence or grade performance.

We also estimate Equation (1) for several subgroups of students: females, males, whites, non-whites, students from high schools with above-median college enrollment, and students from high schools with below-median college enrollment. Consistent with the full sample, unreported

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estimates fail to reject most of the null hypotheses connecting mentor features to postsecondary outcomes. The significant findings from Table 4 appear to be driven by females and students from high schools with less of a history of college enrollment. These subsamples are most sensitive to mentor age, although as in the full sample, effects on any college enrollment tend to be very small relative to the mean. Females with private-sector mentors are 13-16% more likely to enroll in a private or out-of-state university.

The second set of research questions dives into the value of mentorship and college coaching *per se*. Practitioners and researchers have characterized a critical information gap between more and less privileged students at the cusp of college. First-generation students, in particular, face higher and more frequent hurdles in the processes for applying for financial aid, applying for college, and navigating basic logistics at the crossroads between high school and college. In a (likely non-representative) survey of tnAchieves college students administered by the program in 2016, fully one quarter responded that they would not have gone to college without Tennessee Promise, and first-generation status was strongly predictive of this response. Mentors are intended to help bridge this information gap. Irrespective of observable features identified in the first set of questions, are some mentors more effective than others? If so, is their influence limited to the logistics of college enrollment alone, or do they support persistence as well?

We take on these question by quantifying the extent to which each mentor raises college enrollment and persistence over the counterfactual, examining whether residual enrollment and earned credits are correlated among students assigned to the same mentor, and then examining whether mentor effectiveness at the college enrollment margin is associated with effectiveness at the intensive, earned credit margin.

To quantify the counterfactual, we apply an adaptation of Equation (1) to college enrollment and accumulated earned credits for 2007-2014 high school seniors, who may have had access to tnAchieves but who preceded the statewide rollout of Tennessee Promise and accompanying wave of 58,000 signups. We exclude the mentor characteristic vector (which was undefined for the vast majority of students prior to Promise), estimate models with and without school-by-gender fixed effects, add a vector school characteristics (time-varying aggregations of elements in W_i), and include a linear time trend. We estimate the likelihood of college enrollment as a binary outcome for the universe of pre-Promise public school seniors dating back to 2006-07. For cumulative earned credits, we limit Equation (1) to college goers. Coefficient estimates from

these two regressions are mapped to the 2014-15 analysis sample, for whom we compute residuals for any college enrollment and credits earned, with the latter outcome again restricted to college goers.[4]

Figure 1 plots trends in college enrollment residuals. Visual highlights include the effect of the 2009 recession, which raised overall college enrollment nearly five percentage points over expectations, raised two-year enrollment 2.6 percentage points, and raised four-year enrollment 1.6 percentage points. Also evident is the effect of Tennessee Promise, which began with the class of 2015 and resulted in a tick upward in overall college enrollment accompanied by distinct shifts toward two-year colleges and away from four-year universities.

We use these student-level residuals to assess mentor effectiveness. As a starting point, we estimate simple pairwise correlation coefficients between a series of 20 randomly resampled pairs of mentees within a given mentor's assignment.[5] As seen in Table 5, these coefficients have an average value of 0.020 – 0.026 for college enrollment outcomes (with the smaller figure coming from residuals that condition on school-by-gender fixed effects) and comparatively small standard deviations. Similarly, correlation coefficients for earned cumulative credits are 0.026 – 0.029. In ongoing work we are more rigorously testing the non-randomness of residual outcomes associated with particular mentors, but these early findings point to a skill distribution of mentor effectiveness.

A natural follow-up question, then, is whether mentors who are skilled at helping mentees enroll in college are also a factor in their short-term persistence. tnAchieves mentors are expected to stay in contact with mentees through the first semester of college, and anecdotally, many will maintain lines of communication long afterward. Even so, it may be the case that mentors' primary function is to aid students with paperwork and basic requirements prior to college rather than advise them on human capital issues after college.

We compute each mentors' mean residual college enrollment and credit accumulation and then transform these means to be centered at zero with standard deviation equal to one across the 2014-15 cohort of mentors. We then regress normed college credit residuals against normed enrollment residuals, estimating heteroscedasticity-robust standard errors. Results are reported in

[4] We limit the credit analysis to college enrollees to identify the effectiveness of mentors at influencing college persistence over and above their effectiveness at helping students enroll.

[5] We choose 20 random re-samplings because with 6 mentees on average, there are about 15 possible combinations of two for each mentor.

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Table 6. We detect a shallow but significant gradient between these two indices of mentor effectiveness, such that a one standard-deviation increase in a mentors' residual college enrollment is linked to a rise in first-year college credits (conditional on enrolling) of 5-6% of a standard deviation.

(Preliminary) Implications and Discussion

We find a small degree of differentiation among tnAchieves mentors in terms of how effective they raise their mentees' college enrollment and credit accumulation above the counterfactual. That we find any effectiveness gradient is remarkable for two reasons. First, tnAchieves mentorship is more personalized than automated text messages but is nonetheless a very light tough intervention, and expectations of mentors are consistent across settings. Most of the mentor-mentee relationship is conducted electronically with very few in-person meetings. Second, because of the way that mentors are paired to mentees within schools and almost always within gender, we have a limited scope for identifying variation in mentor effectiveness. For comparison, note that Jacob et al. (2010) estimate that each standard deviation rise in teacher-induced achievement persists at a rate of no more than 25% from one year to the next. Teacher quality is heterogeneous with regards to both short-term and long-term student outcomes, and student-teacher interactions are much richer and much more frequent than mentor-mentee interactions in tnAchieves. Nevertheless, we find that each standard deviation rise in mentor effectiveness with respect to college going translates to a 5-6% standard deviation rise with respect to college credit accumulation one year later. Another parallel between mentor and teacher quality is the relative unimportance of observed features, although we acknowledge that what we know about mentor characteristics is small compared to what we typically observe of teachers.

If our preliminary inferences hold as we add more information on mentors, later cohorts of tnAchieves students, and potentially, survey information from mentors and mentees, the next natural question is this: What does good mentorship look like? Answers will have policy and practical implications within and beyond programs like Tennessee Promise.

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Table 1. Descriptive statistics on students, schools, and mentors

	All class of 2014-15 high school seniors	tnAchieves 2014-15 students
Student characteristics		
Female	0.498	0.515
White, non-Hispanic	0.759	0.776
Hispanic	0.057	0.047
Normalized end-of-course achievement	0.171	0.159
	(0.768)	(0.694)
Number of end-of-course records	6.307	6.455
	(1.193)	(1.041)
Best ACT Composite	20.05	19.60
	(5.30)	(4.88)
Number of ACT sittings	2.57	2.56
	(0.94)	(0.93)
School characteristics		
White, Non-Hispanic (%)	0.759	0.783
	(0.275)	(0.267)
Hispanic (%)	0.057	0.057
	(0.061)	(0.059)
Mean normalized end-of-course achievement	0.167	0.161
	(0.344)	(0.296)
Mean number of end-of-course records	6.30	6.34
	(0.37)	(0.28)
Mean ACT Composite	20.01	19.93
	(2.39)	(2.16)
Mean number of ACT sittings	2.55	2.53
	(0.27)	(0.24)
College outcomes in the year after high school		
Any college next year	0.616	0.655
Public TN 2-year	0.299	0.377
Public TN 4-year	0.223	0.200
Other 4-year	0.123	0.103
Credits attempted (0 if not enrolled)	23.09	25.14
	(27.75)	(27.53)
Credits earned (0 if not enrolled)	19.20	20.59
	(25.69)	(25.51)
GPA (if enrolled)	2.17	2.07
	(1.32)	(1.33)
N (students)	60,217	34,140
Schools	388	307

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Table 2. Descriptive statistics on mentors

Mentor characteristics	2014-15
Mentor age	45.39
	(13.33)
Female mentor	0.688
Mentor occupation:	
Education	0.407
Public or Non-profit	0.154
Private sector	0.341
Unknown	0.098
N (mentors)	6,246

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Table 3. Falsification tests: Are mentor characteristics predictive of student features?

	Exogenous student characteristic					
	(1)	(2)	(3)	(4)	(5)	(6)
	White, non-Hispanic	Hispanic	Number of EOC records	Normalized EOC achievement	Number of ACT sittings	Best ACT Composite
Mentor age	-0.00014	-0.00007	-0.00027	0.00000	-0.00053	-0.00462**
	(0.00015)	(0.00010)	(0.00048)	(0.00032)	(0.00043)	(0.00225)
Mentor works in education	-0.00662	0.00276	-0.02220	0.00600	0.00583	0.06730
	(0.00423)	(0.00296)	(0.01350)	(0.00869)	(0.01410)	(0.06520)
Mentor works in public or non-profit sector	0.00087	0.00170	-0.02600	-0.00096	-0.00027	0.07210
	(0.00608)	(0.00457)	(0.01920)	(0.01160)	(0.01840)	(0.08580)
Unknown mentor occupation and industry	0.01560*	0.00452	0.01550	-0.01640	0.00026	-0.01660
	(0.00797)	(0.00483)	(0.02240)	(0.01590)	(0.02190)	(0.10600)
N (students)	33352	33352	33074	33030	30848	30471

Notes: Each column lists results of a regression of an exogenous student characteristic (race, ethnicity, end-of-course (EOC) frequency and achievement measures, ACT frequency and achievement measures) on mentor characteristics listed at left as well as fixed effects for school-by-gender cells. Robust standard errors allow for clustering within school-by-gender cells. * significant at 10%, ** significant at 5%, *** significant at 1%

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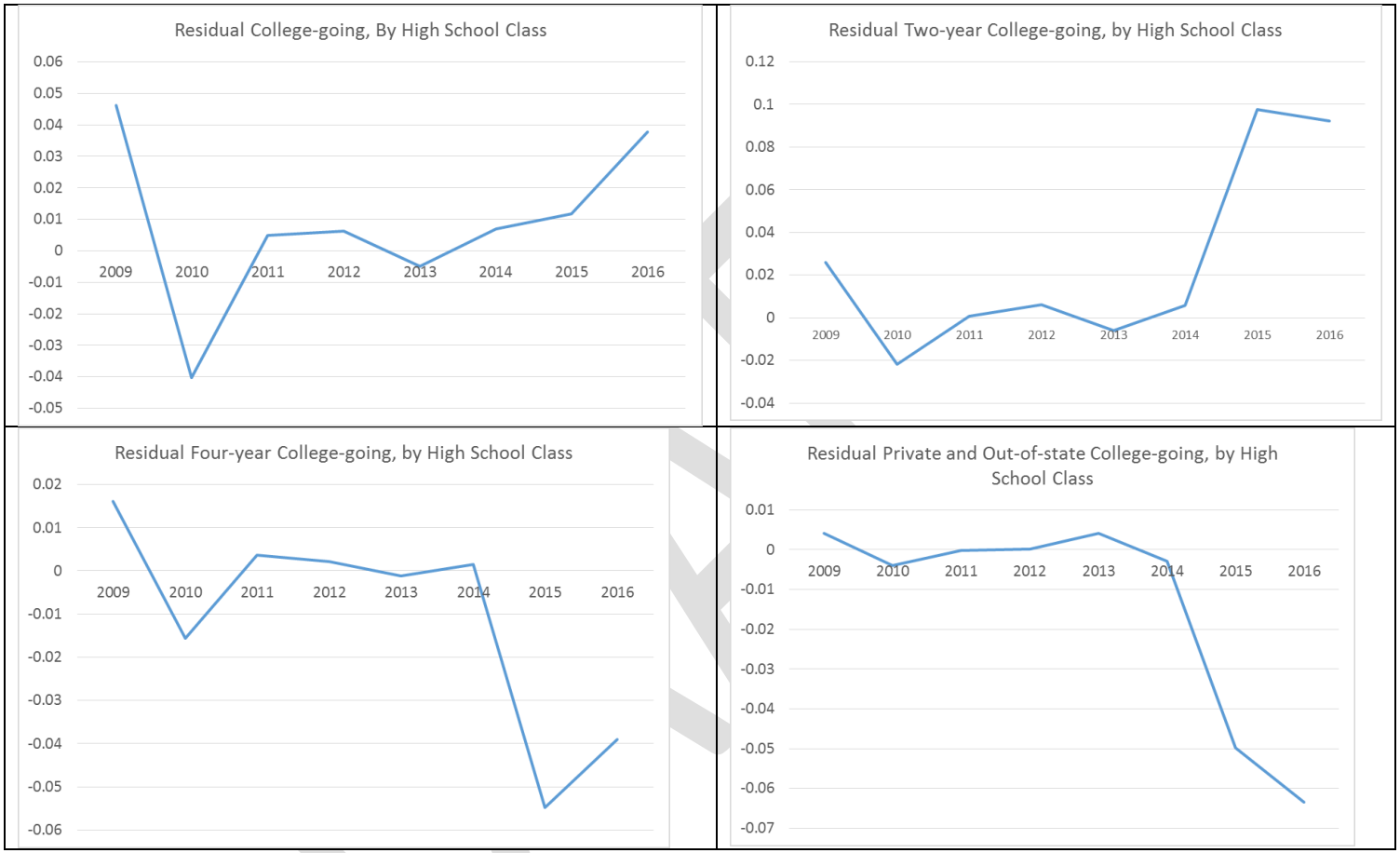
Table 4. Are mentor characteristics predictive of college enrollment and persistence?

	Postsecondary outcome						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Any college enrollment	Enrolled in a TN public 2-year	Enrolled in a TN public 4-year	Enrolled in another 4-year	Credits attempted	Credits Earned	College GPA
Sample mean	0.655	0.377	0.200	0.103	25.14	20.59	2.07
Mentor age	-0.00033*	-0.00064***	0.00040**	-0.000123	-0.00454	0.00132	0.0000886
	(0.00019)	(0.00023)	(0.00018)	(0.00014)	(0.01160)	(0.01160)	(0.00073)
Mentor works in education	-0.00442	0.00247	-0.00614	-0.0022	-0.109	-0.0163	0.011
	(0.00571)	(0.00707)	(0.00516)	(0.00442)	(0.36900)	(0.35400)	(0.02080)
Mentor works in public or non-profit sector	-0.00374	0.00638	0.00141	-0.01330***	0.552	0.332	0.0372
	(0.00722)	(0.00888)	(0.00679)	(0.00509)	(0.45700)	(0.43700)	(0.02700)
Unknown mentor occupation and industry	-0.00759	0.00251	-0.0126	0.000314	-0.733	-0.851	0.00124
	(0.00895)	(0.01080)	(0.00837)	(0.00650)	(0.56900)	(0.54500)	(0.03350)
N (students)	30,323	30,323	30,323	30,323	26,516	26,243	18,541

Notes: Each column lists results of a regression of a postsecondary outcome (e.g., college enrollment) from the year immediately following high school on mentor characteristics listed at left as well as fixed effects for school-by-gender cells. Robust standard errors allow for clustering within school-by-gender cells.
* significant at 10%, ** significant at 5%, *** significant at 1%

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Figure 1. Trends in residual college enrollment



Notes: Predicted and residual college-going, by sector, was estimated from regressions of college choice outcomes on student and school characteristics for cohorts prior to 2014-15. First-year credit estimates and predictions are limited to students who enrolled in college. Figures plot trends in college enrollment outcomes relative to the counterfactual for the high school classes of 2009-2016. Note that the 2015 class was the first affected by statewide Tennessee Promise.

Table 5. Mean pairwise correlation coefficients for within-mentor residuals

	(1)	(2)
Residuals net of school-by-gender fixed effects?	No	Yes
Any college enrollment	0.026	0.020
	(0.010)	(0.009)
Credits earned	0.026	0.029
	(0.012)	(0.012)

Notes: Predicted and residual college-going and credits for the 2014-15 class were mapped from regressions of postsecondary outcomes on student and school characteristics (and where noted, school-by-gender fixed effects) for cohorts prior to 2014-15. First-year credit estimates and predictions are limited to students who enrolled in college. The table lists average pairwise correlation coefficients (and standard deviations, in parentheses) for students with the same mentor in 2014-15.

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Table 6. Are mentors effective at promoting college-going and persistence?

	(1)	(2)
Residuals net of school-by-gender fixed effects?	No	Yes
Normed residual credits earned	0.058***	0.050***
	(0.001)	(0.001)

Notes: Predicted and residual college-going and credits for the 2014-15 class were mapped from regressions of these postsecondary outcomes on student and school characteristics (and where noted, school-by-gender fixed effects) for cohorts prior to 2014-15. First-year credit estimates and predictions are limited to students who enrolled in college. For this analysis, residuals were averaged for each 2014-15 mentor and then normed to have mean zero and standard deviation equal to one across mentors. The table lists coefficients (and robust standard errors, in parentheses) for regressions of mentors' normed earned credit residual against normed residuals for college going. * significant at 10%, ** significant at 5%, *** significant at 1%

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