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Mindset, Mentor, and Money: How Each Influences College Success

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Mindset, Mentor, and Money: How Each Influences College Success

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Abstract

Across society, the consistent influx of students enrolling in higher education institutions without a comparable increase in degree attainment has produced a heightened awareness and a desire to identify the factors related to influencing college success. This dissertation aims to develop a greater understanding of three potentially relevant factors and their respective influences in facilitating college success at the University of Arkansas. First, I evaluate the Student Talent Enrichment Program (STEP) Grant program, designed to fulfill low-income first-year students' financial needs and encourage their persistence on to their second year of college. Second, I study the effectiveness of the BounceBack Mentoring program; it paired peer-mentors with first-year students on academic probation with the goal of changing each student's academic trajectory. Third, I examine the role of non-cognitive skills, such as conscientiousness, and students' subjective expectations about their future performance in helping themselves reach their desired goals and in turn, perform beyond their expectations. In general, my findings suggest that access to the STEP grant program neither harms nor promotes short-run outcomes. I also find that the BounceBack Mentoring program show promise in helping undergraduates who are on academic probation improve their academic performance. In addition, I find that students who possess non-cognitive skills, such as conscientiousness and grit, are actively performing beyond expectations. Such findings are important because they highlight the complications, failures, and rewards of building support systems intended to promote, encourage and facilitate student success in a heavily diverse college student population. Overall, this dissertation and its findings lends itself to the fact that facilitating college success does not come from a single source, but likely is a combination of support programs, additional resources, and internal mindsets.

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Dedication

I dedicate this dissertation to the ones that came before me and the ones that will come after me.

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Introduction

Earning a college degree has a plethora of monetary and non-monetary benefits, such as reporting higher levels of job satisfaction, higher lifetime earnings, increased employment opportunities, decreases in the probability of ever being arrested and better general health (Ost, Pan, & Webber, 2018; Zimmerman, 2014; Oreopolous & Petronijevic, 2013; Oreopoulos & Salvanes, 2011; Hout, 2011). Such benefits can introduce individuals to a better way of life, and due to these tangible benefits, there has been a call to provide more individuals with access to higher education institutions. That call has produced a plethora of programs including: financial aid programs to make college more affordable, application support programs to help students apply to college, and summer bridge programs to make sure students accepted into college show up to their first day of classes after the summer of their senior year in high school (Dynarski, 2008; Page & Scott-Clayton, 2016).

As policymakers created policy, as foundations donated money for scholarships, and as programs reached into marginalized communities, all with the intention of granting access to college, students enrolled. In the U.S., from 2005 to 2014, student enrollment grew from under 18 million students to about 20 million students or 14 percentage-points (Snyder, de Brey, & Dillow, 2018). The growth in enrollment built pathways for individuals who in the past could have discounted the value of college, might not have been able to afford to pursue a degree, or never even considered higher education as an option.

Despite the increase in enrollment, the U.S. has not seen the improvements in either persistence or graduation rates, as one would hope. For example, according to the National Student Clearing House Research Center, since 2009, the first-year persistence rate for incoming freshman students has hovered between 70 and 75% (Persistence & Retention-2018, 2018). This statistic means that within the first year of enrolling at a higher education institution, about 30% of undergraduates do not continue to their second year of schooling.

As you turn to degree completion, the story does not change. In the U.S., only 60% of students who enroll in a higher education institution will earn a degree in six-years (Shapiro et al., 2017; McFarland et al., 2018). Not only do students in the general population fail to earn degrees, disadvantaged subgroups have lower graduation rates than their advantaged counterparts. African American and Hispanic students enroll in college and complete degrees at lower rates than their white counterparts (Musu-Gillette et al., 2017). Additionally, first-generation college students finish college at lower rates than students whose parents have completed at least some college (Cataldi, Bennett, & Chen, 2018).

In light of experiencing a continued rise in enrollment rates of students entering into their higher education institutions without the proportionate rises in both persistence and graduation rates, many colleges and universities are asking: “What is the key to college success?” Throughout the past few decades, the most common factor related to college success is prior academic performance. Most notably, previous literature has connected academic performance measures such as ACT scores (Paszczyk, 1994; Geiser & Studley, 2001), SAT scores (Mattern & Wyatt, 2012), and high school GPA (Armstrong & Carty, 2003) to freshman year performance, college persistence, and degree completion.

However, academically capable students with proven prior academic performance continue to pursue degrees but fail to stay on track towards graduation (Beattie, Laliberte & Oreopoulos, 2018). Such findings have shifted colleges and universities towards reevaluating determinants and barriers to college success. As these institutions move towards facilitating student success, there needs to be greater development in the understanding of what programs, factors or mentalities aid in the promotion of college success.

This dissertation looks at three potential influences: access to need-based financial assistance, peer-mentors trained to help undergraduates on academic probation in their transition from high school, and the development of character skills, in encouraging short-run college outcomes such as GPA and persistence for undergraduates.

In Chapter 1, I evaluate the University of Arkansas's Student Talent Enrichment Program (STEP) Grant program, using an experimental design strategy. The STEP grant program provided first-year students who had high levels of unmet need, (defined as the cost of attendance minus all aid and expected family contribution), a one-time, need-based grant ranging from $2,500 to $10,000. Previous literature shows access to need-based grants positively promotes persistence in undergraduate students (Castleman & Long, 2013; Angrist et al., 2017); however, I fail to detect a distinguishable effect of the STEP grant program on GPA and the probability of sophomore year retention.

In Chapter 2, I rigorously evaluate the BounceBack Mentoring Program developed at the University of Arkansas using a regression discontinuity design. The BounceBack program assigned all first-year students who earned a fall semester GPA below a 2.0 in 2017 and were subsequently placed on academic probation, a peer-mentor who met with the student on probation bi-weekly throughout the spring 2018 semester. Since peer-mentors have a unique potential to influence academic behavior and address non-academic issues, colleges and universities are using them as a tool to help undergraduates transition into college (Ellis & Gershenson, 2016; Asgari & Carter, 2016). Overall, I do not detect an effect of either assignment to nor receipt of the BounceBack mentoring program on students' grade performance, accumulated credits, their probability of being in good academic standing or persistence. A main limitation of the chapter is an inability to disentangle the effect of the program from the effect of being placed on academic probation. However, when compared to ten previous cohorts of entering freshmen on academic probation who experienced some negative effects of probation, it appears that the BounceBack program has diminished the adverse effect of academic probation on the probability of being in good academic standing after the spring semester.

Chapter 3 presents a descriptive analysis of the relationship among character skills or non-cognitive skills, subjective expectations, objective expectations, and academic outcomes for first-year undergraduate students at the University of Arkansas. A person's character can be defined as his or her principles, values, and mindsets that govern his or her decisions and attitudes and are subsequently integrated into every facet of that person's life. Researchers have identified positive associations among character skills, such as conscientiousness and grit, with course grades, class attendance, as well as persistence (Conard, 2006; Lounsbury et al., 2003; Duckworth et al., 2007). This chapter seeks to answer two simple questions: "Are students coming into college with overly high expectations about their potential performance?" and "Are character skills important to meeting expectations and succeeding in college?" After first surveying over 1,100 college freshmen majoring in business and engineering, I find students who performed below objective expectations had the highest levels of idealistic expectations; for example, they expected to attain 4.0 GPAs in college, but they were doing 2.0 GPA caliber work. Second, I find that students meeting and performing above objective expectations had the highest levels of conscientiousness. They valued working hard, and they did not give up so easily when faced with challenges.

This dissertation adds to the literatures examining if need-based grants, peer-mentors, and non-cognitive skills can impact college success. Chapter 1 adds to the literature on need-based grants by providing a rigorous evaluation of a campus-based, need-based grant program. In addition, it provides clear evidence of the effects of a cash drop without any addition of support services. Chapter 2 adds to the literature of peer-mentors by being the first study to evaluate a peer-mentoring program for students on academic probation rigorously. Chapter 3 expands the literature of non-cognitive skills by descriptively evaluating their relationships with students' college success inside of a U.S. context. Secondly, it explores the relationship between non-cognitive skills and both objective and subjective academic expectations.

These are important contributions as colleges and universities continue to emphasize student success. Student success is not new, but the introduction of rigorous evaluations strategies with the new capacity to measure non-academic skills, such as non-cognitive skills, provides a platform to build a greater understanding of the keys to college success.

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Chapter 1[1]

Can You Fulfil an Unmet Financial Need Without Addressing the Actual Need? The Impact of Need-Based Grants on First-Year College Students

Introduction

Over the past decade, colleges and universities have seen substantial increases in enrollment without comparable increases in persistence and graduation. While 77% of traditionally-aged students in 2011 enrolled full-time into a college or university, only 60% of enrollees received a degree four years later (Shapiro et al., 2017). Unfortunately, many of those students not persisting through college come from low-income families. College graduation rates for students with family incomes in the bottom quartile of the income distribution are about 13 percentage points lower than their counterparts whose families are in the top quartile of the income distribution (Bowen et al., 2009).

A primary factor attributed to lower persistence rates for low-income students is an inability to pay for college (Krueger, 2003; Castleman & Long, 2013). Expenses such as tuition, room, and board, and books are barriers to low-income students in pursuit of their degrees. Students unable to meet these expenses have two options: defer their pursuit of a degree until they can afford college or investigate financial aid options to pay for accumulated and future expenses before continuing their college enrollment. One policy used to make college more affordable is need-based grant aid; which is determined by financial need and not required to be repaid. A host of studies finds that access to need-based grant aid positively encourages college enrollment (Page & Scott-Clayton, 2016; Andrews, Imberman, & Lovenheim, 2017). Nevertheless, it is equally important to understand the effectiveness of need-based grant aid

[1] This paper was co-authored with Jonathan N. Mills.

beyond initial enrollment and on long-term outcomes, such as persistence and degree completion.

The causal literature evaluating need-based grants on college persistence and degree completion is growing and generally shows access to grant aid encourages persistence (Angrist et al., 2017; Bettinger, 2015) and degree completion (Castleman & Long, 2013), with some exceptions (Bettinger, 2004; Clotfelter, et al 2017). However, much of the previous work centers around federal and state-level grant programs, leaving a gap in research on campus-based grant programs. Furthermore, recent state switches away from enrollment-based funding of higher education institutions and towards performance-based funding, which rewards persistence and graduation rates instead of enrollment numbers, provide even further incentives for college and universities to develop programs to facilitate student success, with need-based grant programs being one of them (Snyder & Fox, 2016; Hillman, Tandberg, & Fryar, 2015; Dougherty & Reddy, 2013).

This chapter looks to evaluate the effectiveness of the Student Talent Enrichment Program (STEP) to Success Grant program at the University of Arkansas, one such institution-based grant aid program. We do so using a highly rigorous research design exploiting random assignment of the opportunity to receive a need-based grant. The STEP to Success Grant program awarded academically prepared, defined by possessing a high school GPA above 3.0, but financially struggling students with a one-time grant in the fall of 2017 ranging from $2,500 to $10,000 with the intention of improving academic performance and encouraging persistence. Overall, we find little evidence indicating receipt of a grant had an observed effect on any of our short-run outcomes such as academic performance or persistence. Despite the lack of strong evidence, this paper adds to the understanding of need-based grant programs instituted by colleges and universities designed to increase the academic performance and retention rates of academically prepared but financially constrained first-year students.

This chapter proceeds as follows. In the following section, we summarize the existing evidence of the effectiveness of need-based grants in the context of higher education. Next, we describe the specifics of the STEP to Success Grant program. We then review our research design and the data used to estimate the effects of the STEP to Success Grant program. Finally, we present our results and a discussion of our findings.

The Evidence of Need-Based Grant Aid and its Effectiveness in Supporting Collegiate Persistence and Completion

Need-Based Aid and College Enrollment

Researchers have done much work examining the effect of need-based grant aid on college enrollment. Generally, the literature shows that access to need-based grants increases the likelihood of college enrollment for low-income students (Singell, 2001; Castleman & Long, 2013; Angrist et al., 2017). Considering the effects of the need-based Florida Student Access Grant on a cohort of high school seniors and college students, Castleman and Long, (2013) find that for potential college freshmen each additional $1,300 in aid increased the probability of enrolling at a public four-year institution by over three percentage points. In addition, exploiting changes in policy of the Ohio College Opportunity Grant, Bettinger (2015) finds that increased grant-funds improve the likelihood of college enrollment in an Ohio higher education institution. However, enrollment is only the initial step to a degree, and need-based aid could have different impacts on short-term and long-term outcomes such as persistence and completion.

Need-Based Aid, College Persistence, and College Completion

Until recently, rigorous evidence on the effects of need-based grants on college persistence and degree attainment has been scant. A major issue facing studies of such programs is selection bias; recipients of need-based grant programs are not selected at random, but are instead selected on observable factors, such as socioeconomic status and parental education, and as well as unobservable factors such as motivation to apply for aid. This lack of randomized selection makes it very challenging to distinguish the effects of a need-based grant program from those factors determining one's receipt of the grant in the first place. As a method to solving the selection issue, researchers are using quasi-experimental research designs. Various studies are taking advantage of variations in financial aid policies or random variations in aid assignment and are finding that access to need-based aid generally encourages persistence and degree completion (Castleman & Long, 2013; Angrist et al., 2017; Bettinger, 2015; Clotfelter at al., 2017).

Taking advantage of discontinuities in family size and the number of family members enrolled in college, Bettinger (2004) finds that an increase of $1,000 in Pell Grant aid, the largest and most widely distributed need-based grant which awards students who have financial need a varying dollar amount to go towards higher education expenses, decreased dropout rates by about four percentage points. Similary, exploiting the qualifying expected family contribution[2] (EFC) cutoff for the need-based Florida Student Access Grant, Castleman and Long, (2013) find that each additional $1,000 of grant eligibility for college freshmen increases their probability of enrolling in the second semester by 3.3 percentage points. Additionally, an increase of $1,300 in aid eligibility increases the likelihood of graduating in six-years by 22%. Laslty, Bettinger

[2] EFC is an estimation of how much a family can financially contribute to a college education.

(2015) uses a difference-in-difference approach to analyze the shift in need-based aid policies in Ohio and finds that students awarded larger aid packages due to the shift in policy were less likely to drop-out after college enrollment.

Due to the effectiveness of need-based grants facilitating persistence both at the federal and state levels, colleges and universities are moving away from using grants to encourage enrollment solely and towards individually providing need-based grants to encourage persistence with students academically prepared but financially unprepared for college. This chapter most closely relates to the work of Clotfelter and colleagues (2017) and Andrews and colleagues (2017), who evaluate campus-based, need-based grant programs and their impact on encouraging persistence for low-income students.

Clotfelter and colleagues (2017) focus on the Carolina Covenant program, developed at the University of North Carolina at Chapel Hill, which covered the full cost of attendance for incoming high achieving yet low-income students. Using both a regression discontinuity and difference-in-difference strategy to exploit variation in eligibility, the researchers find no distinguishable effect of the program on academic performance, persistence or degree completion. However, after three years of the program's existence, the program developed a comprehensive set of non-financial supports, such as tutoring and professional development and the later cohort participants earned higher GPAs and were more likely to be on track for graduation. Andrews and coauthors (2017) evaluate both the Longhorn Opportunity Scholars (LOS) program at the University of Texas-Austin and the Century Scholars (CS) program at Texas A&M, which both provided low-income students additional grants and academic support services at each of their respective schools. Using a difference-in-difference strategy exploiting variation in program eligibility, Andrews and team (2017) find that participation in the LOS program increased the likelihood of graduating from the University of Texas. This was especially the case for women, as their likelihood of graduation increased by about three percentage points. However, the team failed to detect an effect of participating in the CS program on any college outcomes. Since there is limited and no clear evidence of the effect of need-based grants distributed at the college level, we believe these types of programs need more research.

Our paper contributes to the literature on campus-developed need-based grant programs in two ways. Firstly, we exploit randomization in the opportunity to receive aid to evaluate the effectiveness of a one-time grant awarded to academically prepared first-year college students with high levels of unmet-need, defined as fall cost of attendance minus fall free aid plus estimated family contribution, on their academic performance and the probability of persisting in college. Secondly, we accompany the work of Clotfelter and team (2017) and evaluate the effect of need-based grants in a setting in which they are offered without additional student support services.

The STEP to Success Grant Program

The administration at the University of Arkansas designed the Student Talent Enrichment Program (STEP) to Success Grant program to improve retention of first-time, first-year students facing many potential barriers to success in college. The STEP grant program is but one of a host of new university-led initiatives[3] designed to better facilitate student success as the university's funding structure shifted from an enrollment-based to performance-based mechanism. The STEP grant program restricted participation to academically promising (i.e., high school GPA above

[3] Other university initiatives include a mentoring program for students on academic probation and a mentoring/financial aid program for low-income students. To our knowledge there was no cross-over between students and these other various programs.

3.0) full-time, degree-seeking, first-time freshman with in-state residency and high levels of unmet need.[4] The program awarded students a one-time non-renewable grant ranging from $2,500 to $10,000 towards the end of their first semester (i.e., fall 2017).[5] These grants typically covered 60% to 100% of students' unmet need.[6]

The STEP program's administrators identified eligible students, implemented random assignment, and selected individuals to receive the grant in the fall of 2017. Once selected to receive the grant, program administrators contacted grant recipients via phone and email. Once students were contacted by program administrators and acknowledged their upcoming grant funds, their respective grants were applied directly to the students' university financial accounts. Students who were not selected to receive the grant were neither notified or informed about their potential receipt of a grant.

Grant awards were applied directly to the student's university financial account, initiating three potential outcomes. First, the grant could cover the full balance of the student's account leaving no excess or need. Second, the grant could cover some of the balance, leaving need. Alternatively, the award could be larger than the balance, covering the full amount and producing excess, in which case a student would receive a refund check for the amount of excess.[7] In the following section, we describe the research methodology used to determine if the STEP grants had any impact on short-run student outcomes.

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[4] Unmet need is defined as fall cost of attendance minus fall free aid plus estimated family contribution obtained from the FAFSA.

[5] Program administrators chose grant amounts of $2,500 to $10,000 because they captured a majority of the variation seen in unmet need.

[6] Author's calculations.

[7] Our data do not indicate the number of students that fell within each of the three categories.

Research Methodology

Experimental Design

A key strength of this study is that we can estimate the effects of STEP Grant program using an experimental research design. This research design allows for identification both of the casual impacts on short-run college outcomes of being assigned eligibility to receive STEP funds as well as the impacts associated with actual STEP grant receipt. The foundation of our causal claims is a random assignment process embedded in the STEP grant allocation procedure, a process on which we elaborate on here.

The STEP grant allocation process can broadly be divided into two stages (depicted in Figure 1). First, in Stage 1, the opportunity to receive a STEP grant was randomly assigned to a subset of program-eligible first-time freshmen at the University of Arkansas in the fall semester of 2017. Eligibility for the STEP grants program was restricted to full-time, degree-seeking, first-time freshman with in-state residency who had completed FAFSA, had fall unmet need of at least $2,500, a high school GPA of at least 3.0, and were neither an National Collegiate Athletic Association (NCAA) athlete nor a participant in the University of Arkansas's Engineering Career Awareness Program (ECAP)[8]. A total of 773 of a approximately 5,000 first-time freshmen in fall 2017 met these eligibility criteria. STEP-eligible freshmen were then stratified into 387 pairs by a program administrator built measure of the individual student's probability of one-year retention.[9] Stage 1 concluded with the random assignment of individuals within these pairs to either a treatment condition (opportunity to receive STEP funds) or a control condition (no

[8] ECAP is a program that provides minority students with a full academic scholarship to major in engineering.

[9] The probability of one-year retention is an exponential function of unmet need, a composite academic variable, the number of days enrolled before the semester, housing status, and having a financial hold. This measure was created and produced by the STEP program administrators.

possibility of receiving STEP funds). In total, 386 students were randomly assigned to the STEP treatment group, and 387 students were assigned to the STEP control group.[10]

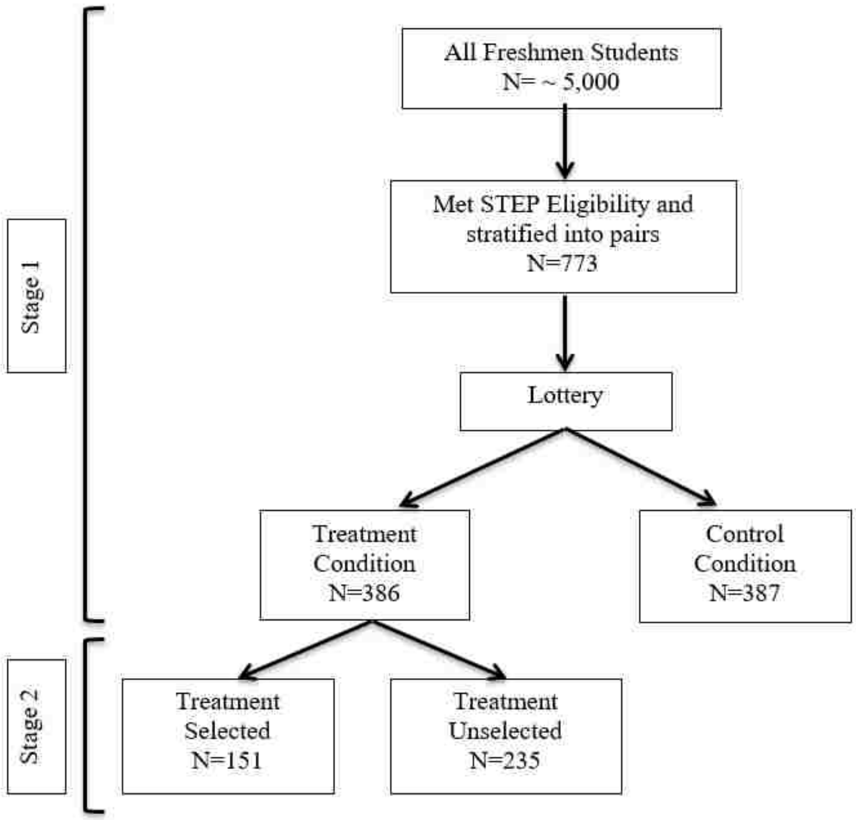

Figure 1: The STEP grant allocation process. This figure illustrates the two-stage process used to allocate STEP grants. In addition, this figure shows that only a subset of treatment students was ultimately awarded grants.

While all members of the STEP treatment group were eligible to receive STEP grants, the program's allocated $650,000 in funding ultimately was insufficient to cover the unmet need for all 386-treatment group members. Instead, in Stage 2, STEP program administrators distributed the limited STEP funds to treatment group members in such a way as to maximize the overall recipient group's probability of one-year retention. First, program administrators mechanically

[10] There was an odd number of students identified in Stage 1, and therefore one randomization pair has only one student. This student was ultimately assigned to the control condition.

allocated an imaginary $650k in $2,500 increments to different students to cover the students' unmeet need (up to a maximum of $10,000 per student) and then calculated the resulting change in treatment group's probability of one-year retention[11] associated with the particular aid allocation. This process was repeated for multiple aid allocations in order to determine the aid allocation scheme that produced the maximal change in one-year retention for the 386 students in the treatment group. The final aid allocation identified in Stage 2 resulted in a total of 151 treatment group students ultimately receiving STEP grant funds and 235 treatment group students who received neither funding nor contact from the STEP program.

Data

Data for our analysis were provided to us directly by the STEP program administrators. Specifically, we received student-level data for all 773 University of Arkansas first-time freshmen eligible for participation in the STEP grant program. The data includes a rich collection of student demographics--such as student gender, ethnicity, high school academic performance, family educational history, and expected family contribution (EFC)—as well as the probabilities of one-year retention calculated by STEP program administrators to assign students to treatment or control conditions in Stage 1 and to either receive or not receive funds in Stage 2. The data additionally include several outcomes of interest: spring 2018 enrollment, spring 2018 accumulated credit hours, spring 2018 term GPA, an indicator of being in good academic standing after the spring 2018 semester, and fall 2018 enrollment.

[11] The probability of one-year retention was calculated by STEP program administrators for each individual student as an exponential function of fall unmet need. They tend summed retention probabilities across all treatment-group members to determine the overall chance in retention probability associated with the given aid allocation.

Table 1 presents descriptive statistics for key demographic variables for the sample of STEP eligible students identified in Stage 1. The first column in Table 1 contains the sample size, and the following columns present the variable's mean, standard deviation, and both the minimum and maximum values, respectively. The sample of STEP eligible students contains roughly the same percentage of females (55%) as both the population of full-time University of Arkansas freshmen (53%) and all full-time undergraduate students (53%) in the fall of 2017, reported by the university[12]. In contrast, the percentage of STEP eligible students identified as white (65%) is noticeably lower than the corresponding university reported percentages among all full-time freshmen and full-time undergraduates (77% and 85% white, respectively). Interestingly, STEP-eligible students appear somewhat to struggle academically in their first semester in college compared to high school, as the sample reports a first-semester average GPA of 2.85 despite reporting an average high school GPA of 3.62. Finally, and as expected given the STEP program unmet need requirements, the majority of STEP-eligible students come from less economically advantaged families, with nearly a third of students with EFC values of less than $1.

Table 1

Descriptive Statistics for the Full Sample

	n	Mean	Std. Dev.	Min	Max
Female	773	0.55	0.50	0.0	1.0
Ethnicity					
African American	773	0.09	0.29	0.0	1.0
White	773	0.65	0.48	0.0	1.0
Other	773	0.09	0.29	0.0	1.0
HS GPA	773	3.62	0.34	3.0	4.4
First Generation	773	0.47	0.50	0.0	1.0
Expected Family Contribution Decile					
Less than $1	772	0.32	0.47	0.0	1.0

[12] https://oir.uark.edu/students/enrollment-reports.php

Table 1 Cont.

	n	Mean	Std. Dev.	Min	Max
From \$1 to \$2,095	772	0.19	0.39	0.0	1.0
From \$2,096 to \$5,683	772	0.17	0.38	0.0	1.0
From \$5,684 to \$10,756	772	0.18	0.38	0.0	1.0
From \$10,757 to \$17,389	772	0.12	0.33	0.0	1.0
From \$17,390 to \$26,040	772	0.02	0.14	0.0	1.0
Fall 17' Cumulative GPA	773	2.85	1.00	0.0	4.0

Notes: Other ethnicity includes Asian, Two or More, Foreign, Hawaiian, Indian, Two or More, Hispanic, and not reported. Std. Dev represents the standard deviation.

Analytic Strategy

In this section, we lay out our analytic strategy for estimating the effects of the STEP grant program on short-run student outcomes. Broadly speaking, we estimate both the causal impact of being randomly assigned eligibility to receive a STEP grant as well as the causal impact of actual STEP grant receipt. Both sets of analyses leverage the random assignment process used to allocate STEP grant eligibility to qualified students to identify causal impacts.

We first estimate the impact of being randomly assigned to the STEP treatment condition, commonly referred to as the intent-to-treat (ITT) estimator. The ITT estimator provides a crisp identification of the causal impact of STEP grant assignment by focusing directly on the point of random assignment. Operationally, we estimate the ITT effect via ordinary least squares (OLS) regressions of the following model:

$$Y_i = \beta_0 + \beta_1 Assign_i + \boldsymbol{X_i'}\,\boldsymbol{\beta_2} + \Sigma\beta_3 R_{ij} + \varepsilon_i \qquad (1)$$

where Y_i is one of our outcomes of interest; $Assign_i$ represents being assigned to the treatment group, $\boldsymbol{X_i'}$ is a vector of various combinations of covariates including a female dummy, ethnicity dummies, standardized high school GPA, first generation status, standardized Fall 2017 cumulative GPA and a EFC decile, where R_{ij} represents a fixed effect for the students stratified pair and ε_i represents the idiosyncratic error term. The estimted parameter for Assign, $\hat{\beta}_1$, is our causal ITT effect of interest.

While the ITT estimator is benefited by strong internal validity, it may not be preferred from a policy perspective because it does not identify the effect of actual STEP grant receipt. This is exacerbated by the facts that only 39% of students in the treatment group received a grant and STEP program administrators did not notify students about the program unless they were ultimately selected to receive a grant. We can, however, take advantage of the nontrivial increase in the probability of accessing STEP funds generated by being randomly assigned to the STEP treatment condition to provide an unbiased estimate of the impact of actually receiving STEP funds on short-run outcomes, or the local average treatment effect (LATE). More specifically, we estimate the impact of receiving a STEP grant on our outcomes of interest via two-stage least squares (2SLS) framework, in which we instrument for actual receipt of a STEP grant with assignment to the STEP treatment condition. We employ the following 2SLS model to evaluate the effect of receiving the grant on our outcomes of interest:

First stage: $$P(Grant_i = 1) = \alpha_0 + \alpha_1 Assign_i + \boldsymbol{X_i'}\boldsymbol{\alpha_2} + \Sigma \alpha_{3_j} R_{ij} + \varepsilon_i \qquad (2)$$

Second stage: $$Y_i = \beta_0 + \beta_1 \widehat{Grant}_i + \boldsymbol{X_i'}\boldsymbol{\beta_2} + \Sigma \beta_{3_j} R_{ij} + \varepsilon_i \qquad (3)$$

where $\widehat{Grant}_i$ represents the predicted probability of receiving a grant conditional on treatment assignment, estimtaed using a linear proability model, and the variables in equation (2) and (3) that overlap with those in equation (1) are defined similarly. The estiamted coefficient on $\widehat{Grant}_i$ in equation (3), $\hat{\beta}_1$, represents the estimated LATE of STEP grant receipt; that is the effect of receiving a grant for all those who faced random assignment and complied with their selection into the treatment selected group.

Subgroup Analysis

In addition to our primary analysis, we evaluate to what extent program impacts can be differentiated by gender, ethnicity and first-generation status. Previous findings in the college aid literature motivate our subgroup analysis. For example, when evaluating a randomly assigned need-based grant program in Nebraska, Angrist et al., (2016) found increased effects for non-white students and first-generation students. On the contrary, Goldrick et al., (2016) found that first-generation students receiving a need-based grant in Wisconsin did not see effects on degree completion while non-first-generation students did see benefits. The observed differential impacts in other grant programs suggests that the STEP program's impacts could be differentiated by subgroups. Specifically, we examine if STEP program effects differ by gender, ethnicity, and first-generation status.

Baseline Equivalence

The validity of our primary analysis hinges on the random assignment process used in Stage 1 of the STEP allocation process to divide eligible students into treatment and control group conditions. It is important, therefore, to first verify the success of the randomization process before proceeding to our primary results. Table 2 presents results for tests of imbalance in baseline characteristics between STEP-eligible students randomly assigned to either the treatment or control condition. The first column in Table 2 presents the analytical sample size and the following two columns present raw averages for the variable of interest for the treatment and control groups, respectively. The fourth column presents the adjusted difference in means between the treatment and control group, which accounts for student randomization pairs. The final column in Table 1 presents the standard error of the adjusted difference, which accounts for group fixed effects.

Table 2

Baseline Equivalence of Assignment and Control Groups on Covariates

	n	Treatment average	Control average	Adjusted difference	SE
Female	387	0.56	0.53	0.03	0.03
Ethnicity					
African American	387	0.10	0.09	0.01	0.02
White	387	0.63	0.66	-0.03	0.03
Other	387	0.09	0.10	0.00	0.02
HS GPA	387	3.62	3.62	0.01	0.02
First Generation	387	0.51	0.43	0.08**	0.04
Expected Family Contribution Decile					
Less than $1	386	0.33	0.31	0.02	0.03
From $1 to $2,095	386	0.19	0.18	0.01	0.03
From $2,096 to $5,683	386	0.17	0.17	0.00	0.03
From $5,684 to $10,756	386	0.18	0.18	0.00	0.03
From $10,757 to $17,389	386	0.11	0.13	-0.03	0.02
From $17,390 to $26,040	386	0.02	0.02	0.00	0.01
Fall 17' Cumulative GPA	387	2.87	2.84	0.04	0.06

Notes: Adjusted differences are differences in means that accounts for the group fixed effects. SE represents standard errors of the adjusted differences, accounting for group fixed effects. Other ethnicity includes Asian, Foreign, Hawaiian, Indian, Two or More, Hispanic, and not reported. In addition, the covariates were not jointly significant; joint F-statistic = 0.59 and p = 0.85. *** p<0.01, ** p<0.05, * p<0.1

In general, we observe limited evidence of an imbalance in baseline characteristics between the STEP treatment and control groups. While STEP treatment students are about eight percentage points more likely to be first-generation college students than control group students, tests for all other variables indicate differences that are not statistically significant. However, because we do see a difference in the first-generation status, we include a first-generation status control and other demographic controls in our analysis to account for this difference and improve model precision.

Results

In this section, we present estimates of the effects of being randomly assigned to potentially receive STEP grant funds as well as estimates of the impacts of actual grant receipt on student academics and retention. Additionally, we evaluate if effects are differentiated across gender, ethnicity, and first-generation status. In brief, it appears that neither assignment to the program nor receipt of a grant to cover unmet need has a statistically significant impact on our short-run outcomes of interests.

The Effect of Assignment to the STEP Grant Program.

Table 3 presents the estimated effects of being assigned to the STEP grant treatment condition on our five outcomes of interest: spring 2018 enrollment, spring 2018 cumulative GPA, spring 2018 credits, the probability of being in good academic standing after the spring 2018 semester, and fall 2018 enrollment. The first column for each outcome, columns 1, 4, 7, 10, and 13 show results for a simple model that only includes stratified pair fixed effects. The second column for each outcome, columns 2, 5, 8, 11, and 14 introduce full demographic controls, including gender, ethnicity, standardized high school GPA, first-generation status, and EFC in addition to stratified pair fixed effects. The final column for each outcome additionally controls for the student's fall 2017 cumulative GPA.

In general, the results presented in Table 2 provide little evidence that assignment to the STEP grant program had any statistically distinguishable impact on short-run student outcomes. Students assigned to the program saw increases in spring 2018 enrollment, spring 2018 GPA, the probability of being in good academic standing and decreases on the probability of enrolling in the spring 2018 semester, but all effects are statistically indistinguishable from zero.

In contrast, fall cumulative GPA is the only consistent predictor of short-run outcomes across our models. For instance, a 1-standard deviation increase in fall cumulative GPA is associated with a 22-percentage point increase in the probability of fall 2018 enrollment, which is a significant change.

It is important to keep in mind, however, that fewer than 50% of students assigned to the STEP treatment condition, were notified about their funds. Given the important role this plays, we evaluate the effect of actual receipt of a grant to cover unmet need in the following section.

Table 3

Estimated Effects of Assignment to the STEP Program

	Spring 18' Enrollment			Spr 18' GPA			Spr 18' Credits			Good Academic Standing			Fall 18' Enrollment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Assignment	0.008	0.003	0.001	0.027	0.036	0.038	-0.413	-0.415	-0.405	0.006	0.007	0.008	-0.018	-0.023	-0.027
	(0.019)	(0.019)	(0.018)	(0.074)	(0.070)	(0.061)	(0.372)	(0.370)	(0.328)	(0.025)	(0.025)	(0.018)	(0.028)	(0.029)	(0.025)
Female		0.010	-0.013		0.027	-0.049		-0.722	-1.076**		-0.002	-0.036		0.006	-0.045
		(0.028)	(0.027)		(0.102)	(0.088)		(0.527)	(0.479)		(0.036)	(0.028)		(0.041)	(0.037)
Ethnicity															
African American		0.035	0.038		-0.053	-0.038		0.272	0.345		0.024	0.031		-0.049	-0.043
		(0.052)	(0.051)		(0.175)	(0.149)		(0.973)	(0.846)		(0.059)	(0.042)		(0.081)	(0.075)
Hispanic		-0.009	-0.021		-0.058	-0.158		0.463	-0.002		0.049	0.005		-0.011	-0.037
		(0.041)	(0.037)		(0.133)	(0.118)		(0.667)	(0.623)		(0.051)	(0.038)		(0.064)	(0.056)
Other		-0.020	-0.013		0.097	0.079		1.513*	1.427*		0.062	0.054		0.050	0.065
		(0.050)	(0.046)		(0.193)	(0.151)		(0.909)	(0.763)		(0.069)	(0.045)		(0.068)	(0.059)
First Generation		0.031	0.026		-0.083	-0.069		-0.052	0.012		-0.013	-0.007		0.017	0.005
		(0.032)	(0.030)		(0.103)	(0.086)		(0.546)	(0.490)		(0.037)	(0.027)		(0.046)	(0.038)
Standardized Fall 17' Cum. GPA			0.100***			0.615***			2.853***			0.274***			0.225***
			(0.021)			(0.057)			(0.305)			(0.020)			(0.021)
Observations	773	772	772	700	699	699	700	699	699	700	699	699	773	772	772
Within R-squared	0.000	0.026	0.120	0.000	0.123	0.351	0.004	0.063	0.254	0.000	0.048	0.454	0.001	0.039	0.257
Pairs	387	387	387	378	378	378	378	378	378	378	378	378	387	387	387

Notes: All models include fixed effects for the student's stratified pair. Robust standard errors in parentheses are clustered at the pair level, Other ethnicity includes Asian, Foreign, Hawaiian, Indian, Two or More, Hispanic, and not reported. All models include controls for standardized HSGPA and EFC dummies. See Table A.1 for remaining coefficient estimates. *** p<0.01, ** p<0.05, * p<0.1

The Effect of Receipt of the STEP Grant Program.

Table 4 presents the local average treatment effect of the actual impact of receiving the STEP grant on our outcomes of interest. We are estimating these effects employing a 2SLS technique, using the assignment to the STEP treatment condition as an instrument for actual receipt of a STEP grant. First stage regression results confirm that roughly 40% of those randomly selected to the STEP treatment condition received a STEP grant.[13]

The remaining columns in Table 4 present estimates of the impact of receiving a STEP grant on student outcomes for three models. The first model includes only controls for stratified pair fixed effects; the second model controls for gender, ethnicity, standardized high school GPA, first-generation status and EFC decile in addition to stratified pair fixed effects; and the final model includes an additional control for the student's standardized fall 2017 cumulative GPA.

The results in Table 4 generally indicate that receipt of a grant failed to significantly impact our short-run outcomes of interest. Not only are these results not statistically significant, but they are also quite small in magnitude, suggesting a true null effect rather than the result of an underpowered analysis.

[13] We only encounter one-way non-compliance. There were no non-compliers in the control group.

Table 4

The Estimated Effects of Receipt of the STEP Grant Program (LATE)

	Spring 18' Enrollment			Spring 18' GPA			Spring 18' Credits			Good Academic Standing			Fall 18' Enrollment		
	LATE			LATE			LATE			LATE			LATE		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Receipt of Grant	0.020	0.007	0.002	0.077	0.101	0.106	-1.157	-1.154	-1.128	0.017	0.020	0.023	-0.046	-0.057	-0.069
	(0.049)	(0.050)	(0.047)	(0.205)	(0.197)	(0.169)	(1.044)	(1.035)	(0.925)	(0.069)	(0.069)	(0.052)	(0.073)	(0.073)	(0.065)
Female		0.010	-0.013		0.031	-0.046		-0.763	-1.117**		-0.001	-0.035		0.004	-0.048
		(0.029)	(0.028)		(0.105)	(0.091)		(0.552)	(0.495)		(0.037)	(0.028)		(0.043)	(0.038)
Ethnicity															
African American		0.035	0.038		-0.065	-0.050		0.410	0.480		0.021	0.028		-0.045	-0.038
		(0.049)	(0.047)		(0.181)	(0.156)		(0.950)	(0.849)		(0.063)	(0.048)		(0.072)	(0.063)
Hispanic		-0.009	-0.021		-0.058	-0.158		0.458	-0.007		0.050	0.005		-0.013	-0.039
		(0.040)	(0.039)		(0.149)	(0.129)		(0.785)	(0.704)		(0.052)	(0.040)		(0.059)	(0.053)
Other		-0.020	-0.013		0.086	0.067		1.643*	1.554*		0.060	0.052		0.052	0.068
		(0.050)	(0.047)		(0.182)	(0.157)		(0.957)	(0.855)		(0.064)	(0.048)		(0.073)	(0.064)
		(0.019)	(0.019)		(0.069)	(0.061)		(0.362)	(0.335)		(0.024)	(0.019)		(0.028)	(0.026)
First Generation		0.031	0.026		-0.081	-0.067		-0.070	-0.005		-0.013	-0.006		0.017	0.005
		(0.030)	(0.028)		(0.110)	(0.095)		(0.580)	(0.518)		(0.038)	(0.029)		(0.044)	(0.039)
Standardized Fall 17' Cum. GPA			0.100***			0.615***			2.857***			0.274***			0.226***
			(0.016)			(0.059)			(0.322)			(0.018)			(0.022)
Constant	0.902***	0.729***	0.743***	2.770***	2.494***	2.452***	13.54***	12.82***	12.63***	0.874***	0.922***	0.904***	0.788***	0.767***	0.798***
	(0.014)	(0.100)	(0.094)	(0.053)	(0.363)	(0.313)	(0.267)	(1.910)	(1.707)	(0.018)	(0.127)	(0.096)	(0.020)	(0.146)	(0.129)
Observations	773	772	772	700	699	699	700	699	699	700	699	699	773	772	772
Pairs	387	387	387	378	378	378	378	378	378	378	378	378	387	387	387

Note: First stage results are for the fully specified model. Standard errors in parentheses account for clustering at the pair level, Other ethnicity includes Asian, Foreign, Hawaiian, Indian, Two or More, Hispanic, and not reported. All models include controls for standardized HSGPA and EFC dummies. See Table A.2 for the first stage results and the remaining coefficient estimates *** $p<0.01$, ** $p<0.05$, * $p<0.1$

The Effect of Receipt of the STEP Grant Program Across Various Subgroups.

It could be the case that the program had no overall effect while significantly improving the outcomes of different subgroups. In this section, in an attempt to capture potential heterogeneous effects we estimate differential effects by gender, ethnicity and first-generation status. Overall, the findings remain unchanged: we observe little evidence indicating the STEP grant program had a distinguishable impact on various subgroups.

Table 5 presents estimated effects for our three subgroups across our five outcomes on interests. The first column (i.e., 1, 4, 7, 10, & 13) for each outcome presents estimates that only control for stratified random pair fixed effects. In addition, the second column (i.e. 2, 5, 8, 11, & 14) controls for gender, ethnicity, standardized high school GPA, first-generation status and EFC in addition to the fixed effects; and the final (i.e. 3, 6, 9, 12, & 15) includes a control for the student's standardized fall 2017 cumulative GPA.

Looking at our first subgroup, gender, in general, we fail to find a distinguishable estimated differential effect of grant receipt between males and females. However, the lone exception is for spring 2018 accumulated credits, seen in column 7. This finding could be chance, due to the lack of overall differences and purposely not controlling for student demographics and achievement in the model. We observe a similar story when evaluating differential effects by ethnicity: African American and non-African American students generally did not experience statistically different effects from the STEP grant program when our models adequately control for student demographics and achievement. Finally, we observe little evidence of differentiated treatment effects between first-generation and non-first generation students; with one exception, spring 2018 GPA. Non-first generation students earn statistically significant higher spring GPAs than their first-generation counterparts, observed in column 6.

Table 5

Differential Effects of the STEP Grant Program by Gender, Ethnicity, and First Generation Status

	Spring 18' Enrollment			Spring 18' GPA			Spring 18' Credits			Good Academic Standing			Fall 18' Enrollment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Gender Subgroup Analysis															
Female	0.007	0.008	0.032	-0.400	-0.170	0.103	-3.849	-3.530	-2.281	-0.105	-0.075	0.047	-0.202	-0.171	-0.118
	(0.098)	(0.097)	(0.097)	(0.415)	(0.391)	(0.337)	(2.100)	(2.055)	(1.843)	(0.137)	(0.135)	(0.104)	(0.146)	(0.144)	(0.127)
Male	0.027	0.006	-0.024	0.473	0.343	0.109	1.310	0.980	-0.093	0.123	0.106	0.001	0.081	0.041	-0.027
	(0.071)	(0.073)	(0.070)	(0.299)	(0.290)	(0.250)	(1.512)	(1.525)	(1.367)	(0.099)	(0.100)	(0.077)	(0.106)	(0.108)	(0.095)
Difference	-0.020	0.002	0.056	-0.873	-0.513	-0.006	-5.159*	-4.510	-2.188	-0.228	-0.181	0.046	-0.283	-0.212	-0.091
	(0.137)	(0.138)	(0.132)	(0.584)	(0.557)	(0.482)	(2.952)	(2.929)	(2.635)	(0.193)	(0.193)	(0.149)	(0.205)	(0.205)	(0.180)
Ethnicity Subgroup Analysis															
African American	-0.093	-0.041	-0.036	-1.236	-0.729	-0.517	-6.961	-5.325	-4.338	-0.400	-0.342	-0.247	-0.190	-0.070	-0.060
	(0.194)	(0.193)	(0.183)	(0.789)	(0.745)	(0.642)	(4.024)	(3.921)	(3.507)	(0.262)	(0.258)	(0.196)	(0.286)	(0.283)	(0.250)
Not African American	0.032	0.013	0.007	0.248	0.203	0.183	-0.431	-0.640	-0.733	0.070	0.065	0.056	-0.026	-0.056	-0.071
	(0.056)	(0.057)	(0.054)	(0.226)	(0.216)	(0.186)	(1.154)	(1.138)	(1.017)	(0.075)	(0.075)	(0.057)	(0.082)	(0.083)	(0.073)
Difference	-0.125	-0.054	-0.042	-1.484*	-0.932	-0.700	-6.530	-4.685	-3.605	-0.470*	-0.406	-0.303	-0.163	-0.014	0.011
	(0.213)	(0.213)	(0.203)	(0.850)	(0.808)	(0.696)	(4.339)	(4.249)	(3.801)	(0.282)	(0.280)	(0.212)	(0.314)	(0.313)	(0.276)
First Gen Subgroup Analysis															
First Generation	0.050	0.057	0.027	-0.361	-0.328	-0.522	-2.122	-1.791	-2.690	-0.010	0.002	-0.084	-0.087	-0.083	-0.150
	(0.079)	(0.078)	(0.075)	(0.332)	(0.319)	(0.280)	(1.696)	(1.674)	(1.510)	(0.111)	(0.111)	(0.085)	(0.117)	(0.115)	(0.101)
Not First Generation	-0.028	-0.046	-0.025	0.531	0.512	0.708**	-0.205	-0.542	0.371	0.052	0.038	0.125	-0.010	-0.030	0.016
	(0.089)	(0.090)	(0.086)	(0.340)	(0.331)	(0.291)	(1.734)	(1.737)	(1.567)	(0.113)	(0.115)	(0.089)	(0.133)	(0.132)	(0.116)
Difference	0.078	0.102	0.052	-0.892*	-0.840	-1.230***	-1.916	-1.249	-3.061	-0.061	-0.036	-0.210	-0.077	-0.053	-0.167
	(0.136)	(0.135)	(0.129)	(0.531)	(0.516)	(0.453)	(2.711)	(2.707)	(2.439)	(0.177)	(0.179)	(0.138)	(0.202)	(0.199)	(0.176)
Controls															
Demographic		X	X		X	X		X	X		X	X		X	X
Fall 2017 GPA			X			X			X			X			X

Note: Demographic controls include gender, ethnicity, standardized HS GPA, first-generation status and EFC. Standard errors in parentheses account for clustering at the pair level, First stage regressions indicate that assignment to the STEP program is an adequate instrument for receipt of the grant. *** p<0.01, ** p<0.05, * p<0.1

Conclusion

This study evaluates a one-time, need-based grant awarded to academically prepared first-year college students with high levels of unmet need, which was designed to encourage academic performance and persistence. As low-income students continue to struggle to obtain a degree, it is imperative that we evaluate programs designed to ensure their success.

Overall we fail to find statistically distinguishable effects for the STEP Grant Program. Neither assignment to potentially receive a grant nor actual receipt improved nor harmed the likelihood of spring 2018 enrollment, spring 2018 GPA, spring 2018 credits completed, the likelihood of being in good academic standing after the spring semester, nor the likelihood of fall 2018 enrollment. Additionally, after evaluating the possibility of differential effects of the STEP grant program across gender, ethnicity, and first-generation sub-groups, we fail to find sufficient heterogeneous effects. The lack of an overall effect in our primary analysis, in addition to an indistinguishable differential effect, leads us to believe that the program failed to improve short-run college outcomes for its participants.

Such findings are discouraging as program administrators poured effort and resources into the program without observing the desired results. However, this study suffers from a small sample size that may lead to underpowered effects, and therefore our observed null results should be interpreted with caution.

From the standpoint of higher education institutions, our findings suggest when colleges and universities are needing to direct their scarce resources towards programs that are shown to work, in light of the weak evidence presented here, it may not be worthwhile to continue to fulfill students unmet needs. Since students who had their unmet need satisfied performed no differently than students who did not have their unmet need met, it could suggest that factors beyond the affordability of college are preventing low-income students from persisting through and completing college. Such factors could include a failure to connect socially at the university, an inability to transition from high school academics to collegiate academics, or the lack of developed non-cognitive skills.

So as universities and colleges develop programs with the goal of meeting a financial need, they should consider meeting non-financial needs as well, to adequately promote college success.

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Appendix

Table A.1

Remaining Estimated Effects of Assignment to the STEP Program

	Spring 18' Enrollment			Spr 18' GPA			Spr 18' Credits			Good Academic Standing			Fall 18' Enrollment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Standardized HS GPA		0.011	-0.020		0.265***	0.096		0.358	-0.423		0.049**	-0.027		0.039	-0.030
		(0.016)	(0.016)		(0.068)	(0.060)		(0.411)	(0.381)		(0.023)	(0.019)		(0.025)	(0.023)
EFC															
Less than $1		0.156	0.176*		0.100	0.207		0.436	0.931		-0.128**	-0.080*		-0.008	0.037
		(0.106)	(0.100)		(0.396)	(0.385)		(1.751)	(1.665)		(0.061)	(0.048)		(0.126)	(0.125)
From $1 to $2,095		0.165	0.161		0.352	0.349		1.594	1.582		-0.026	-0.028		0.089	0.080
		(0.108)	(0.102)		(0.391)	(0.383)		(1.872)	(1.813)		(0.053)	(0.047)		(0.131)	(0.130)
From $2,096 to $5,683		0.176*	0.165		0.587	0.485		2.622	2.146		-0.013	-0.09		0.087	0.063
		(0.106)	(0.102)		(0.408)	(0.398)		(1.748)	(1.666)		(0.057)	(0.049)		(0.131)	(0.130)
From $5,684 to $10,756		0.177	0.168*		0.297	0.283		1.076	1.011		-0.041	-0.047		0.015	-0.004
		(0.107)	(0.101)		(0.390)	(0.383)		(1.736)	(1.674)		(0.059)	(0.052)		(0.128)	(0.128)
From $10,757 to $17,389		0.095	0.107		0.071	0.150		-0.081	0.287		-0.083*	-0.048		-0.103	-0.077
		(0.108)	(0.104)		(0.376)	(0.363)		(1.600)	(1.514)		(0.050)	(0.043)		(0.125)	(0.128)
Observations	773	772	772	700	699	699	700	699	699	700	699	699	773	772	772
Within R-squared	0.000	0.026	0.120	0.000	0.123	0.351	0.004	0.063	0.254	0.000	0.048	0.454	0.001	0.039	0.257
Pairs	387	387	387	378	378	378	378	378	378	378	378	378	387	387	387

Notes: Estimated coefficients correspond to the estimates presented in Table 3. Robust standard errors in parentheses are clustered at the pair level. *** p<0.01, ** p<0.05, * p<0.1

Table A.2

Remaining Estimated Effects of Receipt of the STEP Grant Program (LATE)

	Spring 18' Enrollment			Spring 18' GPA			Spring 18' Credits			Good Academic Standing			Fall 18' Enrollment		
	First Stage	(2)	(3)	First Stage	(5)	(6)	First Stage	(8)	(9)	First Stage	(11)	(12)	First Stage	(14)	(15)
Receipt of a Grant	0.391***			0.359***			0.359***			0.359***			0.391***		
	(0.025)			(0.027)			(0.027)			(0.027)			(0.025)		
Standardized HS GPA		0.010	-0.020		0.257***	0.089		0.445	-0.340		0.047*	-0.028		0.043	-0.025
		(0.019)	(0.019)		(0.069)	(0.061)		(0.362)	(0.335)		(0.024)	(0.019)		(0.028)	(0.026)
EFC															
Less than $1		0.156	0.176*		0.117	0.225		0.240	0.740		-0.124	-0.076		-0.013	0.031
		(0.106)	(0.101)		(0.388)	(0.334)		(2.039)	(1.823)		(0.135)	(0.103)		(0.155)	(0.137)
From $1 to $2,095		0.166	0.161		0.370	0.368		1.387	1.379		-0.023	-0.024		0.083	0.072
		(0.107)	(0.102)		(0.392)	(0.337)		(2.061)	(1.842)		(0.137)	(0.104)		(0.157)	(0.138)
From $2,096 to $5,683		0.176*	0.165*		0.606	0.504		2.409	1.937		-0.009	-0.055		0.083	0.058
		(0.105)	(0.100)		(0.387)	(0.333)		(2.035)	(1.819)		(0.135)	(0.103)		(0.155)	(0.137)
From $5,684 to $10,756		0.178*	0.169*		0.321	0.309		0.802	0.743		-0.036	-0.042		0.007	-0.013
		(0.106)	(0.101)		(0.392)	(0.337)		(2.061)	(1.842)		(0.137)	(0.104)		(0.156)	(0.138)
From $10,757 to $17,389		0.096	0.107		0.086	0.166		-0.254	0.118		-0.080	-0.044		-0.108	-0.083
		(0.104)	(0.099)		(0.383)	(0.330)		(2.015)	(1.801)		(0.134)	(0.101)		(0.153)	(0.135)
Constant		0.729***	0.743***		2.494***	2.452***		12.82***	12.63***		0.922***	0.904***		0.767***	0.798***
		(0.100)	(0.094)		(0.363)	(0.313)		(1.910)	(1.707)		(0.127)	(0.096)		(0.146)	(0.129)
Observations		772	772		699	699		699	699		699	699		772	772
Pairs		387	387		378	378		378	378		378	378		387	387

Note: First stage results are for the fully specified model. Standard errors in parentheses account for clustering at the pair level, Other ethnicity includes Asian, Foreign, Hawaiian, Indian, Two or More, Hispanic, and not reported. *** p<0.01, ** p<0.05, * p<0.1

Intuitional Review Board Approval Letter

UNIVERSITY OF ARKANSAS

To:	Jonathan Norman Mills GRAD 212
From:	Douglas James Adams, Chair IRB Committee
Date:	01/26/2018
Action:	**Exemption Granted**
Action Date:	01/26/2018
Protocol #:	1801095816
Study Title:	the Student Talent Enrichment Program (STEP) Peer Coaching Program

The above-referenced protocol has been determined to be exempt.

If you wish to make any modifications in the approved protocol that may affect the level of risk to your participants, you must seek approval prior to implementing those changes. All modifications must provide sufficient detail to assess the impact of the change.

If you have any questions or need any assistance from the IRB, please contact the IRB Coordinator at 109 MLKG Building, 5-2208, or irb@uark.edu.

cc: Malachi Akeem Nichols, Investigator

Chapter 2[14]

Can you BounceBack from Academic Probation? The Effects of Mentoring on Undergraduates on Academic Probation

Introduction

While college enrollment in the U.S. has risen by almost 30% since 2000, college completion rates have remained relatively flat in the same period (McFarland et al., 2018). To combat the gap between enrollment and degree attainment, colleges and universities are actively building support systems for students who are on the verge of not completing their degrees. These support programs target students who are currently pursuing degrees and differ from programs such as summer melt programs[15] (Castleman, Owen, & Page, 2015) or financial aid programs (i.e., loans, placed-based grants, and tax credits) (Page & Scott-Clayton, 2016), which promote access to college. These post-matriculation programs center around relieving financial constraints, correcting academic unpreparedness, and providing transitionary assistance.

Prior evidence has shown that programs designed to alleviate additional financial expenses incurred after college enrollment have improved the likelihood of a student completing a college course, continuing enrollment, and graduating in four years (Goldrick-Rab, Kelchen, Harris, & Benson, 2012). The sustainability of such programs is questionable, however, due to the finite financial resources of colleges and universities. Also, the evidence on efforts to correct academic unpreparedness through remedial coursework, the most common program instituted, have been varied (Rhinesmith, 2016; Bettinger & Long, 2009). These facts leave colleges and

[14] This paper was co-authored with Jonathan N. Mills.

[15] Summer melt programs introduce high school students to resources and programs in the summer after they graduate from high school, with the intention to prevent these students from enrolling into a university but not attending in the Fall.

universities needing to develop programs that are both sustainable and can impact a student's academic and non-academic skills as well.

As a result, colleges and universities are developing transitionary programs. Transitionary programs provide undergraduate students access to both academic and social support after they have enrolled, which aids in their transition to college life. Academic advisors, for example, can help students navigate the post-secondary landscape. For instance, community college students who met with college-provided academic advisors experienced increases in course registration rates (Scrivener & Weiss, 2013). Similar to academic advisors, colleges are using mentors to offer support to undergraduates who are on the verge of not earning a degree.

Students who are on academic probation are a group whom colleges and universities are developing and focusing mentoring programs on in order to improve the group’s chances of success. First-year college students who are placed on academic probation often enroll in college socially unprepared for collegiate life and academically unprepared for college coursework. Since students’ academic performance during their first year of college is a crucial determinant of their choice to return to college (Braunstein, McGrath, & Pescatrice, 2000), it is imperative to understand the effectiveness of mentoring programs on encouraging college persistence.

Prior literature suggests that undergraduates on academic probation, paired with mentors, earn higher GPAs, are less likely to drop out of college, and are more confident in their ability to navigate college life (Hanger et al., 2011; Boretz, 2012). However, the observed effects are for voluntary programs and are descriptive in nature. Thus, previous literature fails to provide rigorous evidence which disentangles the effect of mentoring from other factors that could lead to the observed effects, such as student motivation to seek additional support. Without the addition of rigorous research, colleges and universities could continue to develop mentoring programs for students on academic probation without an accurate understanding of their true effects. Our study hopes to fill this gap in understanding.

This chapter rigorously evaluates the BounceBack Mentoring program at the University of Arkansas, which paired peer-mentors with first-year undergraduates who earned a GPA below a 2.0 threshold during their first semester of college (i.e., fall 2017) and were subsequently placed on academic probation the following semester (i.e., spring 2018). Peer mentors met with their mentees in a one-on-one setting throughout the spring 2018 semester and conversed on topics including study skills, time management, and test-taking strategies, with the intention of changing the mentees' academic and non-academic behaviors. We evaluate the program's effect on encouraging student persistence and academic success using a regression discontinuity design by taking advantage of the program's use of GPA to assign students either to receive or not receive mentoring.

Overall, we do not find strong evidence of a detectable effect. We find suggestive, but not statistically significant, evidence that qualifying for the BounceBack program increased participating students spring 2018 semester GPA on average, but decreased the probability of the students enrolling for their sophomore year, compared to students just above the 2.0 GPA threshold. In addition, we fail to see a statistically significant effect of the BounceBack program on spring 2018 accumulated credits or being in good academic standing after the spring 2018 semester ended. However, because of the BounceBack Mentoring program design, we cannot disentangle the effect of the mentoring program from the effect of being on academic probation. To combat this limitation, we evaluate the effect of probation absent of the BounceBack Mentoring program across previous cohorts of students. Comparing our estimates of the

BounceBack program to estimates from previous cohorts, it seems the BouceBack Program has diminished any negative effect of academic probation on the probability of being in good academic standing. Despite the limitations, as well as the lack of concrete findings, this chapter expands the literature of mentoring effects in undergraduates on academic probation by being the first one to use a highly rigorous research design in evaluating the effects of peer-mentors on undergraduates who are on academic probation.

This chapter proceeds as follows. In the next section, we present a review of the relevant literature. We then highlight the specifics of the BounceBack Mentoring program. Next, we review our research design and the data used to estimate the effects of the BounceBack Mentoring program. We then present our results and various robustness checks. Finally, we close with concluding remarks.

The Evidence on Mentoring Programs Intended to Ease the Transition to College and Encourage Persistence

While previous research has evaluated previous attempts by colleges and universities to relieve financial constraints and correct academic unpreparedness as methods to encourage persistence in undergraduate students, our study looks to gain a better understanding of the effects of mentoring programs. Mentoring programs intend to increase the chances of undergraduates obtaining degrees by changing academic behavior and influencing non-academic skills. Mentors, who can be peers (Ellis & Gershenson, 2016; Angrist, Lang, & Oreopoulos, 2009), faculty members (Castellanos et al., 2016), community members (Carruthers & Fox, 2016), paid mentoring professionals (Bettinger & Baker, 2014; Tovar & Simon, 2006; Page, Castleman, & Sahadewo, 2016) and mental health counselors (Hanger et al., 2011), often provide academic support in the form of teaching study skills and setting academic goals (Bettinger & Baker, 2014), while also offering advice on social situations, such as overcoming culture shock and healthy living choices (Page, Castleman, & Sahadewo, 2016; Clotfelter, Hemelt, & Ladd, 2017).

Several studies have evaluated the relationship between mentoring and undergraduate student outcomes when mentoring is offered in combination with financial aid (Carruthers & Fox, 2016; Scrivener & Weiss, 2013; Clotfelter, Hemelt, & Ladd, 2017). In general, the estimated effects of mentoring, paired with financial assistance, range from null to positive effects on student academic outcomes, such as GPA and persistence (Carruthers & Fox, 2016; Page, Castleman, & Sahadewo, 2016; Clotfelter, Hemelet, & Ladd, 2017). For instance, undergraduates enrolled in the Accelerated Study in Associate Programs (ASAP) at various community colleges connected to the City University of New York who received a tuition waiver, free textbooks, and required comprehensive mentoring saw higher levels of persistence, credits acquired, and graduation rates (Scrivener & Weiss, 2013). Clotfelter, Hemelt, and Ladd (2017) find suggestive, but not conclusive evidence, of increased grade performance and college graduation within four years from entering freshmen assigned to faculty and peer mentors in addition to having the financial cost of attendance covered at the University of North Carolina. However, despite suggestive evidence that mentoring encourages persistence in undergraduate students, mentoring programs paired with financial assistance create black boxes and present trouble for the researchers in untangling the effects of mentoring from the effects of receiving financial aid.

More researchers are beginning to evaluate standalone mentoring programs in order to separate the effect of mentoring from the effect of financial assistance. One instance of such an occurrence is the evaluation of mentoring via technology-only contact by colleges and universities. Technology-only contact, such as sending emails and text messages to students encouraging them throughout the semester or providing access to mentors online, seems to help undergraduates achieve higher GPAs, matriculate through their degree programs and graduate in four years (Bettinger & Baker, 2014; Page, Castleman, & Sahadewo, 2016). Despite the affordability and effectiveness of technology-only contact, in-person contact can get at the root of longstanding issues and build a level of trust not afforded by technology-only contact and presents itself as a more favorable option to colleges and universities (Oreopoulos & Petronijevic, 2017).

In-person mentoring programs provide undergraduate students' access to peers, faculty or trained professionals who can serve as a support system while students are transitioning into college. Faculty members acting as mentors to undergraduates provide students with someone who challenges them, someone who provides a level of closeness, someone who is committed to his or her wellbeing, and someone who cares (Gullan et al., 2016). Castellanos and colleagues (2016), find that minorities assigned to faculty mentors felt a greater connection to the university and higher levels of college and life satisfaction. In addition to faculty members, upper-level undergraduates are serving as mentors. First-year male arts and sciences students who were assigned to male peer-mentors and participated in the mentoring were more likely to persist into their second year of college (Ellis & Gershenson, 2016). However, assignment to a mentor failed to change outcomes for female students or change subsequent grade performance for both genders. Moreover, students randomly assigned a peer mentor in an introductory psychology class performed better on individual tests and overall in the class (Asgari & Carter, 2016). At the conclusion of the course, mentored students reported mentors motivated them to work harder and imparted them with a confidence in their abilities.

Due to peer mentors having the ability to influence the academic and social aspects of student life, colleges and universities are connecting peer mentors to students on academic probation with the hope of encouraging college persistence (Hanger et al., 2011). Since undergraduates on academic probation are close to dropping out of college, they are becoming a high priority for many colleges and universities. To our knowledge, only two papers have evaluated the effects of mentors on undergraduates who are on academic probation. This chapter aims to expand this knowledge.

Hanger and colleagues (2011) evaluate the effectiveness of a semester-long voluntary course that mental health professionals and peer mentors jointly taught to first-year students on academic probation at San Diego State University. Observing differences in means, students who enrolled in the course and earned course credit had higher GPAs immediately after the program, and a larger number of these students persisted into their sophomore and junior years, compared to the students who had taken the course but failed it, and the students on academic probation who did not enroll in the course. However, due to the voluntary nature of the program, the effects do not adequately account for selection bias. So improvements in observed outcomes for students who enrolled and earned course credit could be related to unobservable characteristics, such as motivation or pressure from parents, and not mentoring.

Bortez (2012) descriptively evaluates the effects of a mid-semester Success Workshop co-led by academic advisors, professional counselors, and peer mentors for students on academic probation at the University of California-Merced between 2005 and 2010. Reviewing responses from self-reported workshop evaluations, participating students reported a greater awareness of how to change their performance and felt that interacting with peer-mentors was the most helpful part of the workshop. Additionally, a higher rate of students who participated in the workshop and were not subsequently dismissed from the university compared to participating students subsequently dismissed, felt motivated to succeed and confidence in their ability to handle the stresses of college. However, this study is merely descriptive and cannot estimate causal effects of mentoring on non-self-reported outcomes that are imperative to persisting, such as semester GPA and credit hours accumulated. Altogether, the effects of mentoring programs for students on academic probation are limited and lack rigor, and as universities and colleges develop programs, there needs to be a greater depth of research literature to guide the development process.

We evaluate a standalone mentoring program where peer-mentors meet one-on-one with undergraduates on academic probation, contributing to the literature in two ways. First, we expand upon the limited literature on mentoring support programs for students on academic probation by being the first to use a highly rigorous research design in evaluating the effects of peer-mentors on undergraduates who are on academic probation. Second, to our knowledge, we evaluate the first mentoring program for students on academic probation whose sole support is a peer mentor as opposed to students supported jointly by mental health professionals, academic advisors, and peer mentors.

The BounceBack Mentoring Program

In the fall semester of 2017, The University of Arkansas created the Student Talent Enrichment Program (STEP) with the goal of improving the retention of first-year students. One program developed from STEP was the BounceBack Mentoring Program, which is the focus of our review.

The BounceBack Mentoring program was designed to help facilitate college success for students on academic probation, who were on the verge of failure. The university placed students who entered the university in the fall of 2017 and earned a GPA below 2.0 in that semester on academic probation in the subsequent semester (i.e., spring 2018). After the spring 2018 semester, the university placed those students who did not raise their term GPA above 2.0 on academic suspension, which prevents them from re-enrolling at the university for one semester. For those students that earned a spring term GPA above a 2.0, but did not earn a cumulative GPA above a 2.0, they were allowed to continue their enrollment at the university while staying on academic probation. Lastly, students who earned a spring term GPA above 2.0 and earned a cumulative GPA above 2.0 shifted off of academic probation onto good academic standing. Program administrators restricted eligibility to full-time, degree-seeking, first-year students at the university who in the fall of 2017 earned a GPA below a 2.0 and then enrolled for the spring 2018 semester.

At the start of the spring 2018 semester, program administrators contacted all students whose fall 2017 GPA was below a 2.0 via phone and email and informed them of their eligibility for the BounceBack Mentoring Program. The program then assigned all eligible freshmen a peer mentor (either a non-freshman undergraduate or a graduate student at the university) to offer them one-on-one assistance during the spring semester of the 2017-18 academic year. Mentors and mentees met in small groups for the first meeting and over the course of the semester met one-on-one for bi-weekly meetings, totaling six sessions.[16] Meeting topics included goal setting, making schedules, using syllabi as semester road maps, organization and time management strategies, understanding learning styles, course assignment help, personal reflection, and study plans for finals. Mentors reported a summary of the discussion, resources referenced, ideas for next steps, and any additional notes to program administrators after each mentor meeting or interaction. Overall, mentors reported seeking to be a part of their mentees' on-campus support network by sharing their experiences, success strategies, and advice from their freshman year. Our analysis covers program effects on a student's spring 2018 semester GPA, spring 2018 accumulated credit hours, the probability of being on good academic standing after the spring 2018 semester and the probability of persisting to the fall 2018 semester.

Research Methodology

Data and Sample

The goal of this evaluation is to determine if qualifying for the BounceBack Mentoring program increases a student's academic performance and his or her probability of continuing in college. We use a regression discontinuity design (RDD) because through a continuous forcing variable—fall 2017 semester GPA, students are assigned to the program, making an RDD appropriate. The RDD assumes that individuals with similar GPAs around the 2.0 GPA cutoff are comparable to one another and allows for the estimation of a marginal average treatment effect for those undergraduates around the cut-off (Thistlethwaite & Campbell, 1960).

[16] Program administrators reported all students participating in the program attended at least one session.

Program administrators provided us with administrative records for 749 students, and of these, 418 were ineligible for the program because they possess a fall 2018 semester GPA above a 2.0. The 749 students represent all students from the fall 2018 cohort who earned a fall 2018 semester GPA below a 2.0 and the next 400 or so students in the entire freshman cohort whose GPA was just above the 2.0 cutoff[17]. The data include student high school academic records, demographics, family characteristics, collegiate academic records, collegiate credit accumulation, and family financial status. To better control for potential differences among students induced by socio-economic status, at times we restricted our sample to Free Application for Federal Student Aid (FAFSA) filers. The FAFSA allows an individual to apply for financial aid at higher education institutions or career schools. When an individual completes a FAFSA, an expected family contribution (EFC), which is an estimation of how much a family can financially contribute to a college education, is produced. However, filing a FAFSA was not a requirement for the BounceBack program, and the inclusion of such controls reduces our sample size and study power, which is a limitation of our study. So in order to increase statistical study power, we ran additional analyses including non-FAFSA filers in supplementary robustness checks.

Table 1 reports descriptive statistics for the entire sample. The first column contains the sample size, the second column presents the mean, and the final column presents the standard deviation. From Table 1, we see that our sample contains more males (58%) than females (42%) and is majority white (76%). This is roughly comparable to all full-time freshman at the university who enrolled in the fall 2017, who were male (46%) and identified as white (77%).[18]

[17] Program administrators chose this section of students above the cutoff because it encapsulated students inside and outside the suggested bandwidth.
[18] https://oir.uark.edu/students/enrollment-reports.php

Additionally, just over 25% of our sample are first-generation students, the group has an average high school GPA of about 3.4, which is a B average, but their cumulative GPA for the fall 2017 semester in college is 1.83, just under a C average. Also, about 35% of the sample are in families whose EFC is between $0 and $6,000.

Further, Table 1 shows results from t-tests of the difference in means between the qualifying group and the control group for the analytic sample within our preferred (+/- 0.25) point bandwidth.[19] Column 4 contains the sample size, columns 5 and 6 present qualifying and control means, column 7 presents the difference in means, and the final column presents the standard errors of those differences. There is no difference between the qualifying and control groups on the majority of demographics, excluding fall 2017 cumulative GPA and EFC from $10,757 to $17,389. We would expect to see a difference in fall 2017 cumulative GPA because of the 2.0 cutoff in qualifying for the program. However, the observed difference in EFC is surprising, and we control for the difference in the coming models.

Table 1

Descriptive Statistics for the Full Sample and Difference of Means Between the Qualifying and Control Groups for the Analytic Sample

	Full Sample			Analytic Sample: Bandwidth (+/- 0.25)				
	N	Mean	SD	N	Qualifying Mean	Control Mean	Difference	SE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	749	0.42	0.49	261	0.488	0.446	0.043	0.066
Ethnicity								
African American	749	0.07	0.25	261	0.058	0.074	-0.016	0.033
White	749	0.76	0.43	261	0.721	0.703	0.018	0.060

[19] A bandwidth of (+/- 0.25) points was chosen following Ost, Pan and Webber (2018) and their use of the bandwidth for a sharp RDD design for a sample of low-performing undergraduate students. We check the selection following the methods of Calanico et al., 2017 and produce a computer-generated optimal bandwidth for a first-order polynomial adjusted for covariates. The optimal bandwidth delivered was 0.269, we stay with a 0.25 bandwidth because of the ease of interpretation as it relates to GPA units.

Table 1 (Cont.)

	Full Sample			Analytic Sample: Bandwidth (+/- 0.25)				
	N	Mean	SD	N	Qualifying Mean	Control Mean	Difference	SE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Other	749	0.08	0.28	261	0.058	0.114	-0.056	0.039
HS GPA	749	3.38	0.34	261	3.398	3.400	-0.002	0.044
ACT	748	24.55	3.35	260	24.430	24.178	0.252	0.440
First Generation	749	0.27	0.44	261	0.302	0.240	0.062	0.058
Fall 17' Cumulative GPA	749	1.83	0.68	261	1.854	2.124	-0.270***	0.010
Expected Family Contribution								
Less than $1	596	0.16	0.37	200	0.209	0.128	0.081	0.054
From $1 to $2,095	596	0.10	0.30	261	0.060	0.090	-0.031	0.041
From $2,096 to $5,683	596	0.09	0.28	261	0.045	0.068	-0.023	0.036
From $5,684 to $10,756	596	0.09	0.29	261	0.060	0.113	-0.053	0.044
From $10,757 to $17,389	596	0.09	0.28	261	0.179	0.090	0.089*	0.049
From $17,390 to $26,040	596	0.10	0.30	261	0.060	0.090	-0.031	0.041
From $26,041 to $39,072	596	0.09	0.29	261	0.104	0.113	-0.008	0.047
From $39,073 to $68,327	596	0.12	0.32	261	0.104	0.105	-0.001	0.046
More than $68,328	596	0.16	0.37	261	0.179	0.203	-0.024	0.060
Not Reported	749	0.20	0.40	261	0.221	0.240	-0.019	0.056

Notes: Other ethnicity includes Asian, Foreign, Hawaiian, Indian, Two or More, Hispanic, and not reported. *p<.10. **p<.05. ***p<.01.

Analytic Strategy

There are four conditions or features of a research setting that are conducive to a sharp RDD (Page, Castleman, & Sahadewo, 2016; Schochet et al., 2010). First, the selection process should be transparent, thereby providing a clear understanding of how individuals qualify for treatment. Second, program receipt should unwaveringly follow the transparent selection process. Following the transparent selection process assures one that other factors are not manipulating selection in and out of treatment. Third, jumps in the outcomes of interest around the cutoff cannot be associated with other potential mechanisms, besides the mechanism of fall 2017 GPA. Results may be biased and lead to incorrect interpretations of the impact of qualifying when different mechanisms have visible jumps in their densities at the cutoff, which suggests that other mechanisms potentially influenced the outcome. Finally, there should be a continuity in the density of fall 2017 GPA around the cutoff because a discontinuity in the density could suggest a non-random manipulation of fall 2017 GPA.

Figure 1 shows a visualization of the relationship between the fall 2017 GPA at the known cutoff, qualifying, and receipt of the BounceBack Mentoring Program. The solid black line represents the 2.0 GPA cutoff, the red triangles represent individuals who have a fall 2017 GPA below 2.0, and the gold Xs represent individuals who have a fall 2017 GPA above a 2.0. The selection process has a high rate of fidelity since 326 of the 331 students whose GPA is below a 2.0 participate in the program[20]. Due to this evidence of strong compliance, we estimate our primary models as a sharp RDD. However, to account for non-compliance, we estimate a fuzzy RDD as a specification check by instrumenting receipt of the program through qualifying

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[20] The five non-compliers received 0 credit hours for the fall semester, which via university policy exempts them from being placed on academic probation.

for to the program, defined by having a GPA below 2.0. Overall, there is no substantive difference between the two models.

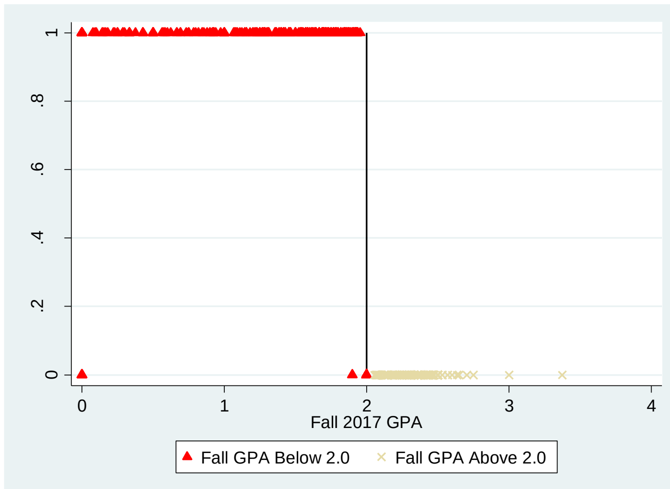

Figure 1: Relationship between Fall 2017 semester GPA and receipt of the BounceBack mentoring program. Overall, there is limited evidence of non-compliance.

Figure 2 shows the relationship between fall 2017 GPA and four outcomes of interest: spring 2018 GPA, spring 2018 credits, the probability of being in good academic standing after the spring 2018 semester, and the probability of fall 2018 retention. We restrict the sample to a (+/- 0.75) point bandwidth[21] (1.25 GPA to 2.75 GPA) on either side. Here we take an initial look at what the effects of the BounceBack program may be, presented using local linear regressions[22]. Qualifying for the program looks to have a moderately positive impact on spring 2018 GPA and a small positive impact on credits earned, but an adverse impact on being in good academic standing after the spring 2018 semester and fall 2018 retention. Since qualifying does not equal receipt of the program, these results represent the effect of having a GPA below 2.0 not

[21] We choose a bandwidth of 0.75 because it is the largest bandwidth analyzed.

[22] Local linear regressions fit a different individual linear regression function to the observations on either side of the cutoff, instead of fitting the same linear function across either side of the cutoff.

an effects of the BounceBack Mentoring program. Additionally, the figures show the linear relationship between our four outcomes and fall 2017 GPA, which guides our subsequent model selection.

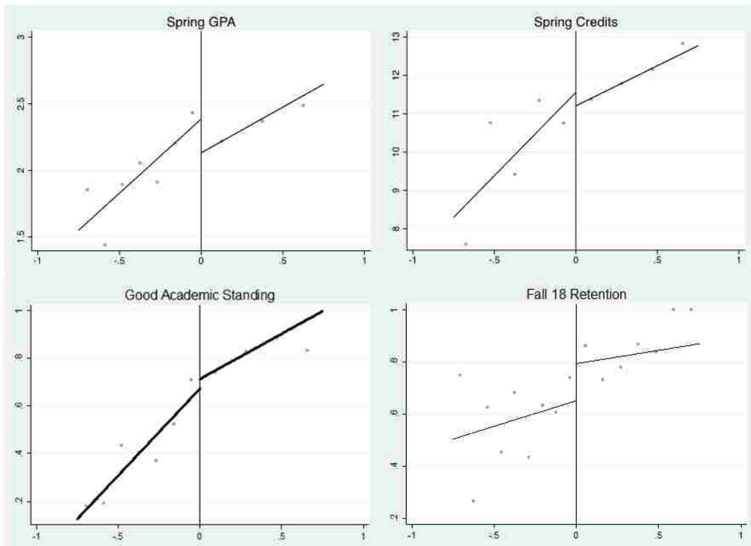

Figure 2: This figure shows outcome measures regressed on Fall 2017 GPA inside of a (+/- 0.75) bandwidth.

Next, we look for the presences of other potential mechanisms influencing the various jumps in our outcomes. Possible jumps caused by different mechanisms, such as demographics, could reference the presence of manipulation and in turn bias our results. Table 1, presents the difference in means of student demographics between the qualifying group and control group in our preferred (+/- 0.25) point bandwidth. A statistically significant difference in means would suggest manipulation or disproportionate influence of outcomes by student demographics. As seen in Table 1, there are no observable differences beyond fall 2017 GPA and EFC of $10,757 to $17,389.

Last, we evaluate the density of fall 2017 GPA around the 2.0 cutoff. Figure 3 shows the density of individuals around the re-centered GPA cutoff, signified by the solid black line, within

0.10 GPA bins. Observing a smooth density of fall 2017 GPA around the cutoff would reduce the potential presence of manipulation. Unfortunately, we see a significant bump in density just above the cutoff, representing a possible manipulation of the forcing variable.

The presence of such an increase in the density of individuals above the 2.0 GPA cutoff is not an uncommon occurrence (Ost, Pan, & Webber, 2018). Since it is the university's standard academic policy that a 2.0 GPA is the cutoff for academic probation placement, we can assume that students would work hard to maintain it at the very least and professors might be inclined to award a 2.0 to help students' who have shown effort. Nevertheless, due to the failure to detect drastic differences in observables seen in Table 1 we believe that students inside our preferred bandwidth are similar to one another on observables and unobservables characteristics, and a sharp RDD would still be appropriate. However, we conduct a "donut" RDD as a robustness check. The donut regression removes those individuals at the bump in density precisely at the cutoff from the estimation and produces unbiased estimates accounting for potential manipulation of of fall 2017 GPA and possible differences in unobservable characteristics (Barreca, Lindo, & Waddell., 2016; Barreca et al., 2011).

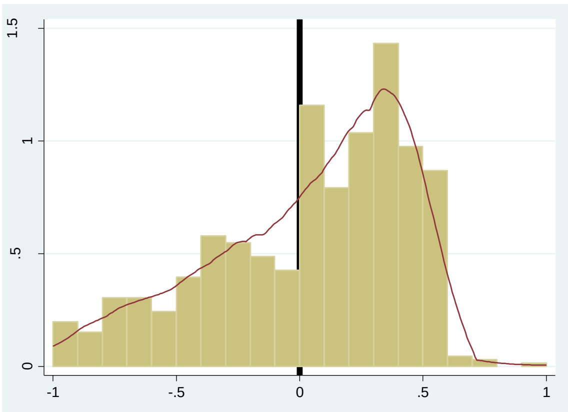

Figure 3: This figure shows the density of our recentered Fall 2017 GPA, forcing variable, within 0.1 GPA bins. Overall, this figure shows the bump in density just above the cutoff.

Hallmarks of an ideal RDD include a transparent and consistent use of a selection process to facilitate receipt of the program, no observable presence of covariate manipulation at the cutoff and sufficient density of the forcing variable around the cutoff. While our empirical situation does not perfectly satisfy these requirements, our primary analysis employs a sharp RDD because we only deviate from these standards slightly. Moreover, we run a series of robustness checks in the forthcoming sections to observe if our deviations from the standards significantly impact our analysis. Subsequently, we follow previous literature (Page, Castleman, & Sahadewo, 2016) and estimate the effect of assignment to the BounceBack Mentoring program through the following reduced-form model:

$$Y_i = \beta_0 + \beta_1 Qualify_i + \beta_2 CenGPA_i + \beta_3 (Qualify_i * CenGPA_i) + \boldsymbol{X}_{\boldsymbol{i}}' \beta_4 + \varepsilon_i \quad (1)$$

where Y_i is one of our outcomes of interest; $Qualify_i$ represents qualifying for the BounceBack Mentoring program (i.e. *having a fall 2017 GPA below 2.0*), $CenGPA_i$ represents fall 2017 GPA recentered at the 2.0 GPA cutoff, $\boldsymbol{X'_i}$ is a vector of covariates identifying student gender, ethnicity, standardized high GPA, first-generation status, and EFC, and ε_i represents the error term clustered at the college level. The inclusion of the interaction between $Qualify_i$ and $CenGPA_i$ allows for the slopes of the regression line to differ on either side of the fall 2017 GPA cutoff.

We estimate the model using a local linear regression framework. Alternatively, we could use quadratic terms to adjust for any non-linearity in our data, but guided by the linear relationship between fall 2017 GPA and our outcomes seen in Figure 2; we prefer linear. We evaluate the choice between a linear and a quadratic framework using the Akaike Information

Criterion (AIC)[23] and fail to find the need for the introduction of quadratic terms (Jacob et al., 2012). Additionally, we do not use higher order polynomials, often introduced to reduce bias in large samples (Card et al., 2014) because inside our small sample size using higher order polynomials could overfit our data (Gelman & Imbens, 2017; Cattaneo, Idrobo, & Titiunik, 2018).

Results

In this section, we present the estimated effects of qualifying for the BounceBack Mentoring program on related college outcomes for students whose first semester GPA was below the 2.0 threshold. Due to our high rate of compliance, we use a sharp RDD estimation approach. In general, we find that qualifying for the BounceBack program has effects that are indistinguishable from zero on all outcomes, but we believe that our null findings are reflective of low statistical power rather than true null effects. However, because of the program design, we cannot distinguish the difference between the effect of academic probation from the BounceBack mentoring program. In spite of this limitation, the BounceBack mentoring program could be reducing the historical negative effect of academic probation experienced by previous cohorts, which is something we explore. In the following section, we present estimated effects of the BounceBack program on spring 2018 GPA, spring 2018 cumulative credit hours, the probability of being in good academic standing after the spring 2018 semester and the probability of fall 2018 retention.

[23] AIC measures model fit.

Table 2 presents the estimated effect of qualifying for the BounceBack program on our outcomes of interest inside of our preferred (+/- 0.25) point bandwidth.[24] Each estimation includes a simple model that does not control for demographics in odd-numbered columns and a sophisticated model that includes student demographic covariates in even-numbered columns.

On the whole, we observe no statistically significant effects. While effects for spring 2018 semester GPA suggest a positive effect, the estimated effects are not statistically significant. Results suggest positive effects of about a 0.25 point increase in GPA associated with the program, however, it is not statistically significant, seen in column 2. Additionally, for our complex models, qualifying for the program increased the number of accumulated credit hours by 0.32 points and increased the probability of being in good academic standing by about 13 percentage points, but the effects are not statistically significant. However, qualifying for the program reduced the probability of fall 2018 enrollment by about ten percentage points, while not being statistically significant.

[24] Estimated effects were produced for a computer generated optimal bandwidth and are virtually the same as effects inside the preferred bandwidth. Results for the optimal bandwidth can be found in Appendix Table A1.

Table 2

RDD Estimated Effects using the Preferred Bandwidth

	Spring 18 Term GPA		Spring 18 Accumulated Credits		Good Academic Standing		Fall 18 Enrollment	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Qualify	0.212	0.248	-0.222	0.324	0.114	0.131	-0.070	-0.109
	(0.320)	(0.318)	(0.515)	(1.474)	(0.161)	(0.139)	(0.106)	(0.073)
Centered Fall 2017 GPA	-0.074	0.405	-0.161	3.988	0.521	0.672	-0.609	-0.331
	(1.115)	(1.334)	(6.227)	(7.132)	(0.308)	(0.434)	(0.395)	(0.222)
Interaction	1.197	-0.188	-0.151	-8.896	1.126	0.680	1.672*	0.503
	(2.886)	(2.944)	(10.44)	(9.095)	(1.469)	(1.561)	(0.699)	(0.689)
Female		0.167		1.183*		0.065		0.050
		(0.142)		(0.494)		(0.086)		(0.087)
African American		-0.259		-2.118		0.100		-0.203*
		(0.273)		(1.330)		(0.154)		(0.098)
Other Race		0.211		1.751		0.049		0.132
		(0.258)		(1.224)		(0.124)		(0.109)
Standardized HS GPA		0.135**		0.535		0.035		0.006
		(0.052)		(0.385)		(0.022)		(0.050)
First Generation		-0.218		-1.064		-0.110		-0.0732
		(0.297)		(1.264)		(0.113)		(0.108)
EFC - Less than $1		-0.152		-1.402		-0.114		-0.169*
		(0.135)		(0.696)		(0.104)		(0.072)
EFC - From $1 to $2,095		-0.080		-1.551		-0.018		0.044
		(0.502)		(1.491)		(0.123)		(0.084)
EFC - From $2,096 to $5,683		-0.343**		-2.334**		-0.194		-0.094
		(0.111)		(0.777)		(0.137)		(0.135)
EFC - From $5,684 to $10,756		-0.011		-0.729		-0.136		-0.143
		(0.339)		(1.102)		(0.085)		(0.101)

Table 2 (Cont.)

	Spring 18 Term GPA		Spring 18 Accumulated Credits		Good Academic Standing		Fall 18 Enrollment	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EFC - From $10,757 to $17,389		-0.341		-2.962**		-0.108**		-0.186*
		(0.288)		(0.988)		(0.035)		(0.088)
EFC - From $17,390 to $26,040		-0.129		-1.413		0.036		-0.212
		(0.397)		(1.260)		(0.097)		(0.146)
EFC - From $26,041 to $39,072		0.078		-1.544		0.106*		-0.054
		(0.109)		(0.897)		(0.048)		(0.101)
EFC - From $39,073 to $68,327		0.153		-1.377		0.050		0.021
		(0.316)		(0.728)		(0.086)		(0.060)
Bandwidth	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
Observations	261	200	261	200	261	200	261	200

Notes: Standard errors in parentheses are clustered at the college level (6 clusters). Interaction is the interaction between qualify and the recentered Fall 2017 GPA. All models are estimated within a bandwidth of (+/- 0.25) points. *** p<0.01, ** p<0.05, * p<0.1

Due to the limitations of not being able to distinguish the effect of being on academic probation from the effect of the BounceBack mentoring program, we add a supplementary analysis evaluating the effect of probation absent of a mentoring program across ten cohorts of incoming first-year students. This analysis provides a comparative understanding of the individual effect of being on academic probation. Using data for all incoming freshmen at the University of Arkansas, whom had in-state residency and entered the university in the fall between 2003 to 2012, we estimate model (1)[25] on a student's cumulative GPA in the spring semester, the probability of being in good academic standing at the end of their spring semester, and the probability of persisting to the fall of their sophomore year.

Table 3 presents the estimated effects of qualifying for academic probation (i.e., earning a GPA below 2.0) on the aforementioned outcomes of interest inside our preferred (+/- 0.25) point bandwidth for entering freshmen from 2003 to 2012. Also, the table contains our original estimates from Table 2. As observed, before the introduction of the BounceBack Program, qualifying for academic probation had an indistinguishable effect on spring cumulative GPA. However, qualifying for probation reduced a student's probability of being in good academic standing after the spring semester by about 11 percentage points, while increasing the probability of persisting to their sophomore year by about 4.5 percentage points, both statistically significant. Comparing these effects to our original estimates, it appears the BounceBack program has softened the negative relationship students experience between being on academic probation and the probability of being in good academic standing at the end of their spring semester. However, it appears that the program has dissipated any positive effect that previous

[25] We control for student gender, ethnicity, first-generation status, Pell grant eligibility, standardized high school GPA and cohort year dummies.

cohorts experienced in the probability of returning to the University the following year. The potential differences across cohorts could explain this counterintuitive finding.

Table 3

The Longitudinal Effects of Academic Probation Prior to the BounceBack Mentoring Program

	Analytic Sample: Bandwidth (+/- 0.25)		
		Freshman Cohorts from 2003 to 2012	
	Spring Cumulative GPA	Good Academic Standing	Sophomore Enrollment
	(1)	(2)	(3)
Qualifying for probation	0.044	-0.114**	0.045**
	(0.029)	(0.040)	(0.016)
Observations	1,553	1,694	1,694
		Original Estimates	
	Spring Term GPA	Good Academic Standing	Sophomore Enrollment
	(4)	(5)	(6)
Qualifying for probation	0.248	0.131	-0.109
	(0.318)	(0.139)	(0.073)
Observations	200	200	200

Notes: All models include controls for gender, ethnicity, standardized HS GPA, first-generation status, and EFC deciles or Pell grant eligibility. Standard errors in parentheses are clustered at the college level (6 clusters).

Overall, it appears that after one semester of participating in the program, students tend to perform no better or worse than students not assigned to the program. Other programs, such as financial aid and peer advising designed to improve academic outcomes for undergraduates have also failed to make statistically significant changes (Page, Castleman, & Sahadewo, 2016; Ellis & Gershenson, 2016) and could be due to the brevity of the program. A student not prepared academically or socially for college might need more than six mentor meetings over the course of an academic semester to change longstanding habits and mindsets. At the same time, our small sample size could be the source of our failure to detect a distinguishable effect. Furthermore, we cannot separate the effects of mentoring from being on probation because of the design of the program. However, compared to ten previous cohorts of entering freshmen, it appears that the BounceBack program has successfully reduced the negative effect of academic probation on the probability of being on good academic standing after the spring semester, but at the cost of failing to return their sophomore year. Ultimately, our estimates are indistinguishable from zero and should be interpreted as such. In the next section, we evaluate the robustness of our results to various specification checks.

Robustness Checks

Our study has several limitations. First, estimates are only produced within a limited bandwidth, removing a portion of the sample. Second, we have a visible bump in the fall 2017 GPA density around the cutoff. Third, we do not have 100% compliance between qualifying and receipt of the program. Therefore in this section, we evaluate the robustness of our results via four different sensitivity checks: varying bandwidths, "donut" regressions, adjusting for non-compliance through a fuzzy RDD, and increasing our sample size. On the whole, we largely observe statistically non-significant results. At best there may be a positive effect for spring 2018 GPA.

Varying Bandwidths

In the following section, we evaluate the robustness of our results across varying bandwidths. Since the RDD produces estimates inside of a narrow bandwidth, we are actively reducing our sample size and overall precision in our estimates. Thus intending to increase sample size and precision, we expand our bandwidth to various lengths. Estimating the effects across various bandwidths gives us a better understanding of the results seen using our preferred bandwidth and whether they are true effects or underpowered effects.

Table 4 shows the effect of qualifying for the BounceBack Program on spring 2018 cumulative GPA, spring 2018 accumulated credit hours, the probability of being in good academic standing after the spring 2018 semester, and the probability of fall 2018 enrollment estimated with fully specified model (1) on four different bandwidths; (+/- 0.20) points (*1.80 to 2.20 GPA*), (+/- 0.50) points (*1.50 to 2.50 GPA*), (+/- 0.75) points (*1.25 to 2.75 GPA*) and (+/- 0.25) points (*1.75 to 2.25 GPA*) for reference. Turning to spring 2018 GPA, we have a consistent positive effect across all bandwidths, with a statistically significant effect at the (+/- 0.5) point bandwidth. When looking at accumulated credits, we observe a positive effect, but the results increase in size noticeably to our preferred bandwidth in column 5, while not being statistically significant. Thirdly, the effect on the probability of being in good academic standing is statistically significant in the smaller band of (+/- 0.20) points but is indistinguishable from zero as the bandwidth enlarges. Lastly, the effect on the probability of fall 2018 enrollment is negative and statistically non-significant from zero in all bandwidths except the band of (+/- 0.50) points. In general, the observed effects remain nondistinguishable from zero. However, the consistent positive effect observed with spring 2018 GPA is highly suggestive of an underpowered positive effect. Nevertheless, the observed effect is still non-significant and should be interpreted with caution.

Table 4

RDD Estimated Effects of the BounceBack Mentoring Program Across Various Bandwidths

	Spring 18 GPA				Spring 18 Accumulated Credits			
	Original Estimates				Original Estimates			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Qualify	0.248	0.597	0.398***	0.317	0.324	0.947	1.473	0.995
	(0.318)	(0.411)	(0.051)	(0.162)	(1.474)	(2.168)	(1.073)	(0.869)
Centered Fall 2017 GPA	0.405	0.579	0.511**	0.620**	3.988	7.017	1.583	2.163
	(1.334)	(1.255)	(0.180)	(0.203)	(7.132)	(7.953)	(1.496)	(1.414)
Interaction	-0.188	2.854	1.097	0.540	-8.896	-8.753	7.261	3.866
	(2.944)	(2.805)	(0.797)	(0.497)	(9.095)	(10.17)	(5.382)	(3.833)
Demographic and EFC Controls	Yes				Yes			
Bandwidth	(+/- 0.25)	(+/- 0.2)	(+/- 0.5)	(+/- 0.75)	(+/- 0.25)	(+/- 0.2)	(+/- 0.5)	(+/- 0.75)
N	200	140	444	490	200	140	444	490

	Good Academic Standing				Fall 18 Enrollment			
	Original Estimates				Original Estimates			
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Qualify	0.131	0.282**	0.005	-0.050	-0.109	-0.062	0.007	-0.113
	(0.139)	(0.095)	(0.113)	(0.078)	(0.073)	(0.099)	(0.083)	(0.059)
Centered Fall 2017 GPA	0.672	0.779	0.336**	0.347**	-0.331	-1.177	0.032	0.076
	(0.434)	(0.931)	(0.085)	(0.090)	(0.222)	(0.703)	(0.049)	(0.046)
Interaction	0.680	2.162	0.612**	0.333**	0.503	2.210	0.763	0.152
	(1.561)	(1.440)	(0.231)	(0.103)	(0.689)	(1.221)	(0.399)	(0.192)
Demographic and EFC Controls	Yes				Yes			
Bandwidth	(+/- 0.25)	(+/- 0.2)	(+/- 0.5)	(+/- 0.75)	(+/- 0.25)	(+/- 0.2)	(+/- 0.5)	(+/- 0.75)
N	200	140	444	490	200	140	444	490

Notes: All models include controls for gender, ethnicity, standardized HS GPA, first-generation status, and EFC deciles. Standard errors in Parentheses are clustered at the college level (6 clusters). Interaction is the interaction between qualify and the recentered Fall 2017 GPA *p<.10. **p<.05. ***p<.01.

Donut Regression

Due to the observed jump in the density of individuals above the cutoff in Figure 3, we follow the work of Barreca, Lindo, and Waddell (2016) and Barreca et al., (2011) and conducted a "donut" regression analysis to account for any possible manipulation. The donut regression removes those individuals at the bump in density precisely at the cutoff from the estimation and produces unbiased estimates accounting for potential manipulation of the forcing variable (Barreca, Lindo, & Waddell, 2016). We drop students with precisely a 2.0 GPA, losing 31 observations or 4.1% of the total sample and 12% of the analytic sample. Table 5 shows results for these estimations, applying model (1) to the preferred bandwidth sample, and original estimates from Table 2 for reference.

Spring 2018 GPA, the probability of being in good academic standing and the probability of fall 2018 enrollment remain unaffected by the use of the donut regression. For example, qualifying for the program increases spring 2018 cumulative GPA by 0.125 points compared to 0.248 points from the original estimates, but the effect remains statistically non-significant. Next, observed in columns 9 and 12, qualifying for the program increases the probability of being in good academic standing after the spring 2018 semester, but reduces the probability of returning for the fall 2018 semester. Nonetheless, the observed effects are statistically non-significant. However, spring 2018 accumulated credit hours appears to be most affected by the removal of students at the 2.0 cutoff. When estimating a “donut” regression, the estimates are negative and marginally significant. Meaning, students that qualify for the program earn about 1.6 fewer credit hours than students that do not qualify. The observed effect could be predictable because students who qualify for academic probation are often advised to reduce their course load and have a higher probability of dropping challenging classes.

Table 5

Estimates employing the Donut Regression

	Spring 18 GPA			Spring 18 Accumulated Credits			Good Academic Standing			Fall 18 Enrollment		
	Original Estimates	Simple	Complex	Original Estimates	Simple	Complex	Original Estimates	Simple	Complex	Original Estimates	Simple	Complex
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Qualify	0.248	0.020	0.125	0.324	-2.432*	-1.691*	0.131	0.089	0.112	-0.109	-0.030	-0.031
	(0.318)	(0.399)	(0.319)	(1.474)	(1.081)	(0.830)	(0.139)	(0.201)	(0.179)	(0.073)	(0.136)	(0.128)
Centered Fall 2017 GPA	0.405	-1.153	-0.733	3.988	-12.63*	-9.444	0.672	0.375	0.454	-0.331	-0.384	0.062
	(1.334)	(1.010)	(1.812)	(7.132)	(5.715)	(9.612)	(0.434)	(0.220)	(0.425)	(0.222)	(0.482)	(0.624)
Interaction	-0.188	2.276	1.424	-8.896	12.32	6.867	0.680	1.272	0.973	0.503	1.447	0.161
	(2.944)	(2.505)	(3.415)	(9.095)	(7.934)	(13.78)	(1.561)	(1.284)	(1.585)	(0.689)	(0.799)	(1.173)
Female	0.167		0.029	1.183*		0.611	0.065		0.038	0.050		0.040
	(0.142)		(0.214)	(0.494)		(0.404)	(0.086)		(0.100)	(0.087)		(0.092)
African American	-0.259		-0.162	-2.118		-2.212	0.100		0.242	-0.203*		-0.196
	(0.273)		(0.344)	(1.330)		(1.529)	(0.154)		(0.133)	(0.098)		(0.115)
Other Ethnicity	0.211		0.113	1.751		1.656	0.049		0.040	0.132		0.116
	(0.258)		(0.241)	(1.224)		(1.171)	(0.124)		(0.095)	(0.109)		(0.103)
Standardized HS GPA	0.135**		0.115	0.535		0.517	0.035		0.034	0.006		0.005
	(0.052)		(0.062)	(0.385)		(0.378)	(0.022)		(0.025)	(0.050)		(0.051)
First Generation	-0.218		-0.283	-1.064		-1.159	-0.110		-0.157	-0.073		-0.084
	(0.297)		(0.321)	(1.264)		(1.259)	(0.113)		(0.107)	(0.108)		(0.118)
EFC - Less than $1	-0.152		-0.032	-1.402		-0.537	-0.114		-0.122	-0.169*		-0.136
	(0.135)		(0.114)	(0.696)		(0.585)	(0.104)		(0.074)	(0.072)		(0.095)
EFC - From $1 to $2,095	-0.080		-0.127	-1.551		-1.916	-0.018		-0.087	0.044		0.038
	(0.502)		(0.587)	(1.491)		(1.559)	(0.123)		(0.176)	(0.084)		(0.102)

Table 5 (Cont.)

	Spring 18 GPA			Spring 18 Accumulated Credits			Good Academic Standing			Fall 18 Enrollment		
	Original Estimates	Simple	Complex	Original Estimates	Simple	Complex	Original Estimates	Simple	Complex	Original Estimates	Simple	Complex
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
EFC - From $2,096 to $5,683	-0.343**		-0.226	-2.334**		-1.726*	-0.194		-0.150*	-0.094		-0.086
	(0.111)		(0.136)	(0.777)		(0.692)	(0.137)		(0.063)	(0.135)		(0.153)
EFC - From $5,684 to $10,756	-0.011		-0.009	-0.729		-0.308	-0.136		-0.161	-0.143		-0.176
	(0.339)		(0.402)	(1.102)		(1.312)	(0.085)		(0.107)	(0.101)		(0.107)
EFC - From $10,757 to $17,389	-0.341		-0.324	-2.962**		-2.779*	-0.108**		-0.120***	-0.186*		-0.218
	(0.288)		(0.243)	(0.988)		(1.159)	(0.035)		(0.028)	(0.088)		(0.109)
EFC - From $17,390 to $26,040	-0.129		0.105	-1.413		-0.650	0.036		0.080	-0.212		-0.167
	(0.397)		(0.312)	(1.260)		(2.013)	(0.097)		(0.070)	(0.146)		(0.192)
EFC - From $26,041 to $39,072	0.078		0.116	-1.544		-1.602	0.106*		0.136**	-0.054		-0.079
	(0.109)		(0.128)	(0.897)		(1.110)	(0.048)		(0.051)	(0.101)		(0.091)
EFC - From $39,073 to $68,327	0.153		0.072	-1.377		-1.485	0.050		0.004	0.021		0.031
	(0.316)		(0.331)	(0.728)		(0.835)	(0.086)		(0.087)	(0.060)		(0.065)
Observations	200	230	176	200	230	176	200	230	176	200	230	176

Notes: Standard errors in parentheses are clustered at the college level, (6 clusters). Other ethnicity includes Asian, Foreign, Hawaiian, Indian, Two or More, Hispanic, and not reported. Interaction is the interaction between qualify and the recentered Fall 2017 GPA. *p<.10. **p<.05. ***p<.01.

Accounting for Non-Compliance Through a Fuzzy RDD

We conducted our primary analysis as a sharp RDD despite evidence of non-compliance. Even though we have about 98% compliance between qualifying and receiving treatment, the sharp RDD produces effects measuring the impact of qualifying for the program independent of receiving the treatment. Thus to adjust for students who qualified for the program but did not participate; we conduct a fuzzy RDD. In the fuzzy RDD, qualifying for the program first predicts receipt of the mentoring program and is estimated inside our preferred bandwidth using the following model:

$$Receipt_i = \beta_0 + \beta_1 Qualify_i + \beta_2 CenGPA_i + \beta_3 (Qualify_i * CenGPA_i) + \beta_4 X_i + \varepsilon_i \qquad (2)$$

$$Y_i = \beta_0 + \beta_1 \widehat{Receipt}_i + \beta_2 CenGPA_i + \beta_3 (Qualify_i * CenGPA_i) + \beta_4 X_i + \varepsilon_i \qquad (3)$$

where $Receipt_i$ represents assignment to a mentor in the program and $\widehat{Receipt}_i$ represents the causal effect of participating in the BounceBack program. The additional variables are consistent with the specifications explained in model (1).

Table 6 shows the first stage results of our fuzzy RDD analysis. As expected we see that assignment to the program is a strong predictor of receipt ranging from about 95% to 97%. Additionally, we have adequate joint F-statistics across all models according to Staiger and Stock’s (1997) recommended standard of 10, suggesting instrument relevance.

Table 6

First Stage Regression Results

	Spring 18 GPA		Spring 18 Accumulated Credits		Good Academic Standing		Fall 18 Enrollment	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Qualify	0.968***	0.953***	0.968***	0.953***	0.968***	0.953***	0.968***	0.953***
	(0.019)	(0.026)	(0.019)	(0.026)	(0.019)	(0.026)	(0.019)	(0.026)
Demographic and EFC Controls		X		X		X		X
Joint F-Statistic	2549.33	1349.68	2549.33	1349.68	2549.33	1349.68	2549.33	1349.68
Observations	261	200	261	200	261	200	261	200
R-squared	0.983	0.979	0.983	0.979	0.983	0.979	0.983	0.979

Notes: All models include recentered Fall 2017 GPA, an interaction term between qualify and the recentered Fall 2017 GPA. Demographic and EFC controls include gender, ethnicity, standardized HS GPA, first-generation status, and EFC deciles. Standard errors in parentheses are clustered at the college level, (6 clusters). All models have Joint F-Statistics above 10. *p<.10. **p<.05. ***p<.01.

Table 7 shows the estimates of actual receipt of the BounceBack program. As compared to the sharp RDD estimates, the estimates shown here account for students whose GPA was below 2.0 but did not participate in the program. Results for the fully specified models almost mirror the results found in Table 2 but are larger in magnitude because of the adjustment for non-compliance. While we do not have a true sharp RDD, the results for the fuzzy RDD justify that we are close to a sharp RDD and that non-compliance does not overly influence our original estimates. Such consistency is promising for our main model specification results, especially so for spring 2018 cumulative GPA because it suggests true program effects not influenced by non-compliers.

Table 7
Estimated Effect of Receipt of the BounceBack Program

	Spring 18 Term GPA			Spring 18 Accumulated Credits			Good Academic Standing			Fall 18 Enrollment		
	Original Estimates	Simple	Complex	Original Estimates	Simple	Complex	Original Estimates	Simple	Complex	Original Estimates	Simple	Complex
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Receipt		0.219	0.260		-0.229	0.340		0.118	0.137		-0.072	-0.114
		(0.312)	(0.346)		(1.662)	(1.868)		(0.143)	(0.162)		(0.136)	(0.153)
Qualify	0.248			0.324			0.131			-0.109		
	(0.318)			(1.474)			(0.139)			(0.073)		
Centered Fall 2017 GPA	0.405	-0.074	0.404	3.988	-0.161	3.987	0.672	0.521	0.672	-0.331	-0.609	-0.331
	(1.334)	(0.908)	(0.989)	(7.132)	(4.830)	(5.338)	(0.434)	(0.415)	(0.463)	(0.222)	(0.394)	(0.437)
Interaction	-0.188	1.228	-0.125	-8.896	-0.184	-8.813	0.680	1.143	0.713	0.503	1.662*	0.475
	(2.944)	(1.963)	(2.132)	(9.095)	(10.45)	(11.50)	(1.561)	(0.898)	(0.997)	(0.689)	(0.852)	(0.943)
Female	0.167		0.168	1.183*		1.184	0.065		0.066	0.050		0.050
	(0.142)		(0.135)	(0.494)		(0.730)	(0.086)		(0.063)	(0.087)		(0.060)
African American	-0.259		-0.264	-2.118		-2.125	0.100		0.097	-0.203*		-0.201*
	(0.273)		(0.261)	(1.330)		(1.407)	(0.154)		(0.122)	(0.098)		(0.115)
Other Ethnicity	0.211		0.208	1.751		1.747	0.049		0.047	0.132		0.134
	(0.258)		(0.231)	(1.224)		(1.246)	(0.124)		(0.108)	(0.109)		(0.102)
Standardized HS GPA	0.135**		0.138*	0.535		0.538	0.035		0.036	0.006		0.005
	(0.052)		(0.073)	(0.385)		(0.393)	(0.022)		(0.034)	(0.050)		(0.032)
First Generation	-0.218		-0.215	-1.064		-1.059	-0.110		-0.108	-0.073		-0.075
	(0.297)		(0.164)	(1.264)		(0.887)	(0.113)		(0.077)	(0.108)		(0.073)
EFC - Less than $1	-0.152		-0.143	-1.402		-1.390	-0.114		-0.109	-0.169*		-0.173
	(0.135)		(0.249)	(0.696)		(1.341)	(0.104)		(0.116)	(0.072)		(0.110)
EFC - Less than $2,095	-0.080		-0.080	-1.551		-1.551	-0.018		-0.018	0.044		0.044
	(0.502)		(0.272)	(1.491)		(1.468)	(0.123)		(0.127)	(0.084)		(0.120)

Table 7 (Cont.)

	Spring 18 Term GPA			Spring 18 Accumulated Credits			Good Academic Standing			Fall 18 Enrollment		
	Original Estimates	Simple	Complex	Original Estimates	Simple	Complex	Original Estimates	Simple	Complex	Original Estimates	Simple	Complex
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
EFC - Less than $5683	-0.343**		-0.343	-2.334**		-2.335	-0.194		-0.194	-0.094		-0.094
	(0.111)		(0.310)	(0.777)		(1.674)	(0.137)		(0.145)	(0.135)		(0.137)
EFC - Less than $10,756	-0.011		-0.010	-0.729		-0.727	-0.136		-0.135	-0.143		-0.144
	(0.339)		(0.259)	(1.102)		(1.395)	(0.085)		(0.121)	(0.101)		(0.114)
EFC - Less than $17,389	-0.341		-0.343	-2.962**		-2.964**	-0.108**		-0.109	-0.186*		-0.186*
	(0.288)		(0.239)	(0.988)		(1.289)	(0.035)		(0.112)	(0.088)		(0.106)
EFC - Less than $26,040	-0.129		-0.129	-1.413		-1.413	0.036		0.036	-0.212		-0.212*
	(0.397)		(0.275)	(1.260)		(1.482)	(0.097)		(0.128)	(0.146)		(0.121)
EFC - Less than $39,072	0.078		0.0782	-1.544		-1.545	0.106*		0.106	-0.054		-0.054
	(0.109)		(0.243)	(0.897)		(1.312)	(0.048)		(0.114)	(0.101)		(0.108)
EFC - Less than $68,327	0.153		0.153	-1.377		-1.376	0.050		0.050	0.021		0.021
	(0.316)		(0.247)	(0.728)		(1.332)	(0.086)		(0.115)	(0.060)		(0.109)
Observations	200	261	200	200	261	200	200	261	200	200	261	200

Notes: Standard errors in parentheses are clustered at the college level, (6 clustered). Other ethnicity includes Asian, Foreign, Hawaiian, Indian, Two or More, Hispanic, and not reported. Interaction, is the interaction between qualify and the recentered Fall 2017 GPA. *p<.10. **p<.05. ***p<.01.

Sample Expansion

In this section, we attempt to improve our study power by increasing our sample size using two approaches. In our first attempt to increase our sample size, we include students who did not file a FAFSA. FAFSA completion is not required to enroll at the University nor to participate in the program. Thus some students within our specified bandwidth lack an expected family contribution, produced by filing a FAFSA, which serves as a control for socioeconomic status, and are not included in our analytic sample. We include these observations while estimating models with dummy variables identifying filing a complete FAFSA, starting to file but not completing the FAFSA, and neither starting or filing a FAFSA[26]. This approach allows us to include students previously excluded from the analysis. In our last attempt to expand our sample size, we run various specifications of model (1), disregarding specific bandwidths to include everyone in our full sample.

Sample Expansion Including Non-FAFSA Fillers

Table 8 shows results for model specification (1), including an additional 61 non-FAFSA filers within our preferred (+/- 0.25) point bandwidth. The effect on spring 2018 GPA remains similar to our main findings in Table 2; the effect on spring 2018 credits is negative and non-significant compared to the original estimates which were positive and non-significant; the effect on good academic standing is positive and non-significant, similar to the original estimates and, the effect on fall 2018 enrollment reduces in magnitude but does not switch direction. Overall, it appears that students not included in the original estimation have a small impact on our findings, but the effects remain indistinguishable from zero.

[26] Neither starting or filling a FAFSA represents the reference category in the analysis.

Table 8

RDD Analysis Including non-FAFSA fillers

	Spring 18 GPA		Spring 18 Accumulated Credits		Good Academic Standing		Fall 18 Enrollment	
	Original Estimates		Original Estimates		Original Estimates		Original Estimates	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Qualify	0.248	0.151	0.324	-0.237	0.131	0.083	-0.109	-0.064
	(0.318)	(0.286)	(1.474)	(0.737)	(0.139)	(0.154)	(0.073)	(0.071)
Centered Fall 2017 GPA	0.405	-0.211	3.988	-0.274	0.672	0.409	-0.331	-0.593
	(1.334)	(0.776)	(7.132)	(4.320)	(0.434)	(0.238)	(0.222)	(0.354)
Interaction	-0.188	0.844	-8.896	-0.534	0.680	1.068	0.503	1.619***
	(2.944)	(2.026)	(9.095)	(8.444)	(1.561)	(1.318)	(0.689)	(0.336)
Female	0.167	0.245	1.183*	1.167	0.065	0.103	0.050	0.003
	(0.142)	(0.122)	(0.494)	(0.587)	(0.086)	(0.065)	(0.087)	(0.092)
African American	-0.259	-0.175	-2.118	-2.263	0.100	0.080	-0.203*	-0.239*
	(0.273)	(0.248)	(1.330)	(1.281)	(0.154)	(0.148)	(0.098)	(0.099)
Other Race	0.211	0.326	1.751	1.659	0.049	0.088	0.132	0.097
	(0.258)	(0.243)	(1.224)	(0.834)	(0.124)	(0.146)	(0.109)	(0.109)
Standardized HS GPA	0.135**	0.088	0.535	0.362	0.035	0.029**	0.006	0.002
	(0.0519)	(0.049)	(0.385)	(0.400)	(0.022)	(0.011)	(0.050)	(0.030)
First Generation	-0.218	-0.266	-1.064	-1.220	-0.110	-0.141	-0.073	-0.101
	(0.297)	(0.202)	(1.264)	(0.830)	(0.113)	(0.095)	(0.108)	(0.062)
FAFSA Completed		0.239		2.673**		0.099*		0.144
		(0.153)		(0.735)		(0.039)		(0.098)
FAFSA Incomplete		0.323**		1.744		0.000		0.153
		(0.125)		(0.991)		(0.108)		(0.097)
Constant		1.959***		8.973***		0.606***		0.781***
		(0.230)		(1.265)		(0.094)		(0.093)
Observations	200	261	200	261	200	261	200	261

Notes: Standard errors in parentheses are clustered at the college level, (6 clusters). Other ethnicity includes Asian, Foreign, Hawaiian, Indian, Two or More, Hispanic, and not reported. Interaction, is the interaction between qualify and the recentered Fall 2017 GPA. All models are for a bandwidth of (+/- 0.25) *p<.10. **p<.05. ***p<.01.

Sample Expansion Including All Available Records

Finally, we attempt to address concerns about limited statistical power in our primary analyses by expanding the sample. Since a linear model could not adequately identify the relationship between fall 2017 GPA[27] and our outcomes of interest while simultaneously controlling for potential differences between students with fall 2017 GPAs far away from the cutoff as we expand our sample, we introduce higher order polynomial functions of fall 2017 GPA using the following quadratic model:[28]

$$\mathrm{Y_i} = \beta_0 + \beta_1 \mathrm{Qualify_i} + \beta_2 \mathrm{CenGPA_i} + \beta_3 (Qualify_i * CenGPA_i) + \beta_4 \mathrm{CenGPA_i^2} + \beta_5 \left(Qualify_i * CenGPA_i^2\right) + \beta_5 \boldsymbol{X_i'} + \varepsilon_\mathrm{i} \quad (4)$$

where $CenGPA^2{}_i$ represents a second-order polynomial function of the recentered GPA around the 2.0 cutoff, and the variables in equation (4) that overlap with those in equation (1) are defined similarly.

Table 9 shows estimates using model (4) on the effect of qualifying for the program on our outcomes of interest. The impact on spring 2018 GPA and spring 2018 credits increases in magnitude and is statistically significant compared to the results found in Table 2. In addition, as we add more flexibility to the model, the observed positive effect on the probability of being in

[27] The results for the linear model can be found in the Appendix Table A2.
[28] Upon visual inspection of the relationship between the outcome variables and the centered cutoff across the entire sample, we chose a more flexible model over a liner model. We refrain from using higher order polynomials following the work of Gelman & Imbens, (2017) and Cattaneo, Idrobo, & Titiunik, (2018).

good academic standing after the spring 2018 semester in our original estimates is no longer present. Lastly, the negative effect observed with fall 2018 enrollment becomes marginally significant.

Table 9

RDD Estimates Including All Available Records

	Spring 18 GPA			Spring 18 Accumulated Credits			Good Academic Standing			Fall 18 Enrollment		
	Original Estimates	Simple	Complex	Original Estimates	Simple	Complex	Original Estimates	Simple	Complex	Original Estimates	Simple	Complex
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Qualify	0.248	0.236**	0.231**	0.324	0.888	0.821*	0.131	0.002	-0.002	-0.109	-0.140*	-0.147**
	(0.318)	(0.063)	(0.068)	(1.474)	(0.442)	(0.388)	(0.139)	(0.060)	(0.057)	(0.073)	(0.058)	(0.056)
Centered Fall 2017 GPA	0.405	1.547**	1.477***	3.988	6.541***	6.009**	0.672	0.525***	0.497***	-0.331	-0.108	-0.136
	(1.334)	(0.397)	(0.346)	(7.132)	(1.575)	(1.661)	(0.434)	(0.081)	(0.060)	(0.222)	(0.093)	(0.083)
Interaction	-0.188	-0.725	-0.798	-8.896	-1.480	-1.514	0.680	0.426*	0.420**	0.503	0.402*	0.394
	(2.944)	(0.643)	(0.614)	(9.095)	(2.294)	(2.701)	(1.561)	(0.196)	(0.161)	(0.689)	(0.192)	(0.218)
Squared Centered Fall 2017 GPA		-1.678**	-1.668**		-8.140**	-8.000**		-0.251	-0.246**		0.325**	0.330**
		(0.548)	(0.575)		(2.346)	(2.662)		(0.126)	(0.091)		(0.095)	(0.108)
Squared Interaction		1.670**	1.622**		8.426***	8.137**		0.567***	0.556***		-0.312***	-0.328***
		(0.426)	(0.455)		(1.872)	(2.058)		(0.083)	(0.064)		(0.060)	(0.058)
Female			0.122			0.327			0.062			0.035
			(0.078)			(0.243)			(0.036)			(0.033)
African American			-0.087			-1.023*			-0.023			-0.073**
			(0.126)			(0.439)			(0.093)			(0.025)
Other Race			0.130			0.139			0.022			-0.037
			(0.183)			(0.488)			(0.070)			(0.048)
Standardized HS GPA			0.164*			0.763**			0.039*			0.030**
			(0.066)			(0.276)			(0.017)			(0.009)
First Generation			-0.176			-1.051**			-0.080*			-0.068*
			(0.101)			(0.348)			(0.032)			(0.027)
FAFSA Completed			-0.018			0.746*			0.046*			0.008
			(0.100)			(0.305)			(0.019)			(0.042)
FAFSA Incomplete			0.112			0.377			0.013			-0.001
			(0.085)			(0.734)			(0.052)			(0.070)
Observations	200	749	749	200	749	749	200	749	749	200	749	749

Notes: Standard errors in parentheses are clustered at the college level, (6 clusters). Other ethnicity includes Asian, Foreign, Hawaiian, Indian, Two or More, Hispanic, and not reported. Interaction is the interaction between qualifying and the recentered Fall 2017 GPA. *p<.10. **p<.05. ***p<.01.

Conclusion

Our study aims to understand the impacts of a university mentoring program developed to pair undergraduates on academic probation with peer mentors with the goal of improving academic performance and persistence. As more students enroll in higher education and fail to earn a degree, colleges and university are actively developing support services for these students. Students on academic probation are one group in need of support services to help them overcome their experienced challenges in academic and overall transition into collegiate life.

Overall, we do not find strong evidence indicating the BounceBack Mentoring program improved or harmed student academics. Undergraduates who qualified for the BounceBack Mentoring program do not perform any better or worse on spring 2018 GPA, spring 2018 accumulated credits, the probability of being on academic probation after the spring 2018 semester, or enrolling in fall 2018. However, after various sensitivity checks, we find suggestive but not conclusive evidence that qualifying for the program did increase spring 2018 GPA, but reduced the probability of persisting to their sophomore year. This could signify that our null results are indicative of low statistical power and not true effects.

Despite the lack of concrete evidence that the BounceBack Mentoring program improved academic outcomes, the suggestive positive effect on GPA is promising for colleges and universities considering implementing peer mentoring programs to improve the academic performance of students on academic probation. As institutions continue to develop mentoring programs with the hopes of addressing issues with student persistence, the evaluation of the programs' effectiveness is imperative if colleges and universities are going to close the gap between enrolling and earning a degree.

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Appendix

Table A1.

RDD Estimated Effects Using the Optimal Bandwidth

	Spring 18 GPA		Spring 18 Accumulated Credits		Good Academic Standing		Fall 18 Enrollment	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Qualify	0.210	0.300	-0.355	0.367	0.085	0.139	-0.117	-0.125
	(0.303)	(0.312)	(0.430)	(1.404)	(0.159)	(0.131)	(0.087)	(0.063)
Centered Fall 2017 GPA	0.276	0.896	1.057	5.813	0.560	0.762	-0.542	-0.242
	(1.345)	(1.631)	(6.845)	(8.224)	(0.321)	(0.444)	(0.437)	(0.281)
Interaction	0.592	-0.577	-3.359	-11.67	0.802	0.596	1.145	0.211
	(2.837)	(2.804)	(11.06)	(10.29)	(1.444)	(1.367)	(0.748)	(0.561)
Female		0.131		1.021**		0.057		0.040
		(0.146)		(0.383)		(0.085)		(0.085)
African American		-0.289		-2.227		0.097		-0.208*
		(0.280)		(1.293)		(0.152)		(0.098)
Other Race		0.172		1.606		0.038		0.127
		(0.262)		(1.170)		(0.126)		(0.106)
Standardized HS GPA		0.153**		0.608		0.038		0.010
		(0.059)		(0.403)		(0.022)		(0.048)
First Generation		-0.148		-0.808		-0.107		-0.058
		(0.254)		(1.070)		(0.103)		(0.098)
EFC - Less than $1		-0.158		-1.429*		-0.110		-0.173**
		(0.154)		(0.677)		(0.106)		(0.066)
EFC - Less than $2,095		-0.091		-1.520		-0.038		0.058
		(0.496)		(1.381)		(0.131)		(0.080)
EFC - Less than $5683		-0.218*		-1.847		-0.166		-0.076
		(0.091)		(1.022)		(0.121)		(0.141)
EFC - Less than $10,756		-0.021		-0.777		-0.137		-0.147
		(0.347)		(1.117)		(0.086)		(0.100)
EFC - Less than $17,389		-0.332		-2.930**		-0.105**		-0.185*
		(0.279)		(0.999)		(0.034)		(0.088)
EFC - Less than $26,040		-0.124		-1.412		0.038		-0.214
		(0.387)		(1.279)		(0.096)		(0.146)
EFC - Less than $39,072		0.095		-1.394		0.126		-0.041
		(0.099)		(0.935)		(0.066)		(0.106)
EFC - Less than $68,327		0.225		-1.125		0.060		0.035
		(0.279)		(0.725)		(0.080)		(0.064)
Observations	266	204	266	204	266	204	266	204

Notes: Standard errors in parentheses are clustered at the college level, (6 clusters). Interaction is the interaction between qualify and the recentered Fall 2017 GPA. All models are for a bandwidth of (+/- 0.269) *** p<0.01, ** p<0.05, * p<0.1

Table A2.

RDD Estimates Including All Available Records with a Linear Model

	Spring 18 GPA		Spring 18 Accumulated Credits		Good Academic Standing		Fall 18 Enrollment	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Qualify	0.100	0.118	0.044	0.074	-0.200***	-0.200***	-0.120	-0.121
	(0.086)	(0.090)	(0.434)	(0.443)	(0.042)	(0.039)	(0.064)	(0.071)
Centered Fall 2017 GPA	0.402	0.339	0.989	0.547	0.354***	0.328***	0.114	0.089
	(0.330)	(0.280)	(1.227)	(1.041)	(0.042)	(0.036)	(0.058)	(0.045)
Interaction	0.437	0.435	3.493*	3.669**	-0.046	-0.039	0.155*	0.163**
	(0.351)	(0.292)	(1.497)	(1.280)	(0.033)	(0.024)	(0.066)	(0.049)
Female		0.120		0.318		0.063		0.036
		(0.079)		(0.282)		(0.039)		(0.033)
African American		-0.084		-1.016*		-0.030		-0.074**
		(0.123)		(0.433)		(0.094)		(0.023)
Other Race		0.126		0.115		0.016		-0.037
		(0.176)		(0.460)		(0.070)		(0.048)
Standardized HS GPA		0.165*		0.767**		0.042**		0.030**
		(0.066)		(0.273)		(0.014)		(0.009)
First Generation		-0.179		-1.060**		-0.077*		-0.068*
		(0.098)		(0.331)		(0.032)		(0.028)
FAFSA Completed		-0.014		0.761*		0.041*		0.007
		(0.093)		(0.318)		(0.019)		(0.040)
FAFSA Incomplete		0.119		0.411		0.012		-0.002
		(0.075)		(0.686)		(0.056)		(0.073)
Constant	2.207***	2.182***	11.500***	11.050***	0.719***	0.678***	0.790***	0.795***
	(0.124)	(0.119)	(0.429)	(0.604)	(0.015)	(0.026)	(0.016)	(0.042)
Observations	749	749	749	749	749	749	749	749
R-squared	0.192	0.229	0.193	0.224	0.368	0.387	0.196	0.209

Notes: Standard errors in parentheses are clustered at the college level, (6 clusters). Other includes Asian, Foreign, Hawaiian, Indian, Two or More, Hispanic, and not reported. Interaction is the interaction between qualify and the recentered Fall 2017. *p<.10. **p<.05. ***p<.01.

Institutional review Board Approval Letter

UNIVERSITY OF ARKANSAS

To:	Jonathan Norman Mills GRAD 212
From:	Douglas James Adams, Chair IRB Committee
Date:	01/26/2018
Action:	**Exemption Granted**
Action Date:	01/26/2018
Protocol #:	1801095816
Study Title:	the Student Talent Enrichment Program (STEP) Peer Coaching Program

The above-referenced protocol has been determined to be exempt.

If you wish to make any modifications in the approved protocol that may affect the level of risk to your participants, you must seek approval prior to implementing those changes. All modifications must provide sufficient detail to assess the impact of the change.

If you have any questions or need any assistance from the IRB, please contact the IRB Coordinator at 109 MLKG Building, 5-2208, or irb@uark.edu.

cc: Malachi Akeem Nichols, Investigator

Chapter 3[29]

College Readiness, Student Expectations, and Success: The Role of Non-Cognitive Skills

Introduction

Since Gary Becker's groundbreaking work in 1962, *Investment in Human Capital: A Theoretical Analysis*, human capital investments have been evaluated for their monetary and non-monetary returns on those investments. In the U.S., the investment returns from higher education have consistently grown over time even as college costs have risen and the percentage of high school graduates enrolling in college has increased (Goldin & Katz, 2007; Oreopoulos & Petronijevic, 2013). However, the rate at which students graduate from college remains relatively flat. Shapiro and team (2012) estimate that the current U.S. population includes over 31 million adults who enrolled in college during the past 20 years but left before completing a degree. One reason for students electing not to complete a degree could be that something happened between the time the student enrolled in college and when he or she dropped out that caused another alternative to have a higher rate of return, such as a full-time employment offer at a higher wage or an unexpected change in family obligations. However, it is also possible that the initial enrollment decision was revealed to be suboptimal once the student had more complete information regarding the costs and benefits of a college degree. Also the reality of highly demanding coursework or unexpected educational expenses could also contribute to college drop-out rates.

The growing number of college non-completers is not entirely problematic. Previous studies have found positive returns for attending college, even for students who do not graduate (Greenstone & Looney, 2013). However, there is some public concern about the high level of

[29] This paper was co-authored with Gema Zamarro Rodriguez and Julie Trivitt

student loan debt and the perception that it is particularly burdensome for students who do not complete a degree (Tompor, 2017) and are then more likely to default on their student loans (Delisle, 2014).

Recognizing the value of a college degree, policy makers are encouraging institutions to design programs and tools to facilitate and inform students of their likelihood of success. Thus far, most of the interventions intended to help graduation rates such as, tutoring, remediation, and online information, have proven to be somewhat ineffective (Page & Scott-Clayton, 2016). In addition, the ineffectiveness of the programs evauated in Chapters 1 and 2 could suggest the traditional barriers to college success, such as academic ability and credit constraints, are no longer the only prominent barriers and administrators need better tools to identify and support students at risk of leaving college before graduation.

In this chapter, we explore the survey responses of over 1,100 undergraduate students majoring in business and engineering at the University of Arkansas. In addition to the usual academic performance data, cognitive ability measures, and demographics, our survey includes measures of non-cognitive skills and personality traits as well as student expectations about college success. The collection of self-reported expectations allows us to identify students' subjective expectations about their future success in college, whether these expectations are realistic, and to what extent non-cognitive skills are associated with these expectations. Moreover, we compare student's subjective expectations to their academic progress, given their demographic background and preparation at entrance. We identify students performing both below and above objective expectations and the non-cognitive skills related to their objective performance. We find that non-cognitive skills are associated with subjective expectations and objective performance in college, even after controlling for cognitive ability and time spent studying, but that the relationship among specific non-cognitive skills, academic expectations, and academic performance varies by discipline.

The remainder of this chapter is organized as follows: the next section reviews the relevant literature on non-cognitive skills, subjective expectations, and college success. We then discuss the data collection process and resulting dataset. Next, we lay out the empirical strategy for understanding the determinants of students' subjective expectations by predicting their expected academic performance based on their background and preparation at college entrance. We refer to them as "objective expectations" or "objective academic expectations". Then, we discuss student subjective expectations relative to their actual performance at the end of the first year and identify characteristics associated with having unrealistic subjective expectations and performing above (or below) what is objectively expected, based on their background and preparation at entrance. Finally, we discuss the implications of our results and present our conclusions.

The Evidence on Existing and Novel Predictors of College Success

Cognitive Skills, Non-Cognitive Skills, and College Outcomes

There is considerable recent research on the factors relevant in predicting college success, including socio-economic status, gender, family background, and cognitive ability (Richardson, Abraham & Bond, 2012; Poropat, 2009; Cheng, Hitt & Mills, 2013; Stephan et al., 2015; Kuh, Cruce, Shoup & Kinzie, 2008). In particular, cognitive ability is one of the most widely used metrics in predicting college achievement, often measured through high school grade point average (HSGPA), ACT, and SAT scores (Frey & Determan, 2004; Bettinger, Evans & Pope, 2013). More recently, however, researchers and policymakers have begun to explore other factors associated with college success in light of stagnating persistence rates despite increasing enrollment rates (Turner, 2004).

Another strand of research studies the predictive power of non-cognitive or character skills on desirable later life outcomes, beyond those of cognitive measures. Non-cognitive skills such as conscientiousness, neuroticism, and grit have been found to be associated with economic, academic and health outcomes (Lleras, 2008; Heckman, Stixrud & Urzua, 2006; Almlund et al., 2011). These effects have been measured at various stages of life including childhood (Heckman et al., 2013), adolescence (Duckworth & Quinn, 2009), adulthood (Borghans et al., 2008) and late adulthood (Jackson et al., 2015). Because of their inherent relevance to a variety of desirable outcomes and populations, this chapter contributes along with those analyzing their impacts of non-cognitive skills in a higher education setting.

The Big Five Personality traits: agreeableness, neuroticism, openness, extraversion, and conscientiousness, have become some of the most pertinent non-cognitive traits in predicting relevant life outcomes (Kyllonen et al., 2014; Conard, 2006). Conscientiousness, defined as how organized, efficient, and dutiful a person is, has been found to be an important determinant of success among the college population. In a sample of undergraduates at the University of California, Riverside, Wagnerman and Funder (2007) discovered that self-reported conscientiousness accounted for 18% of the variation in freshman year GPA and 37% of the variation in senior year GPA. Conard (2006) similarly found conscientiousness to be predictive of college GPA, course performance, and class attendance even after controlling for SAT scores in a sample of undergraduate students.

On the other hand, other Big Five Personality traits, such as neuroticism, the emotional instability of a student, and extraversion, the sociability of a student, are consistently shown to be negatively related with college outcomes, both inside and outside of the U.S. (Poropat, 2009; Burks et al., 2015; Komarraju, Karau & Schmeck, 2009; Chamorro-Premuzic & Furnham, 2003; O'Connor & Paunonen, 2007). However, the results are less clear for agreeableness defined as how trusting or cooperative a student is. In a sample of undergraduate students at the University of Minnesota, Morris, agreeableness was shown to be positively associated with graduating in both four and six years (Burks et al., 2015). Paradoxically, agreeableness has been shown to have no relationship with exam grades for students enrolled at the University of London (Chamorro-Premuzic & Furnham, 2003), but both positive and negatives relationships with GPA for both students inside and outside the U.S. (Komarraju, Karau & Schmeck, 2009; Poropat, 2009). Finally, although the literature on openness is relatively small, it also suggests possible positive associations with short-run outcomes such as course grades (Lounsbury et al., 2003).

Additionally, non-cognitive skills and attitudes, including grit and growth mindset, have been shown to be salient in predicting higher education academic outcomes. In a sample of undergraduates attending an ivy league college, Duckworth et al. (2007) found grit, defined as persistence in accomplishing long-term goals, to be associated with college GPA ($r=0.34$), even after controlling for SAT performance. Within a sample of freshmen attending Columbia University, growth mindset, the perception that one's ability is malleable and not fixed, was associated with higher intrinsic motivation, predicted a higher final course grade and more importantly, predicted grade improvement from the first exam to the final exam in a chemistry course (Grant & Dweck, 2003). Overall, the research highlights the relevance of non-cognitive skills in important college outcomes, but to our knowledge, the literature to date has not examined how the effect of these skills vary across sub-groups of the college student population.

Motivation, Subjective Expectations, and College Success

Additional research looks at students' college goals, expectations, and motivation (Hall & Sverdlik, 2016; Beattie, Laliberte & Oreopoulos, 2018; Komarraju, Karau & Schmeck, 2009; Clark & Schroth, 2010; Beattie, Laliberté, Michaud- Leclerc & Oreopoulos, 2017) and explores how well students perform in college based on past performance and how their own goals or subjective expectations set them up for success or failure. Only three studies, to our knowledge, look at the relationship between subjective academic expectations and subsequent performance.

Hall and Sverdlik (2016) look at the effects of a motivational intervention on subjective expectations for students in science, technology, engineering, or mathematics (STEM) majors. Intervention participants were given tools to help calibrate their subjective expectations, which were measured by students' reports of how well they expected to do at the university on a 1 to 10 Likert scale, as well as their expected GPA at the end of the current semester.[30] The results were somewhat paradoxical. Participants showed higher subjective expectations and optimism but lower actual GPAs than the control group. This finding, suggests that participants failed to match their higher subjective expectations after treatment to the requirements of their field of study.

Our study is more closely related to the work of Beattie, Laliberte, and Oreopoulos (2018) and the complementing work of Beattie, Laliberté, Michaud-Leclerc and Oreopoulos (2017) who studied the relationships among past performance, objective expected performance

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[30] Hall and Sverdlik (2016) collected an additional measure of subjective expectations measured by their expected GPA by the coming fall semester (i.e. cumulative GPA).

based on a student's background, student experiences, mental health, and non-cognitive skills in a sample of about 6,000 first-year college students studying economics in Canada. Their dataset, like ours, included information on high school academic performance, college performance, and non-cognitive skills, which the authors used to study the characteristics of "divers" and "thrivers." Divers were defined as students who, given their background, are expected to perform academically well but do not meet those objective expectations and thrivers are those who perform beyond their academic objective expectations, given their background and preparation. Beattie and coauthors (2018) find that divers are more likely to procrastinate and rate themselves as less conscientious. Thrivers spend more hours studying and have higher expectations for their GPA at the end of the current school year. While Beattie and coauthors (2017) find that thrivers are more likely to use university resources and divers often face personal issues beyond the issues experienced at the university.

Overall, there is scant literature on the relationship between subjective expectations and actual performance. However, since a student's subjective expectations of their future earnings influence their college enrollment decision (Anttanasio & Kauftmann, 2017; Anttanasio & Kauftmann, 2014) and high school persistence (Jensen, 2012), it is apparent that subjective expectations actively influence behavior. Since a student's subjective expectations about his ability and the difficulty of his degree program can play an essential role in preventing or rebounding from failure (Stinebrickner & Stinebrickner, 2012), we believe the pertinent issue of connecting subjective expectations and actual performance deserves more study. Our paper contributes to the field in three ways. First, we study how freshmen students form their subjective expectations of college success and to what extent non-cognitive skills are associated with such subjective expectations. Second, we expand the work of Hall and Sverdlik (2016) and

Beattie, Laliberte, and Oreopoulos (2018) to analyze the extent to which student subjective expectations are realistic or unrealistic given their current academic trajectory. Lastly, we complement the work of Beattie, Laliberte, and Oreopoulos (2018) by analyzing the relationship between non-cognitive skills and the variation of college performance above and below objective expectations, given student background and high school performance, in the context of U.S. students majoring in two different fields of study, business and engineering. These are all important contributions, given the heterogeneity of the student body across different fields of study and countries, and the importance of better understanding how a student's subjective expectations relate to actual performance and non-cognitive skills. Once the relationships are better understood, targeted interventions can be developed to promote college persistence and graduation.

Data

We collected data for this project from students majoring in business and engineering in the fall semester of 2016 at the University of Arkansas. Previous attempts at asking freshmen to voluntarily complete surveys were disappointing. To obtain a larger and more representative sample for this project, the online survey was part of a voluntary class assignment for extra credit[31] in the freshman business course (FBC) or the freshman engineering course (FEC), respectively. A total of 1,183 surveys were collected.[32] Survey results were combined with administrative records to get the outcomes of interest and relevant control variables. Eleven

[31] Students had to go through all of the questions and get a completion code to get credit for the assignment, although they were not required to answer any of the questions for class credit.
[32] We have a take-up rate of 23.8% for all first time degree-seeking freshmen, but a take-up rate of 47% for all freshmen enrolled in the college of business and college of engineering.

students were subsequently dropped from the sample for having a major other than business or engineering, giving us an analytic sample of 1,172 students.

Survey

Our survey was deployed during the 2016-2017 academic year and contains questions pertaining to the students' non-cognitive skills, their subjective expectations for their college career, and general background characteristics. Out of 217 total questions, on average 96% of questions received a response. The non-cognitive measures include conscientiousness, agreeableness, neuroticism, openness, and extraversion, which come from the Big Five Inventory of personality traits (John, Donahue & Kentile, 1991). Other non-cognitive measures collected include grit[33], growth mindset[34], and locus of control[35] (Duckworth & Quinn, 2009; Wellborn et al., 1989). These non-cognitive survey questions ask students to rate how well various statements describe themselves using variations of a five-point Likert-type scale (i.e., *Strongly Disagree, Disagree, Neither Agree or Disagree, Agree, Strongly Agree*). Each response was averaged to develop a total score for a given trait ranging from 1 to 5, with higher scores representing higher levels of that particular trait. Items were reverse coded when the statements are phrased to indicate a lack of that trait. We evaluate the reliability of each measure using Cronbach's alpha as can be seen in Appendix Table A.1 alongside more detailed information on all non-cognitive skills survey questions. The reliability of the measures ranged from 0.64 – 0.83 in business and 0.63 – 0.88 in engineering, compared to the acceptable standard of 0.70.

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[33] The grit scale used is the eight-item Grit-S scale modeled from Duckworth and Quinn (2009).
[34] The growth mindset scale used in a two-item scale modeled from the Education Longitudinal Study of 2002.
[35] The locus of control scale used is a six-item scale developed from the Students' Perception of Control Questionnaire (SPOCQ) (Wellborn et al., 1989).

Included in the survey are students' subjective expectations of their expected GPA at the completion of their college career, which is a key outcome of interest. The subjective expectation measure is the response to the following question from the survey, "What overall GPA do you predict to have by the time you finish your undergraduate education?" It is measured on a 0 to 4 scale.

In addition, the survey collected direct measures of cognitive ability through a Numeracy Ability Test (NAT) on a 0 to 8 scale (Lipkus, Samsa & Rimer, 2001) and a Cognitive Reflection Test (CRT) on a 0 to 5 scale (Toplak, West & Stanovich, 2014). The CRT is designed to measure a participant's ability to reflect on decisions before making them, i.e., critical thinking, while the Numeracy scale measures the ability to solve problems involving basic probability and mathematical concepts. We also incorporate a measure of study habits, assessed as the self-reported number of hours spent studying per week, ranging from 0 to 12 hours or more.[36] Finally, the survey includes questions covering student demographics such as gender, ethnicity, private school attendance, homeschool attendance, mother's education, and father's education.

Administrative Data

We link our survey data to student administrative records to gather information on our outcome variables of interest and additional controls, including students' end of freshman year cumulative grade point average or their May 2017 cumulative GPA (measured on a 0 to 4 scale). As a control for students' cognitive ability in some models, we use information on ACT scores and high school GPA (HSGPA), measured on a 0 to 36 scale and a 0 to 4 scale, respectively. We also collect information about students' high school location, allowing us to create regional state

[36] Hours spent studying is measured on a 1 to 5 point scale, where 1-5 represents 0-2 hours, 3-5 hours, 6-8 hours, 9-11 hours, and 12+ hours, respectively.

dummies to control for variation in high school quality that could affect HSGPA. In addition, we created dummy variables signifying if the student completed the survey before early progress grades. Early progress grades are designed to give students feedback on their academic performance while the semester is in progress and grades can still be improved, which could influence their reported subjective expectations on final college GPA. Lastly, we include a measure of total credit hours accumulated at the end of the first spring semester after starting school, which was May 2017.

Summary Statistics

Table 1 shows summary statistics for our sample of 1,172 college freshmen, by comparing the 684 students majoring in business to the 488 students majoring in engineering. Business students are less likely to be male but more likely to be white. Students majoring in engineering have significantly higher academic performance and cognitive ability, as seen by their higher HSGPAs, ACT, CRT and NAT scores.

Most students, over 88%, completed the survey before early progress grades were released, which reduces the potential bias in reported subjective expectations. In terms of college academics, business students have significantly lower end of freshman year GPAs, and subjective expected GPAs at graduation and fewer accumulated credit hours. Students in both majors report the same average amount of time spent studying per week.

Table 1
Summary Statistics of Student Characteristics and College Performance

	Business Students		**Engineering Students**		
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Diff.**
Demographics					
Male	0.59	0.49	0.71	0.46	-0.12***
White	0.78	0.41	0.73	0.44	0.05**
Black	0.05	0.21	0.03	0.16	0.02*
Hispanic	0.05	0.22	0.07	0.26	-0.02
Asian	0.03	0.16	0.06	0.25	-0.04***
Native American	0.01	0.09	0.00	0.05	0.01
Two or More	0.09	0.28	0.10	0.31	-0.02
HSGPA	3.54	0.35	3.87	0.37	-0.33***
ACT	24.60	2.71	28.65	4.01	-4.04***
Private School Attendance	0.35	0.48	0.32	0.47	0.04
Homeschool Attendance	0.03	0.17	0.05	0.23	-0.02**
Cognitive Reflection Test	0.81	0.99	1.86	1.52	-1.05***
Numeracy Ability Test	3.93	1.68	5.15	1.86	-1.23***

Table 1 (Cont.)

	Business Students		Engineering Students		
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Diff.**
Coll. Deg. Highest Edu - Mother	0.71	0.46	0.64	0.48	0.06**
Coll. Deg. Highest Edu - Father	0.70	0.46	0.63	0.48	0.07**
First Generation College Student	0.11	0.31	0.18	0.38	-0.07***
Survey Taken					
Before Early Progress Grades	0.80	0.40	1.00	0.00	-0.20***
College Academics					
Total Semesters	1.97	0.29	2.01	0.25	-0.04**
GPA - May 2017	3.07	0.68	3.25	0.76	-0.19***
Accumulated Credit Hours	26.21	6.51	27.40	5.88	-1.19***
Subjective Expected GPA	3.50	0.27	3.59	0.29	-0.09***
Study Hours Per Week	3.03	1.07	3.03	1.06	0.00

Notes: Std. Dev represents the standard deviation. Diff. represents the difference in means between business and engineering students. *** p<0.01, ** p<0.05, * p<0.1

Table 2 shows summary statistics for students' self-reported non-cognitive skills. There are no significant differences in reported levels of conscientiousness, agreeableness, neuroticism, or growth mindset between business and engineering students. Business students do report significantly lower levels of openness and grit than engineering students, while engineering students report significantly lower levels of extraversion and locus of control.

Table 2

Summary Statistics of Students' Non-Cognitive Skills

	Business Students				Engineering Students				
	Mean	**Std. Dev.**	**Alpha**	**Obs.**	**Mean**	**Std. Dev.**	**Alpha**	**Obs.**	**Diff.**
Conscientiousness	3.52	0.51	0.77	674	3.51	0.53	0.78	478	0.00
Agreeableness	3.77	0.47	0.73	674	3.72	0.51	0.75	478	0.04
Neuroticism	2.83	0.59	0.77	674	2.81	0.63	0.78	478	0.02
Openness	3.42	0.48	0.77	674	3.48	0.46	0.74	478	-0.06**
Extraversion	3.47	0.64	0.83	674	3.16	0.76	0.88	479	0.31***
Grit	3.19	0.46	0.65	669	3.24	0.52	0.74	474	-0.05*
Growth Mindset	3.97	0.59	0.69	668	3.91	0.57	0.63	469	0.06
Locus of Control	2.72	0.51	0.64	670	2.66	0.51	0.66	476	0.06*

Notes: Std. Dev represents the standard deviation. Diff. represents the difference in means between business and engineering students. *** p<0.01, ** p<0.05, * p<0.1

Pairwise correlations between the non-cognitive skills and the outcomes of interest are shown in Table 3. The top portion of Table 3 shows these correlations for business students and as expected conscientiousness, grit, and reported study hours are each positively correlated with both May 2017 cumulative GPA and subjective expectations. Smaller but significant positive and negative correlations are observed between May 2017 cumulative GPA and with agreeableness and extraversion, respectively. Surprisingly, locus of control has a small but negative correlation with both May 2017 cumulative GPA and subjective expectations. In contrast, we do not see similar patterns for engineers. Conscientiousness is the only measure that shows a positive and significant correlation with May 2017 cumulative GPA among engineers. Again, locus of control is shown to be negatively correlated with our outcomes of interest. Overall, these findings show the potential heterogeneous effects of non-cognitive skills across majors, which is a possibility we explore in our analysis.

Table 3

Pairwise Correlations between GPA, Subjective Final GPA, and Non-Cognitive Measures for Business and Engineering Students

	2	3	4	5	6	7	8	9	10	11	
1. GPA - May 2017	0.306*	0.246*	0.078*	-0.001	-0.137*	-0.082*	0.131*	0.034	-0.120*	0.121*	
2. Subjective Final GPA	1.000	0.195*	0.086*	-0.013	0.101*	0.115*	0.105*	0.086*	-0.039	0.126*	
3. Conscientiousness		1.000	0.353*	-0.236*	0.145*	0.106*	0.605*	0.169*	-0.345*	0.181*	
4. Agreeableness			1.000	-0.285*	0.195*	0.189*	0.252*	0.236*	-0.193*	0.068	
5. Neuroticism				1.000	0.074	-0.178*	-0.329*	-0.043	0.299*	-0.042	**Business**
6. Openness					1.000	0.246*	0.058	0.127*	-0.030	0.106*	
7. Extraversion						1.000	0.129*	0.043	-0.128*	0.084*	
8. Grit								0.119*	-0.321*	0.152*	
9. Growth Mindset								1.000	-0.117*	0.016	
10. Locus of Control									1.000	-0.027	
11. Study Hours Per Week										1.000	
1. GPA - May 2017	0.463*	0.125*	0.060	-0.044	0.016	-0.034	0.077	0.032	-0.100*	-0.020	
2. Subjective Final GPA	1.000	0.157*	0.086	-0.073	0.095*	0.041	0.078	0.066	-0.124*	-0.043	
3. Conscientiousness		1.000	0.333*	-0.237*	0.067	0.143*	0.647*	0.120*	-0.341*	0.171*	
4. Agreeableness			1.000	-0.272*	0.136*	0.218*	0.288*	0.173*	-0.218*	0.039	
5. Neuroticism				1.000	0.153*	-0.360*	-0.268*	-0.071	0.211*	0.019	**Engineering**
6. Openness					1.000	0.105*	0.046	0.149*	0.013	-0.006	
7. Extraversion						1.000	0.149*	0.097*	-0.037	0.172*	
8. Grit								0.042	-0.264*	0.226*	
9. Growth Mindset								1.000	-0.166*	-0.024	
10. Locus of Control									1.000	-0.006	
11. Study Hours Per Week										1.000	

Notes: * p<0.05 or better

Empirical Strategy

Subjective Expectations of college GPA at graduation

By examining our initial analysis, our goal is to identify how students form their subjective expectations about college success as they enter college. Students' subjective expectations could be influenced by past academic experiences in high school as well as non-cognitive skills that they possess and perceive to be relevant to reach their expectations. Because of the concerns of high correlation between grit and conscientiousness, as the literature has argued, grit could be a sub-factor of conscientiousness (Credé, Tynan & Harms, 2017). Therefore, we run separate models including either all five of the Big Five personality traits or "grit" using equations 1 and 2 shown below, respectively. In each equation, the non-cognitive and cognitive skills measures are standardized, to have mean zero and standard deviation one, to ease interpretation. Since business and engineering students appear to be different on the summary statistics presented above, we estimate separate models for each major with both following these linear regression models:

$$SubjGPA_i = \beta_0 + \beta_1 HSGPA_i + \beta_2 ACT_i + Big5_i' \beta_3 + \beta_4 GM_i + \beta_5 LOC_i + \beta_6 Num_i + \beta_7 CRT_i + X_i' \beta_8 + RegionDummies_i' \beta_9 + \varepsilon_i \quad (1)$$

$$SubjGPA_i = \beta_0 + \beta_1 HSGPA_i + \beta_2 ACT_i + \beta_3 Grit_i + \beta_4 GM_i + \beta_5 LOC_i + \beta_6 Num_i + \beta_7 CRT_i + X_i' \beta_8 + RegionDummies_i' \beta_9 + \varepsilon_i \quad (2)$$

where $SubjGPA_i$ is the reported subjective expected final GPA at graduation for student *i*, $HSPGA_i$ is their actual high school GPA, ACT_i is the ACT composite score, $Big5_i$ represents all five self-reported Big 5 personality traits, $Grit_i$ represents self-reported grit, GM_i represents self-reported growth-mindset, LOC_i represents self-reported locus of control, Num_i is the student's score on the numeracy ability test, CRT_i is the students's score on the cognitive reflection test, and X_i is a vector of student level characteristics including gender, ethnicity, taking the survey before early progress grades and two dummies indicating if the student's mother and father completed college. $RegionDummies_i$ is a vector of region level dummies indicating the state of high school attendance, and ε_i is an idiosyncratic error.

Expected Performance Based on Background Characteristics

In this analysis, our goal is to differentiate students performing below and above objective expectations. To accomplish this goal, we follow the methodology of Beattie, Laliberte, and Oreopoulos (2018) and classify students as meeting or not meeting their objective expected level of performance based on past academic performance and various student-level characteristics.

To identify students who are meeting or not meeting their objective expected level of performance, we regress their May 2017 cumulative GPA on the set of high school academic variables (i.e. ACT and HSGPA), demographic variables, regional dummies and background characteristics that have been found to be predictive of college GPA (Beattie, Laliberte & Oreopoulos, 2018; Cheng, Hitt & Mills, 2013; Geiser & Santelices, 2007; Kuh, et al., 2008), separately for each major using the following equation:

$$GPA_i = \beta_0 + \beta_1 HSGPA_i + \beta_2 ACT_i + \beta_3 Z_i + \beta_4 RegionDummies_i + \varepsilon_i \quad (3)$$

where GPA_i is the May 2017 cumulative GPA for student i and Z_i is a vector of student-level characteristics including gender, race, and two dummies indicating if the student's mother and father completed college. The variables in equation (3) that overlap with those in equations (1) and (2) are defined similarly.

Using the estimated coefficients from equation (3), student level residuals are computed and represent the amount of current academic performance not explained by past performance and student level characteristics. We standardize the estimated residual values to have mean zero and a standard deviation of one. Standardized residuals are then grouped into quartiles. Students in the bottom quartile of the standardized residuals are labeled as "Below Objective Academic Expectations," students in the top quartile are labeled as "Above Objective Academic Expectations," and students in the middle 50% of the distribution represent "Meeting Objective Academic Expectations."

Unrealistic Subjective Expectations

As a supplementary analysis to the investigation on students' subjective expectations described above, we study to what extent students' subjective expectations could be considered realistic by comparing their reported subjective expectations with their actual academic trajectory at the end of the freshman year. Because enough time has not elapsed since data collection during the 2016-2017 academic year, GPA at graduation is still unavailable. To overcome this limitation, we compare their subjective expectations of GPA at graduation to a projected final GPA that is a function of current performance and course load to determine to what extent their reported subjective expectations can be considered unrealistic.

To estimate projected final GPA at graduation given end of freshman year performance, we use data from about 15,000 freshmen across nine cohorts from 2004 to 2012 at the same institution from which our data were collected. [37] Using this data, we then run the following regression for business and engineering students separately:

$$FinalGPA_i = \beta_0 + \beta_1 GPA_i + \beta_2 Hours_i + \varepsilon_i \quad (4)$$

where $FinalGPA_i$ is the cumulative GPA at graduation for student *i*, *GPA* is the cumulative GPA at the end of freshman year for student *i* and $Hours_i$ is the total hours accumulated by the end of the freshman year. The estimated coefficients ($\widehat{\beta_0}, \widehat{\beta_1}$ and $\widehat{\beta_2}$) from equation (4) allow us to predict cumulative GPA at graduation for business and engineering students within our analytic sample. This predicted cumulative GPA at graduation would represent the final GPA for each student in our sample if they continue on the academic trajectory shown during freshman year. We then subtract this predicted cumulative GPA at graduation from the student's reported subjective GPA at graduation to result in a measure of unrealistic subjective expectations. Essentially, unrealistic subjective expectations are measured as the distance between what students report they are expecting as a final GPA and what trajectory their current academic achievement predicts them to be on. Positive numbers represent greater levels of unrealistic subjective expectations in final GPA at graduation and negative numbers capture an under confidence in their subjective expectations. For example, a student who has a subjective expectation of a 4.0 GPA upon graduation and a predicted GPA of 3.0 at graduation, given their freshman year performance, is considered to have a 1.0-unit of unrealistic subjective expectation.

[37] The data for each individual cohort contributes to the use of 4 and 6-year graduation rates and were the source of analysis for Cheng, Hitt and Mills (2013).

A student who has a subjective expectation of 2.0 GPA but has a predicted GPA at graduation of 3.0 would have -1.0 units of unrealistic subjective expectation, meaning that student is on track to meet (or surpass) his personal goal or subjective expectations.

Unrealistic Subjective Expectations and Non-cognitive Skills

Additionally, we explore what skills, traits, or actions are associated with the amount of unrealistic subjective expectations a student possesses. To evaluate this relationship, we estimate the following two equations separately for business and engineering students:

$$UnrealisticExp_i = \beta_0 + Big5_i'\beta_1 + \beta_2 GM_i + \beta_3 LOC_i + \beta_4 Num_i + \beta_5 CRT_i + \beta_6 HW_i + \varepsilon_i \quad (5)$$

$$UnrealisticExp_i = \beta_0 + \beta_1 Grit_i + \beta_2 GM_i + \beta_3 LOC_i + \beta_4 Num_i + \beta_5 CRT_i + \beta_6 HW_i + \varepsilon_i \quad (6)$$

where $UnrealisticExp_i$ represents the amount of unrealistic subjective expectations produced in the previous section and HW_i is the student's reported number of study hours per week. The variables in equations (5) and (6) that overlap with those in equations (1) and (2) are defined similarly.

Characteristics of Students Below and Above Objective Academic Expectations

Finally, we also study what non-cognitive skills characterize students performing below and above objective academic expectations, as estimated following the strategy presented above. To measure the association among various non-cognitive skills, cognitive skills, and student performance (above, below or at objective academic expectations) we use a set of multinomial logistic regression models shown below. In each equation, the non-cognitive and cognitive measures are standardized to ease interpretation (i.e., presented in terms of standard deviation changes).

$$P\left(Y = j_{\ 1,2,3} \middle| \, Noncogs + Cogs\right) = \ln\left(\frac{P(Y = j)}{P(Y = 2)}\right)$$

$$= \beta_0 + Big5_i'\beta_1 + \beta_2 GM_i + \beta_3 LOC_i + \beta_4 Num_i + \beta_5 CRT_i + \beta_6 HW_i + \varepsilon_i \quad (7)$$

$$P\left(Y = j_{\ 1,2,3} \middle| \, Noncogs + Cogs\right) = \ln\left(\frac{P(Y = j)}{P(Y = 2)}\right)$$

$$= \beta_0 + \beta_1 Grit_i + \beta_2 GM_i + \beta_3 LOC_i + \beta_4 Num_i + \beta_5 CRT_i + \beta_6 HW_i + \varepsilon_i \quad (8)$$

where Y takes value 1 if a student *i* is classified as performing below objective academic expectations at the end of the freshman year, given his/her high school performance and background, value 2 if the student is performing at objective academic expectations, and 3 if performing above objective academic expectations. $Big5_i$ represents self-reported Big 5 personality traits, $Grit_i$ represents self-reported grit scale, GM_i represents self-reported growth-mindsets, LOC_i represents self-reported locus of control, Num_i is the individual's score to the numeracy ability test, CRT_i is the individual's score to the cognitive reflection test, HW_i is the student's reported number of study hours per week and ε_i is the idiosyncratic error assumed to follow a logistic distribution.

We present estimated coefficients as relative odds ratios, which provide us with an estimate of the proportionate change in the probability of performing either above or below objective expectations relative to meeting objective expectations when the explanatory variable changes by one unit.

Results

Subjective Expectations on GPA at Graduation

Table 4 shows the relationship among a student's reported subjective expected GPA at graduation, past high school academic performance, and self-reported non-cognitive skills for business and engineering students separately. Overall, we observe that students both in business and engineering are coming into college with high initial reported subjective expectations. Across both business and engineering, the average student is reporting to expect a 3.6 and a 3.8 GPA at graduation, respectively, shown by the estimate of the constant. These high subjective expectations are found to increase with past high school academic performance as measured by HSGPA and ACT. For instance, across columns 1 through 5, in business, a one standard deviation increase in HSGPA and ACT score is associated with 0.040 to 0.043 point and a 0.062 to 0.066 point increases in subjective GPA at graduation, respectively. The estimates are even larger in engineering with effects for HSGPA and ACT scores ranging from 0.078 to 0.088 points and 0.075 to 0.085 points, respectively.

Table 4

The Relationship between Subjective Expectations, Cognitive Ability, and Non-cognitive Skills

	Business Students					**Engineering Students**				
	Subjective Expected GPA									
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
HSGPA	0.043***	0.041***	0.042***	0.040***	0.041***	0.088***	0.082***	0.081***	0.079***	0.078***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
ACT	0.062***	0.064***	0.065***	0.064***	0.066***	0.075***	0.082***	0.082***	0.085***	0.085***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.018)	(0.020)	(0.020)	(0.020)	(0.020)
Conscientiousness		0.037***	0.040***				0.030**	0.029**		
		(0.011)	(0.011)				(0.012)	(0.013)		
Agreeableness		-0.003	-0.005				0.007	0.007		
		(0.011)	(0.011)				(0.013)	(0.013)		
Neuroticism		-0.005	-0.009				-0.020	-0.019		
		(0.011)	(0.011)				(0.014)	(0.014)		
Openness		0.014	0.013				0.022*	0.023*		
		(0.010)	(0.010)				(0.013)	(0.012)		
Extraversion		0.018*	0.019*				0.008	0.009		
		(0.010)	(0.010)				(0.012)	(0.012)		
Grit				0.029***	0.029**				0.029**	0.025**
				(0.011)	(0.011)				(0.013)	(0.013)
Growth Mindset			0.018		0.021*			-0.006		0.001
			(0.011)		(0.011)			(0.013)		(0.013)
Locus of Control			0.018		0.010			-0.007		-0.014
			(0.012)		(0.012)			(0.013)		(0.012)

Table 4 (Cont.)

	Business Students					Engineering Students				
	Subjective Expected GPA									
z-scores	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Numeracy Ability Test		-0.015	-0.016	-0.012	-0.014		-0.018	-0.018	-0.018	-0.021
		(0.013)	(0.013)	(0.013)	(0.014)		(0.020)	(0.020)	(0.020)	(0.020)
Cognitive Reflection Test		0.013	0.014	0.014	0.015		0.011	0.010	0.015	0.016
		(0.012)	(0.012)	(0.012)	(0.012)		(0.016)	(0.017)	(0.017)	(0.017)
Constant	3.687***	3.596***	3.625***	3.641***	3.665***	3.829***	3.839***	3.837***	3.838***	3.833***
	(0.082)	(0.087)	(0.084)	(0.088)	(0.086)	(0.058)	(0.064)	(0.065)	(0.057)	(0.058)
Controls			Yes					Yes		
Observations	641	641	641	641	641	441	441	441	441	441
R-squared	0.196	0.229	0.235	0.209	0.215	0.312	0.344	0.345	0.323	0.325

Notes: Controls include gender dummies, ethnicity dummies, parental education levels, region dummies, and a before early progress grade dummy. Heteroskedasticity-robust standard errors in parentheses, explanatory variables are standardized to have a mean of zero and a standard deviation of one, and *** p<0.01, ** p<0.05, * p<0.1.

Further, estimates of the predictive power of our reported non-cognitive skills in predicting reported subjective GPA at graduation appear to be statistically significant. In business, reported conscientiousness, extraversion, grit and growth mindset, show significant positive associations. In column 3, a one standard deviation increase in conscientiousness is associated with a 0.04-point increase in reported subjective GPA at graduation. Similar patterns are seen in engineering. Conscientiousness, openness, and grit are all positively related to subjective expectations. For example, in column 10, a one standard deviation increase in grit is associated with a 0.025-point increase in reported subjective GPA at graduation. These results suggest students are forming their subjective expectations of GPA at graduation based on their academic experiences in high school and perceived non-cognitive skills. Students seem to recognize the importance of non-cognitive skills to succeed.

Objective Expected Performance Based on Background at College Entrance

Table 5 shows the regression results for the model presented in equation (3) of the relationship among end of the freshman year cumulative GPA, past high school academic performance, and background characteristics, for business and engineering students separately. This analysis studies students' actual GPA performance at the end of their freshman year and differentiates students performing below and above objective expectations. We then study the relationship between students' reported non-cognitive skills and the probability of each student performing at each of these levels.

High school GPA and ACT scores are significant predictors of May 2017 cumulative GPA across both samples. For instance, a one standard deviation increase in HSGPA is associated with a statistically significant 0.26-point increase in May 2017 cumulative GPA for students majoring in business and a 0.43-point increase for students majoring in engineering. Overall, student demographics and preparation at college entrance allow us to explain about 27% and 45% of the variation in May 2017 cumulative GPA for business and engineering students, respectively. This result is consistent with those found in previous literature (Kuh et al., 2008; Stephan et al., 2015).

Table 5

Objective Expected Performance Based on Background Characteristics

	Business Students	**Engineering Students**
	GPA - May 2017	
	(1)	(2)
HSGPA	0.264***	0.434***
	(0.034)	(0.050)
ACT	0.110***	0.086**
	(0.030)	(0.049)
Constant	3.124***	2.689***
	(0.304)	(0.252)
Controls	Yes	Yes
Observations	608	432
R-squared	0.268	0.453

Notes: Heteroskedasticity-robust standard errors in parentheses and *** p<0.01, ** p<0.05, * p<0.1. Controls include gender dummies, ethnicity dummies, parental education levels, and region dummies. Explanatory variables are standardized to have a mean of zero and a standard deviation of one.

Unrealistic Subjective Expectations on College GPA at Graduation

In this section, we study the relationship between students' reported subjective expectations of final college GPA at graduation and their expected actual GPA based on their observed May 2017 cumulative GPA. This evaluation allows us to get a better understanding of the degree to which students enter college with realistic (or unrealistic) expectations of their performance. Understanding students' expectations entering college is important because students with larger amounts of unrealistic subjective expectations would need to overcome the challenge of performing at their desired reported GPA at graduation.

We first estimate an equation for the relationship between objective cumulative GPA at the end of freshman year and final college GPA, based on data from 9 cohorts of students observed from freshman year to graduation during the years 2004 and 2012, as described in equation (4) above. Table 6 shows the estimated coefficients from the regression equation presented in model (4). The results from both business and engineering majors indicate that cumulative GPA at the end of the freshman year and the number of credit hours completed by then are significant predictors of actual college GPA at graduation, explaining almost 80% of the variation.

Table 6

Regression Analysis on Projected Final GPA

	Business Students	**Engineering Students**
	Final GPA	
	(1)	(2)
2nd Sem. Cumulative GPA	0.819***	0.841***
	(0.0122)	(0.0142)
Accumulated Credit Hours	0.0104***	0.00462**
	(0.00167)	(0.00195)
Constant	0.264***	0.306***

Table 6 (Cont.)

	Business Students	Engineering Students
	Final GPA	
	(1)	(2)
	(0.0342)	(0.0372)
Observations	2,593	2,193
R-squared	0.790	0.789

Notes: Heteroskedasticity-robust standard errors are presented in parentheses, explanatory variables are standardized to have a mean of zero and a standard deviation of one and *** p<0.01, ** p<0.05, * p<0.1

Using these regression coefficients, we predict expected objective GPA at graduation, given May 2017 cumulative GPA for students in our sample. Table 7 shows descriptive statistics for these projected college GPAs at graduation based on the estimated coefficients of model (4) presented earlier. We use these estimates to compare freshmen students' subjective college GPA at graduation with their objective predicted GPA, based on the actual performance at the end of their freshman year. This comparison allows us to study whether students hold realistic or unrealistic subjective expectations of their college success. To do so, we compute the difference of a student's reported subjective GPA at graduation and the projected expected actual GPA at graduation as the amount of unrealistic expectations and study the results for students in both majors and for all three objective freshman year performance categories identified above (i.e. students performing below objective expectations, meeting expectations or above objective expectations). In column 1 of Table 7, we observe business students performing below objective expectations are averaging over one point lower in projected objective college GPA compared to students performing above expectations. In column 3, those same students are found to have significantly larger amounts of unrealistic subjective expectations on their college GPA at graduation, averaging around one point of unrealistic expectations. This result means that students who are performing below expectations are reporting they expect to perform almost a full grade point better than their current performance would predict.

The second half of Table 7 shows a similar pattern for students majoring in engineering. Engineering students performing below objective expectations are projected to have a college GPA over a point lower at graduation and present higher amounts of unrealistic subjective expectations, compared to students performing above objective expectations.

Table 7
Projected Final GPA and Unrealistic Expectations

	Business Students			
	Projected GPA at Grad.		**Unrealistic Expectation**	
	(1)	(2)	(3)	(4)
	Mean	Std. Dev.	Mean	Std. Dev.
All	3.05	0.59	0.45	0.57
Meeting	3.16	0.42	0.34	0.42
Below	2.37	0.41	1.06	0.58
Above	3.50	0.26	0.07	0.30
Difference between Below and Above	-1.13***		0.99***	
	Engineering Students			
	Projected GPA at Grad.		**Unrealistic Expectation**	
	Mean	Std. Dev.	Mean	Std. Dev.
All	3.17	0.66	0.42	0.59
Meeting	3.28	0.55	0.33	0.47
Below	2.52	0.69	1.00	0.63
Above	3.57	0.32	0.06	0.30
Difference between Below and Above	-1.06***		0.95***	

Notes: Std. Dev represents the standard deviation. *** p<0.01, ** p<0.05, * p<0.1

Figures 1 and 2 show the distribution of unrealistic subjective expectations for business and engineering students, respectively. Even though all groups have some amount of unrealistic subjective expectations, students performing below objective expectations seem to have the highest levels of unrealistic subjective expectations and students above expectations seem to have the lowest levels. This finding suggests incoming freshmen, in general, may have overly optimistic subjective expectations about college performance. It is therefore important to study the characteristics and non-cognitive skills possessed by these students, whose freshman year performance does not meet their subjective expectations. If this level of optimism among students performing under objective expectations is not supplemented with the characteristics and non-cognitive skills displayed by students meeting or exceeding objective expectations, these students are likely to have a difficult time meeting their high subjective expectations in college.

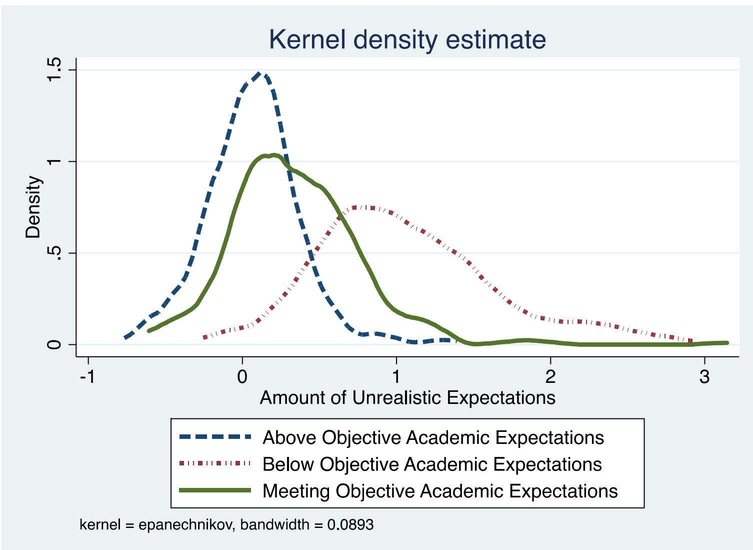

Figure 1: Distribution of Unrealistic Subjective Expectations for Business Students. This figure shows that students performing below objective academic expectations have the greatest levels of unrealistic expectations.

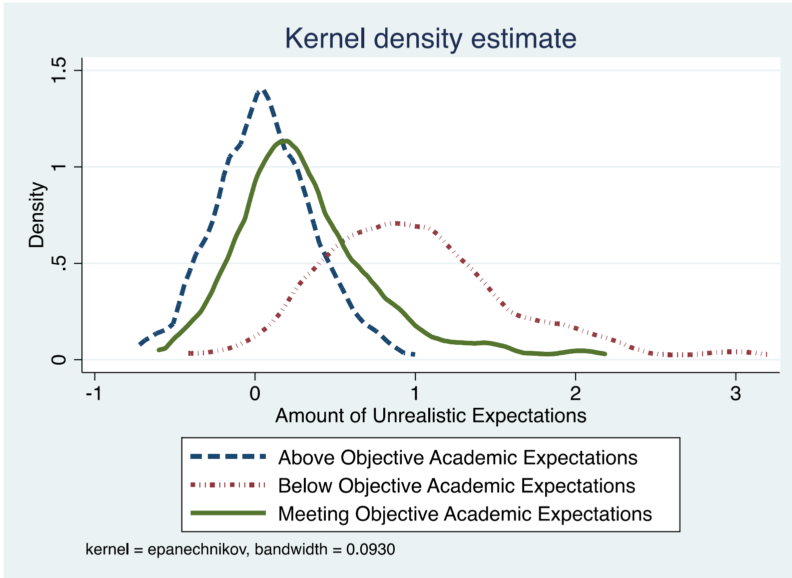

Figure 2: Distribution of Unrealistic Subjective Expectations for Engineering Students. This figure shows that students performing below objective academic expectations have the greatest levels of unrealistic expectations.

Unrealistic Subjective Expectations and Non-cognitive Skills

Table 8 shows the relationship among unrealistic subjective expectations, cognitive measures, non-cognitive skills, and study hours for business and engineering students. Evident within the table are the heterogeneous effects of non-cognitive skills across majors. For business students, as presented in column 3, a one standard deviation increase in conscientiousness and neuroticism is associated with a 0.09 and a 0.05 point decrease in the amount of unrealistic subjective expectations, respectively. Alternatively, increases in openness, extraversion, and locus of control are positively related to unrealistic subjective expectations. Turning to grit, a one standard deviation increase is associated with a 0.05-point decrease in the amount of unrealistic subjective expectation, as seen in column 4. The grit effect is no longer statistically significant, however, when we control for reported study hours per week. Lastly, scores on the numeracy ability test consistently show a negative relationship with unrealistic subjective expectations across all models. In contrast, for engineering students, not a single non-cognitive skill is statistically related to unrealistic subjective expectations. However, increases in the cognitive reflection test performance showed a consistent negative relationship with the amount of unrealistic subjective expectations.

Table 8

Relationship between Unrealistic Subjective Expectations, Cognitive Measures, Study Hours, and Non-Cognitive Skills

	Business Students						Engineering Students					
	Unrealistic Expectations											
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Conscientiousness	-0.109***	-0.098***	-0.093***				-0.045	-0.044	-0.042			
	(0.022)	(0.023)	(0.023)				(0.030)	(0.029)	(0.030)			
Agreeableness	-0.018	-0.017	-0.016				-0.007	-0.005	-0.005			
	(0.022)	(0.022)	(0.022)				(0.030)	(0.030)	(0.030)			
Neuroticism	-0.040*	-0.052**	-0.051**				0.000	0.004	0.006			
	(0.022)	(0.022)	(0.023)				(0.032)	(0.032)	(0.032)			
Openness	0.113***	0.106***	0.112***				0.027	0.019	0.019			
	(0.022)	(0.022)	(0.022)				(0.030)	(0.030)	(0.030)			
Extraversion	0.055**	0.057***	0.058***				0.032	0.029	0.032			
	(0.022)	(0.022)	(0.022)				(0.026)	(0.025)	(0.028)			
Grit				-0.052**	-0.043*	-0.039				-0.036	-0.034	-0.033
				(0.022)	(0.024)	(0.024)				(0.030)	(0.030)	(0.031)
Growth Mindset		0.018	0.015		0.023	0.023		0.001	0.000		0.003	0.003
		(0.021)	(0.021)		(0.022)	(0.022)		(0.026)	(0.026)		(0.027)	(0.027)
Locus of Control		0.040*	0.042*		0.040*	0.042*		-0.007	-0.006		0.001	0.001
		(0.022)	(0.022)		(0.022)	(0.022)		(0.030)	(0.030)		(0.028)	(0.028)
Numeracy Ability Test	-0.085***	-0.091***	-0.090***	-0.104***	-0.100***	-0.098***	-0.040	-0.031	-0.032	-0.034	-0.038	-0.038
	(0.025)	(0.026)	(0.026)	(0.026)	(0.027)	(0.027)	(0.042)	(0.042)	(0.042)	(0.041)	(0.042)	(0.041)

Table 8 (Cont.)

	Business Students						Engineering Students					
	Unrealistic Expectations											
z-scores	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Cognitive Reflection Test	0.017	0.028	0.025	0.029	0.031	0.028	-0.106***	-0.106***	-0.108***	-0.106***	-0.103***	-0.103***
	(0.025)	(0.024)	(0.024)	(0.026)	(0.026)	(0.026)	(0.037)	(0.038)	(0.038)	(0.037)	(0.037)	(0.038)
Study Hours Per Week			-0.036			-0.028			-0.012			-0.006
			(0.022)			(0.022)			(0.031)			(0.029)
Constant	0.444***	0.441***	0.443***	0.443***	0.442***	0.444***	0.424***	0.419***	0.419***	0.419***	0.419***	0.419***
	(0.021)	(0.021)	(0.021)	(0.022)	(0.022)	(0.022)	(0.027)	(0.027)	(0.027)	(0.026)	(0.027)	(0.027)
Observations	637	630	626	632	630	626	467	458	458	463	458	458
R-squared	0.103	0.109	0.114	0.033	0.039	0.042	0.063	0.055	0.055	0.051	0.051	0.051

Notes: Explanatory variables are standardized to have a mean of zero and a standard deviation of one, heteroskedasticity-robust standard errors in parentheses and *** p<0.01, ** p<0.05, * p<0.1

Characteristics of Students Below and Above Objective Academic Expectations

Finally, we study the characteristics of students who perform below and above objective expectations in their freshman year based on their background at college entrance. Tables 9 and 10 show the relative odds ratios of performing below or above objective expectations relative to meeting expectations for business and engineering majors, respectively. As can be seen in the tables, non-cognitive skills vary on their effect within major and across major. In column 5 of Table 9, a one-standard-deviation increase in conscientiousness decreases the relative odds of performing below expectations compared to meeting expectations by about 0.77 times for business students. Conversely, a one-standard-deviation increase in conscientiousness increases the relative odds of performing above expectations compared to meeting expectations by about 1.4 times, seen in column 6. Higher openness also increases the relative odds of performing below expectations, suggesting that students who are more imaginative and open to new ideas are more likely to underperform academically at the end of their freshman year in business. Similar patterns exist for grit. In Table 9, column 12, a one-standard-deviation increase in grit increases the relative odds of performing above rather than meeting expectations by about 1.2 times. Neither the cognitive measures nor study hours per week show relevance in predicting performance placement for business majors.

For engineering students, a different story emerges, as seen in Table 10. Only one non-cognitive measure shows relevance in characterizing student performance in engineering, extraversion. Being more outgoing or extraverted increases the relative odds of performing below expectations by about 1.2 times, seen in column 5. The only other consistent finding is the positive influence of the cognitive reflection test on meeting expectations versus performing below expectations. This result is important because of the negative relationship the cognitive reflection test has on the amount of unrealistic expectations seen in Table 8. These results imply that engineering students who critically think about their decisions are more successful in navigating college.

Table 9

Non-Cognitive and Cognitive Skills Associated with Students Performing Below and Above Objective Academic Expectations: Business

	Below Expectations	**Above Expectations**	**Below Expectations**	**Above Expectations**	**Below Expectations**	**Above Expectations**	**Below Expectations**	**Above Expectations**	**Below Expectations**	**Above Expectations**	**Below Expectations**	**Above Expectations**
z-scores	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Conscientiousness	0.770**	1.509***	0.761**	1.492***	0.773**	1.447***						
	(0.085)	(0.166)	(0.087)	(0.172)	(0.089)	(0.169)						
Agreeableness	0.966	1.028	0.953	1.006	0.960	1.013						
	(0.106)	(0.114)	(0.106)	(0.114)	(0.108)	(0.115)						
Neuroticism	0.886	1.063	0.891	1.059	0.899	1.072						
	(0.096)	(0.111)	(0.098)	(0.114)	(0.100)	(0.116)						
Openness	1.177	0.873	1.184	0.870	1.199*	0.857						
	(0.123)	(0.092)	(0.125)	(0.092)	(0.128)	(0.092)						
Extraversion	1.149	1.081	1.151	1.086	1.165	1.081						
	(0.122)	(0.110)	(0.122)	(0.111)	(0.125)	(0.111)						
Grit							0.901	1.302***	0.905	1.281**	0.920	1.247**
							(0.090)	(0.126)	(0.096)	(0.133)	(0.098)	(0.131)
Growth Mindset			1.018	1.102	1.002	1.103			1.007	1.107	0.998	1.104

Table 9 (Cont.)

	Below Expectations	Above Expectations	Below Expectations	Above Expectations	Below Expectations	Above Expectations	Below Expectations	Above Expectations	Below Expectations	Above Expectations	Below Expectations	Above Expectations
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
			(0.101)	(0.116)	(0.102)	(0.117)			(0.097)	(0.112)	(0.098)	(0.113)
Locus of Control			1.001	1.032	1.004	1.023			1.012	0.993	1.016	0.990
			(0.106)	(0.115)	(0.107)	(0.114)			(0.104)	(0.106)	(0.105)	(0.106)
Numeracy Ability Test	0.844	0.918	0.830	0.907	0.835	0.903	0.811*	0.940	0.815*	0.934	0.822*	0.926
	(0.097)	(0.111)	(0.0967)	(0.111)	(0.098)	(0.110)	(0.093)	(0.112)	(0.094)	(0.112)	(0.096)	(0.112)
Cognitive Reflection Test	0.989	1.092	1.001	1.106	0.989	1.115	1.002	1.089	1.002	1.093	0.989	1.102
	(0.117)	(0.122)	(0.119)	(0.124)	(0.118)	(0.125)	(0.117)	(0.121)	(0.117)	(0.122)	(0.116)	(0.123)
Study Hours Per Week					0.867	1.140					0.877	1.158
					(0.090)	(0.115)					(0.088)	(0.115)
Constant	0.390***	0.385***	0.397***	0.391***	0.397***	0.392***	0.412***	0.406***	0.414***	0.408***	0.414***	0.408***
	(0.039)	(0.039)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.041)	(0.040)	(0.041)	(0.041)
Observations	674	674	667	667	663	663	669	669	667	667	663	663

Notes: Explanatory variables are standardized to have a mean of zero and a standard deviation of one. Coefficients are relative odds ratios, standard errors in parentheses and *** p<0.01, ** p<0.05, * p<0.1

Table 10

Non-Cognitive and Cognitive Skills Associated with Students Performing Below and Above Objective Academic Expectations: Engineering

	Below Expectations	Above Expectations	Below Expectations	Above Expectations	Below Expectations	Above Expectations	Below Expectations	Above Expectations	Below Expectations	Above Expectations	Below Expectations	Above Expectations
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Conscientiousness	1.051	1.164	1.015	1.123	1.017	1.101						
	(0.134)	(0.146)	(0.134)	(0.147)	(0.136)	(0.146)						
Agreeableness	0.872	0.901	0.870	0.903	0.869	0.902						
	(0.112)	(0.115)	(0.113)	(0.117)	(0.113)	(0.117)						
Neuroticism	0.988	0.848	0.986	0.849	0.988	0.836						
	(0.132)	(0.113)	(0.133)	(0.114)	(0.134)	(0.114)						
Openness	0.920	1.082	0.928	1.098	0.927	1.101						
	(0.111)	(0.131)	(0.114)	(0.135)	(0.114)	(0.136)						
Extraversion	1.235*	1.012	1.242*	1.023	1.246*	0.996						
	(0.158)	(0.128)	(0.160)	(0.131)	(0.164)	(0.130)						
Grit							1.031	1.200	1.021	1.178	1.016	1.154
							(0.121)	(0.138)	(0.125)	(0.142)	(0.127)	(0.142)
Growth Mindset			1.050	0.983	1.050	0.989			1.040	0.999	1.040	1.002

Table 10 (Cont.)

	Below Expectations	Above Expectations	Below Expectations	Above Expectations	Below Expectations	Above Expectations	Below Expectations	Above Expectations	Below Expectations	Above Expectations	Below Expectations	Above Expectations
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
			(0.129)	(0.118)	(0.129)	(0.119)			(0.124)	(0.117)	(0.124)	(0.118)
Locus of Control			0.934	0.917	0.934	0.917			0.954	0.911	0.953	0.909
			(0.120)	(0.120)	(0.120)	(0.120)			(0.118)	(0.115)	(0.118)	(0.115)
Numeracy Ability Test	1.340*	1.194	1.232	1.113	1.233	1.121	1.293	1.168	1.221	1.109	1.223	1.115
	(0.219)	(0.197)	(0.211)	(0.192)	(0.212)	(0.193)	(0.214)	(0.194)	(0.209)	(0.189)	(0.209)	(0.191)
Cognitive Reflection Test	0.726**	1.003	0.738*	1.010	0.737*	1.026	0.723**	1.025	0.736*	1.036	0.739*	1.050
	(0.117)	(0.157)	(0.119)	(0.159)	(0.120)	(0.162)	(0.115)	(0.159)	(0.117)	(0.161)	(0.118)	(0.165)
Study Hours Per Week					0.990	1.127					1.024	1.103
					(0.122)	(0.138)					(0.124)	(0.133)
Constant	0.400***	0.403***	0.415***	0.418***	0.414***	0.415***	0.411***	0.410***	0.420***	0.419***	0.420***	0.417***
	(0.047)	(0.047)	(0.049)	(0.049)	(0.049)	(0.049)	(0.048)	(0.048)	(0.049)	(0.049)	(0.049)	(0.049)
Observations	478	478	469	469	469	469	474	474	469	469	469	469

Notes: Coefficients are relative odds ratios, standard errors in parentheses and *** p<0.01, ** p<0.05, * p<0.1

Robustness Checks

As a robustness check to the analysis performed on objective expectations, unrealistic expectations, and the characteristics of students below and above objective expectations, we estimated two additional specifications. In the first alternative specification, we define performing above objective expectations as being in the top 15% and performing below objective expectations as being in the bottom 15% of the residual distribution produced from equation (3), instead of considering the top and bottom quartiles as we did previously. In the second specification, we define performing above and below objective expectations as being in the top 5% and bottom 5% of the distribution, respectively.

For business students, we find little evidence of change in the interpretation of the results presented above using the first alternative specification. Students performing below expectations have the greatest amount of unrealistic expectations and the possession of conscientiousness and grit both increase the likelihood of performing above expectations. However, study hours per week gained significance in increasing the likelihood of performing above expectations. In the second alternative specification, the direction of the results discussed around unrealistic expectations and the characteristics of students performing above and below objective expectations remained unchanged, but are now non-distinguishable from zero. This lack of statistical significance found by the second specification could be explained by the small sample size located in the top and bottom 5% of the distribution.

For engineers, under both alternatives specifications for defining students performing above, below, and meeting objective expectations, the results from above remain qualitatively the same; however, various non-cognitive skills become statistically significant in both specifications. In the first alternative specification, agreeableness decreases your likelihood of performing below expectations, while students who are open to new experiences are more likely to perform above expectations. Similar to the findings for business students, an increase in study hours increases the chances of performing above expectations. In the second specification, openness remains a significant predictor of performing above expectations while neuroticism decreases those chances. Results for both specifications using the full models of equations (7) and (8) in business and engineering can be found in the Appendix Tables A.2 and A.3, respectively.

Conclusion

This chapter contributes to the literature on non-cognitive skills and college success in three ways. First, we try to understand what factors are related to students' subjective expectations of college success, whether those subjective expectations are realistic, given performance at the end of their freshman year, and whether non-cognitive skills are associated with these subjective expectations. Second, we study the extent to which students are performing above or below objective expectations, based on their previous performance and background, and whether or not they have realistic or unrealistic subjective expectations about their future performance. Lastly, we complement the work of Beattie, Laliberte, and Oreopoulos (2018) by analyzing the relationship between non-cognitive skills and a wide distribution of first-year college outcomes, but within the context of the U.S. and for both students majoring in business and engineering, compared to students majoring in economics in Canada.

Among the factors related to students' reported subjective GPA at graduation, we find that across both majors students' high school academic performance plays a big role in influencing the subjective expectations among freshmen students. In addition, through heterogeneous in their effects across majors, non-cognitive skills, such as conscientiousness and grit, are also found to be significantly associated with students' reported subjective GPA at graduation.

We then compare students' reported subjective GPA at graduation to their predicted objective GPA, given actual performance at the end of the freshman year, and build measures of unrealistic subjective expectations. Students performing below objective expectations have the greatest amounts of unrealistic subjective expectations on their GPA at graduation as compared to students meeting objective expectations and performing above objective expectations. These students average about a full grade point of idealistic expectations about their GPA. It appears that students on the cusp of being unsuccessful in college are the students with the greatest levels of unrealistic subjective expectations. To put this finding in perspective, let's take a student at the end of his freshman year who has a 2.0 GPA, 30 completed credit hours, projected to have a 2.0 GPA at the end of their college career, but expects to have a 3.0 GPA when he graduates. To overcome a grade point of unrealistic subjective expectations and to reach a 3.0 GPA at graduation, it will require this student to take at least 16 credit hours for each of the next two semesters and attaining 4.0 GPAs for both semesters. Once the 3.0 GPA is achieved, the student will have to maintain his performance for the rest of his college career to meet his desired subjective expectations. This task is daunting for students without the necessary non-cognitive skills.

How can we better help students achieve their ambitious goals? One possible intervention would be to partner with students in promoting the effort and non-cognitive skills, such as conscientiousness and time management, necessary to reaching their subjective expectations and succeeding in their respective fields (Hall & Sverdik, 2016). Thus it is imperative to identify and understand what skills are required to succeed in college.

Our results suggest there is no single pattern of non-cognitive skills that characterize students with large amounts of unrealistic subjective expectations or students performing below or above objective expectations in both fields of study. In addition, we corroborate results by Beattie, Laliberte, and Oreopoulos (2018) among business students. In this case, being more organized and reliable or conscientious is found to be significantly associated with lower amounts of unrealistic subjective expectations a student has and higher odds of performing above objective expectations. Similar patterns are observed for grit, or not giving up so easily, reduces the amount of unrealistic subjective expectations while increasing the odds of performing above objective expectations.

However, results are very different among engineering students. For our main specification in engineering, only a single non-cognitive skill identified students in either tail. Students who self-report higher levels of extraversion, have higher relative odds of performing below objective expectations. However, with a more restrictive definition of performing below and above objective expectations, greater levels of openness increased the odds of performing above expectations while increased neuroticism decreased those odds.

This lack of a consistent pattern may reflect self-selection of students into engineering and business, or they could be due to the differing requirements by major. The engineering college at the university requires all students to meet weekly with a peer mentor to cover the behaviors required (i.e., high school college transition, academic success strategies, and personal wellness) to achieve success in their respective engineering program. Mentoring could mask the influence of non-cognitive skills behind the influence of peer advice on how to be successful in engineering. For university administrators, this finding alludes to the need of analyzing groups of students separately to better identify the skills needed to help students achieve success within their respective degree fields. Therefore, the results we saw from previous work on economics students in Canada, by Beattie, Laliberte, and Oreopoulos (2018) and Beattie, Laliberté, Michaud- Leclerc, and Oreopoulos, (2017) might not fit all students in all fields.

We propose not to judge whether a student's subjective expectations are too high but to determine if their performance, attitudes, and non-cognitive skills can be developed to prepare them to reach those optimistic subjective expectations. For the reason that if this level of optimism among students performing under expectations is not combined with the levels of effort and non-cognitive skills required to meet or exceed expectations, these students may have a difficult time satisfying their high expectations in college.

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Appendix

Table A.1

Survey Questions of all Non-cognitive Skills

Construct	Introduction to Construct	Question	Likert-Scale	Alpha Business	Alpha Engineering	Authors
Conscientiousness	Here are a number of questions about yourself; there are no right or wrong answers. Please answer to the best of your ability. Indicate your level of agreement with the following statements:	1. I am someone who does a thorough job 2. I am someone who can be somewhat careless 3. I am someone who is a reliable worker 4. I am someone who tends to be disorganized 5. I am someone who tends to be lazy 6. I am someone who perseveres until the task is finished 7. I am someone who does things efficiently 8. I am someone who makes plans and follows through with them 9. I am someone who is easily distracted	(1) Strongly Disagree (2) Disagree (3) Neither Agree nor Disagree (4) Agree (5) Strongly Agree	0.77	0.78	John, Donahue and Kentile (1991)
Agreeableness		1. I am someone who tends to find fault with others 2. I am someone who is helpful and unselfish with others 3. I am someone who starts quarrels with others 4. I am someone who has a forgiving nature 5. I am someone who is generally trusting 6. I am someone who can be cold and aloof 7. I am someone who is considerate and kind to almost everyone 8. I am someone who is sometimes rude to others 9. I am someone who likes to cooperate with others		0.73	0.75	
Neuroticism		1. I am someone who is depressed, blue 2. I am someone who is relaxed, handles stress well 3. I am someone who can be tense 4. I am someone who worries a lot 5. I am someone who is emotionally stable, not easily upset 6. I am someone who can be moody 7. I am someone who prefers work that is routine 8. I am someone who gets nervous easily		0.77	0.78	
Openness		1. I am someone who is original, comes up with new ideas 2. I am someone who is curious about many different things 3. I am someone who is ingenious, a deep thinker 4. I am someone who has an active imagination 5. I am someone who is inventive 6. I am someone who values artistic, aesthetic experiences 7. I am someone who remains calm in tense situations 8. I am someone who likes to reflect, play with ideas 9. I am someone who has few artistic interests 10. I am someone who is sophisticated in art, music, or literature		0.77	0.74	

Table A.1 (Cont.)

					Alpha		
Construct	**Introduction to Construct**	**Question**		**Likert-Scale**	**Business**	**Engineering**	**Authors**
Extraversion		1. I am someone who is talkative 2. I am someone who is reserved 3. I am someone who is full of energy 4. I am someone who generates a lot of enthusiasm 5. I am someone who tends to be quiet	6. I am someone who has an assertive personality 7. I am someone who is sometimes shy, inhibited 8. I am someone who is outgoing, sociable		0.83	0.88	
Grit	On the following pages you will see a number of statements that may or may not apply to you. When responding, think of how you compare to most people -- not just the people you know well, but most people in the world. There are no right or wrong answers, so just answer honestly!	1. New Ideas and projects sometimes distract me from previous ones 2. Setbacks don't discourage me 3. I have been obsessed with a certain idea or project for a short time but later lost interest 4. I am a hard worker 5. I often set a goal but later choose to pursue a different one	6. I have difficulty maintaining my focus on projects that take more than a few months to complete 7. I finish whatever I begin 8. I am diligent	(1) Strongly Disagree (2) Disagree (3) Neither Agree nor Disagree (4) Agree (5) Strongly Agree	0.65	0.74	(Duckworth and Quinn, 2009)
Growth Mindset	Whether a person does well or poorly in college may depend on a lot of different things. In the questions that follow, you may feel that some of these things are easier for you to change than others. In college, how possible is it for you to change:	1. Being talented 2. Liking a subject 3. Your level of intelligence 4. Putting forth a lot of effort 5. Being attentive in class	6. How easily you give up	(1) Not at all possible to change (2) A little possible to change (3) Somewhat possible to change (4) Quite possible to change (5) Completely possible to change	0.69	0.63	Developed from from the Classroom Mindset from the Panorama Student Survey.
Locus of Control	How much do you agree or disagree with each of the following statements about yourself? Remember, this is not a test and there are no right or wrong answers:	1. Good luck is more important than hard work for success 2. Every time I try to get ahead, something or somebody stops me 3. Planning only makes a person unhappy since plans hardly ever work out anyway 4. People who accept their condition in life are happier than those who try to change things 5. I often feel like I don't have control over my life	6. When I make plans, I am almost certain I can make them work	(1) Strongly Disagree (2) Disagree (3) Neither Agree nor Disagree (4) Agree (5) Strongly Agree	0.64	0.66	Developed from the Students' Perception of Control Questionnaire (SPOCQ). Wellborn et al., (1989)

Table A.2

Non-Cognitive and Cognitive Skills Associated with Students Performing Below and Above Objective Academic Expectations: Business

	15%				5%			
	B.E	**A.E.**	**B.E**	**A.E**	**B.E**	**A.E**	**B.E**	**A.E**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Conscientiousness	0.651***	1.302*			0.598**	1.139		
	(0.089)	(0.176)			(0.131)	(0.245)		
Agreeableness	0.863	1.066			0.866	1.139		
	(0.114)	(0.143)			(0.182)	(0.244)		
Neuroticism	0.896	1.133			0.777	1.247		
	(0.118)	(0.143)			(0.168)	(0.261)		
Openness	1.410***	0.934			1.362	0.865		
	(0.179)	(0.118)			(0.274)	(0.175)		
Extraversion	1.127	0.897			1.111	1.121		
	(0.145)	(0.107)			(0.229)	(0.221)		
Grit			0.823	1.260*			0.804	1.064
			(0.105)	(0.157)			(0.165)	(0.214)
Growth Mindset	1.045	1.161	0.877	0.942	0.963	1.071	0.923	1.093
	(0.125)	(0.149)	(0.119)	(0.133)	(0.182)	(0.215)	(0.167)	(0.213)
Locus of Control	1.046	0.935	0.976	0.948	1.078	0.824	1.132	0.843
	(0.127)	(0.124)	(0.134)	(0.131)	(0.211)	(0.179)	(0.214)	(0.176)
Numeracy Ability Test	0.916	0.906	1.025	1.163	0.852	0.806	0.841	0.819
	(0.126)	(0.128)	(0.118)	(0.144)	(0.188)	(0.176)	(0.184)	(0.178)
Cognitive Reflection Test	0.960	0.960	1.103	0.972	1.283	0.825	1.273	0.828
	(0.135)	(0.133)	(0.130)	(0.123)	(0.268)	(0.208)	(0.260)	(0.207)
Study Hours Per Week	0.944	1.298**	0.953	1.295**	0.751	0.963	0.760	0.971
	(0.115)	(0.154)	(0.113)	(0.152)	(0.151)	(0.187)	(0.148)	(0.188)
Constant	0.168***	0.172***	0.185***	0.176***	0.041***	0.045***	0.046***	0.047***
	(0.021)	(0.021)	(0.022)	(0.021)	(0.009)	(0.009)	(0.009)	(0.009)
Observations	663	663	663	663	663	663	663	663

Notes: Explanatory variables are standardized to have a mean of zero and a standard deviation of one. Coefficients are relative odds ratios, standard errors in parentheses and B.E and A.E represent below expectations and above expectations, respectively.

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

Table A.3

Non-Cognitive and Cognitive Skills Associated with Students Performing Below and Above Objective Expectations: Engineering

	15%				5%			
	B.E	**A.E.**	**B.E**	**A.E**	**B.E**	**A.E**	**B.E**	**A.E**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Conscientiousness	0.871	0.914			0.851	0.747		
	(0.139)	(0.141)			(0.226)	(0.179)		
Agreeableness	0.705**	0.981			0.701	0.996		
	(0.108)	(0.152)			(0.178)	(0.248)		
Neuroticism	0.901	0.838			1.120	0.627*		
	(0.145)	(0.135)			(0.294)	(0.163)		
Openness	1.043	1.347**			0.970	1.797**		
	(0.153)	(0.201)			(0.232)	(0.469)		
Extraversion	1.250	1.008			1.264	0.769		
	(0.194)	(0.158)			(0.311)	(0.207)		
Grit			0.911	1.226			1.008	1.038
			(0.135)	(0.183)			(0.239)	(0.258)
Growth Mindset	1.145	0.878	1.110	0.926	1.250	0.989	1.189	1.138
	(0.171)	(0.123)	(0.159)	(0.126)	(0.314)	(0.244)	(0.284)	(0.265)
Locus of Control	0.924	1.071	0.993	1.143	0.668	1.090	0.762	1.210
	(0.137)	(0.163)	(0.145)	(0.168)	(0.165)	(0.268)	(0.190)	(0.275)
Numeracy Ability Test	1.272	1.243	1.236	1.198	1.134	1.431	1.105	1.312
	(0.261)	(0.256)	(0.252)	(0.241)	(0.376)	(0.494)	(0.358)	(0.441)
Cognitive Reflection Test	0.671**	0.836	0.692*	0.900	0.538*	0.518*	0.555*	0.606
	(0.132)	(0.160)	(0.132)	(0.169)	(0.178)	(0.174)	(0.178)	(0.197)
Study Hours Per Week	1.172	1.282*	1.192	1.218	0.675	1.076	0.670	0.978
	(0.171)	(0.185)	(0.169)	(0.173)	(0.170)	(0.263)	(0.167)	(0.231)
Constant	0.174***	0.177***	0.183***	0.180***	0.040***	0.038***	0.043***	0.046***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.012)	(0.011)	(0.011)	(0.011)
Observations	469	469	469	469	469	469	469	469

Notes: Explanatory variables are standardized to have a mean of zero and a standard deviation of one. Coefficients are relative odds ratios, standard errors in parentheses and B.E and A.E represent below expectations and above expectations, respectively.

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

Institutional Review Board Approval Letters

UNIVERSITY OF ARKANSAS

To:	Gema Zamarro Rodriguez BELL 4188
From:	Douglas James Adams, Chair IRB Committee
Date:	11/01/2018
Action:	**Expedited Approval**
Action Date:	10/29/2018
Protocol #:	1709067710R003
Study Title:	Validating Measures of Noncognitive Skills among Undergraduate Students
Expiration Date:	11/09/2019
Last Approval Date:	11/10/2018

The above-referenced protocol has been approved following expedited review by the IRB Committee that oversees research with human subjects.

If the research involves collaboration with another institution then the research cannot commence until the Committee receives written notification of approval from the collaborating institution's IRB.

It is the Principal Investigator's responsibility to obtain review and continued approval before the expiration date.

Protocols are approved for a maximum period of one year. You may not continue any research activity beyond the expiration date without Committee approval. Please submit continuation requests early enough to allow sufficient time for review. Failure to receive approval for continuation before the expiration date will result in the automatic suspension of the approval of this protocol. Information collected following suspension is unapproved research and cannot be reported or published as research data. If you do not wish continued approval, please notify the Committee of the study closure.

Adverse Events: Any serious or unexpected adverse event must be reported to the IRB Committee within 48 hours. All other adverse events should be reported within 10 working days.

Amendments: If you wish to change any aspect of this study, such as the procedures, the consent forms, study personnel, or number of participants, please submit an amendment to the IRB. All changes must be approved by the IRB Committee before they can be initiated.

You must maintain a research file for at least 3 years after completion of the study. This file should include all correspondence with the IRB Committee, original signed consent forms, and study data.

cc: Julie R Trivitt, Investigator
Kaitlin Anderson, Investigator
Mohammad Danish Shakeel, Investigator
Malachi Akeem Nichols, Investigator
Dillon S Fuchsman, Investigator

UNIVERSITY OF ARKANSAS

To:	Julie R Trivitt WCOB 402
From:	Chair, Douglas James Adams IRB Committee
Date:	11/07/2018
Action:	**Review Not Required**
Action Date:	11/07/2018
Protocol #:	1709073114
Study Title:	Profiles of Successful College Students and Best Predictors of College Success

Please keep this form for your records. Investigators are required to notify the IRB if any changes are made to the referenced study that may change the status of this determination. Please contact your IRB Administrator if you have any questions regarding this determination or future changes to this determination.

Conclusion

This dissertation looks at three components that could help promote college success for undergraduates students: access to need-based grants, access to peer mentors paired with first-year students on academic probation, and possessing non-cognitive skills such as conscientiousness and grit.

Chapter 1 rigorously evaluates a one-time, need-based grant awarded to low-income, but academically promising, undergraduate students with high amounts of unmet need, intended to encourage high grade performance and persistence. Despite previous findings suggesting that both federal and state-developed need-based grant programs encourage year-to-year persistence and academic performance and persistence, access to these particular need-based grants failed to positively influence GPA, accumulated credits, or sophomore year enrollment.

Chapter 1 is not without limitations despite the ability to estimate the effects of the STEP grant program using an experimental research design. First, the presented effects could be underpowered effects due to the relatively small sample size for an experimental research design. The presented null effects could be a statistical power issue and not true effects. Secondly, since the STEP grant program was produced on campus for a select group of students with specific characteristics, the estimated effects might not be generalizable to other universities.

Chapter 2 rigorously examines the BounceBack mentoring program where freshmen students on academic probation were assigned a peer mentor to help change their academic and non-academic behavior during their first semester on academic probation. I fail to find a distinguishable effect of the program on term GPA, accumulated credits, or the probability of returning to their second year of school. However, after various robustness checks, I paradoxically find suggestive evidence that the BounceBack program increased spring term GPA, but reduced the probability of students returning for their sophomore year of college. When compared to ten previous cohorts of first-year students on academic probation without adding supports, it seems that the BounceBack program has alleviated the previously seen adverse effects of the probability of returning to good academic standing, but as the cost of returning their sophomore year.

Chapter 2 suffers from three main limitations. First, since the regression discontinuity design produces estimates inside a limited bandwidth, the estimated effects of the mentoring program cannot be extrapolated to those outside of the specified bandwidth. Such design prevents the declaration of an effect of the entire program and only gives us the confidence of the effect on individuals in a limited bandwidth. Second, this chapter suffers from sample size concerns. The small size of the program, in addition to the use of a limited bandwidth, reduces statistical power and the precision of our estimates. Lastly, similar to the caveat of Chapter 1, due to the uniqueness of the University of Arkansas and the targeted student population, the estimated effects could lack generalizability to other higher education contexts.

Chapter 3 provides a descriptive look at the relationship among non-cognitive skills, objective academic expectations, subjective academic expectations, and student success. I find no single pattern of non-cognitive skills characterizing students performing below or above objective expectations across majors. However, those students who are performing below objective expectations possess the highest levels of unrealistic expectations about their future performance.

Chapter 3 is limited by the sole use of self-reported non-cognitive measures. Though these survey results are readily used and convenient, they are susceptible to potential biases such as students providing socially desirable answers or using varying reference groups (Duckworth & Yeagar, 2015). Additionally, the focus on a subset of college-going students limits the exportability of our results to the wider university population and other colleges and universities.

Despite the comprehensive set of limitations, Chapter 1 builds on the scant amount of literature devoted to campus-developed, need-based grant programs by evaluating a new need-based grant program using an experimental research design. Chapter 2 adds to the descriptive research of peer-mentoring effects on students on academic probation by being the first to rigorously research a peer-mentoring program for first-year students on academic probation. Chapter 3 expands our understanding of the relationship among non-cognitive skills, subjective expectations, and objective expectations in the context of undergraduates attending a public U.S. university.

Taking the contributions of literature together, this dissertation expands our understanding of the multifaceted nature of college success when placed inside of the context of each respective student group being educated in a higher education institution. “College success” is a vague term, especially when universities have various requirements for specific degree programs and student populations each with a prescribed definition of student success.

The goal is not to distill the various definitions of success into one definition. The goal is to continue to develop support programs with the intention of aligning student success with the continued creation, building, and execution of such programs. Being able to retain each student who enters the university will not emerge from a single program or a single tuition check. It will occur when the holistic approach of supporting the student academically by providing a group of peers to connect with, and by instilling the values of hard work, time management, and life balance.

References

Duckworth, A., and Yeager, D., (2015). Measurement matters assessing personal qualities other than cognitive ability for educational purposes. *Educational Researcher,* 44 (4), 237-251.